Teruaki Nanseki *Editor*

Agricultural Innovation in Asia

Efficiency, Welfare, and Technology

Springer

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Preface

Agriculture is an essential industry in our daily lives. It has the longest history among many industries and is an innovative industry. Smart farming and digital agriculture have recently become a hot issue in technological innovation. These technological innovations are important, but there are only one type of innovation in agriculture.

This book covers all kinds of innovations, such as product innovation, process innovation, marketing innovation, organizational innovation, institutional innovation, and technological innovation. Both definitions and types of innovation are discussed in the book. The major objective of this book is to demonstrate the impact of these innovations on agri-food systems and life in rural areas. Furthermore, the book provides empirical findings on factors affecting agricultural innovation implementation and smart farming technologies.

We began a research project on agricultural innovation in 2019. The project focuses not only on agricultural innovations in developed countries, including Japan and major EU countries, but also on agricultural innovation in developing countries in Asia. Our main research output on developed countries has been published as a book in Japanese whose title translates as "Agricultural Innovation in the Era of Digital & Genome Revolution" (Agriculture and Forestry Statistics Publishing Inc., editor: T. Nanseki).

Our main research output on both developing and developed countries in Asia is now published as this book in English titled "Agricultural Innovation in Asia: Efficiency, Welfare, and Technology." This new book mainly focuses on new technology adoption, the efficiency of agricultural production, and rural welfare and social innovations through institutional changes. These topics are closely related to innovation, including product, process, marketing, organizational, institutional, and technological innovation. Part I, II, and III of this book cover product and process innovation, marketing and organizational innovation, and social innovations through institutional changes, respectively. Part IV focuses on smart farming, which is closely related to agricultural innovation, particularly process innovation in agricultural production.

In the original research proposal, we had planned to conduct field surveys and workshops in the country of each author. Because of COVID-19, however, most of these plans have not been implemented on time. Despite these difficulties, our research team worked well as a team. A major reason for the success of this process may be that all the first authors of the chapters, except the editor, have received their doctoral degrees under my supervision.

We hope that this book will contribute to the development of agriculture, rural areas, and improving the living standards of farmers via income, household livelihood, and food security.

Fukuoka, Japan Teruaki Nanseki

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The editor gratefully acknowledges the financial support from the Japan Society for the Promotion of Science Grand-in-Aid for Scientific Research, KAKENHI (grant number: JP19H00960). Special thanks goes to Dr. Thi Ly Nguyen, a former researcher of the research project. She completed all required tasks and fully supported the editor. Thanks also goes to Dr. Yoshihiro Uenishi, Assistant Professor of the laboratory, and Dr. Jie Mi, researcher of the research project. They contributed to the finalization of the complete draft and publishing process.

Teruaki Nanseki

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Editor and Contributors

About the Editor

Professor Teruaki Nanseki was born in Okayama, Prefecture in Japan. His academic specialties are agricultural and farm management, and agricultural informatics. In 1991, he was conferred a doctorate in agronomy by Kyoto University. Both his bachelor's and master's degrees in agronomy were from Okayama University. He worked in the national research institutes for agriculture and food science for over 20 years. He has been a professor at Kyushu University since 2007. His research works cover not only theory, methods, and information system development in the major fields, but also their applications and practices in the real world. His first research topic focuses on the management of risk, information, and human resources of farms. The second topic examines the development and growth of both farms and agriculture. The third topic emphasizes on agricultural innovation, smart farming, and digital agriculture. These research topics are closely connected. He has been the president of the Japanese Society of Agricultural Informatics since 2019. Moreover, he was the president of the Japanese Society of Farm Management from 2014 to 2016.

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Agricultural Innovation and Its Impacts on Farming and Rural Welfare

Teruaki Nanseki and Thi Ly Nguyen

1 Innovation and Agricultural Innovation

1.1 Definition and Types of Innovation

The term innovation has attracted the attention of many scholars. Some of them mentioned this directly. One of the most well-known pioneers was Schumpeter, who influenced the theory of innovation (OECD, 2005). Innovation is defined as *the* "*Innovation or development combines factors in a new way or it consists in carrying out new combinations*" (Schumpeter, 1939, 1983). Thus, innovation is considered to be a component of economic growth. Schumpeter (1983) divided innovation into five types: new products (*a new good that consumers are not yet familiar with or a new quality of a good*), new methods of production that are *not yet tested adequately by the manufacturer,* new sources of supply of raw materials or half-manufactured goods, *irrespective of whether this source already exists or whether it has first to be created*, opening of new markets (*that is, a market into which the particular branch of manufacture of the country in question has not previously entered, whether or not this market has existed before*), and newly introducing or reorganizing any industry.

Rogers (1983) stated that "*an innovation is an idea, practice, or object perceived as new by an individual or other unit of adoption*" when he developed the theory of diffusion. The diffusion approach allows one to assess the impact of development programs on many aspects such as agriculture (Rogers, 1983).

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However, some scholars have not directly stated the definition of innovation; they have compared innovation with invention. For example, Fagerberg (2009) distinguished them as "*Invention is the first occurrence of an idea for a new product or process, while innovation is the first attempt to carry it out into practice*". The World Bank (2006) stated that "*invention culminates in the supply (creation) of knowledge, but innovation encompasses the factors affecting the demand for, and use of knowledge in novel and useful ways. The notion of novelty is fundamental to invention, but the notion of the process of creating local change, new to the user, is fundamental to innovation*". Additionally, innovation is considered the main source of output growth and productivity (OECD, 2005). Therefore, it is important to measure innovation and its contribution.

Recently, the OECD has developed a way to measure innovation by releasing four editions of the Manual on Guidelines for Collecting and Interpreting Innovation Data in 1992, 1997, 2005, and 2018. The first two editions focused on the measurement of innovation in technological development of new products and production techniques in firms. That is why, the definition of innovation was expressed through the definition of technological production innovation and technical process innovation as follows: "*A technological product innovation is the implementation/commercialisation of a product with improved performance characteristics such as to deliver objectively new or improved services to the consumer. Technological process innovation involves the implementation or adoption of new or significantly improved production or delivery methods. It may involve changes in equipment, human resources, working methods, or a combination of these*" (OECD, 1997). Moreover, innovation is not limited to a technological aspect but also a non-technological aspect. Therefore, the 2005 edition of the Manual expanded to a non-technological aspect, including marketing and organizational innovations. Therefore, OECD (2005) defined that "*An innovation is an implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations*" and suggested that we measure innovation across industries that include not only R&D intensive industries but also services sectors and low-technology manufacturing. Based on this definition and guidance, innovation can be measured across countries when it develops around the world (OECD, 2005). In particular, OECD (2005) pointed out that innovation must be implemented and might be new to the firm, new to the market, or new to the world. Some countries have applied this manual to measure innovation at the firm level, as shown by OECD (2009). However, the fourth version redefined it as "*An **innovation** is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)*" (OECD/Eurostat, 2018). Based on this definition, OECD/Eurostat (2018) suggested that data collection and measurement of innovation should be limited to the business enterprise sector, which is one of the four sectors in the System of National Accounts of the United Nations. The other three sectors are the general government, households, and non-profit institutions serving households to build an economy.

Table 1 Definitions and four types of innovation (OECD, 2005)

Type	Definition
Type 1: Product innovation	A product innovation is the introduction of a good or a service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics
Type 2: Process innovation	A process innovation is the implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software
Type 3: Marketing innovation	A marketing innovation is the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing
Type 4: Organizational innovation	An organizational innovation is the implementation of a new organizational method in the firm's business practices, workplace organization or external relations

The OECD (2005) divided innovation into four main types: product innovation, process innovation, marketing innovation, and organizational innovation, with the aim of measuring innovation across industries and countries (Table 1).

1.2 Definition and Types of Agricultural Innovation

Feder and Umali (1993) defined agricultural innovation as "*a technological factor that changes the production function and regarding which there exists some certainty, whether perceived or objective or both*". According to this definition, Feder and Umali (1993) reviewed the impact factors on the adoption of agricultural innovations in terms of single agricultural technology, such as high-yielding varieties, or in terms of a package of agricultural technologies, such as fertilizers, herbicides, and chemicals. Agricultural innovation usually refers to the agricultural technologies adopted by farms. This definition of agricultural innovation usually follows the diffusion term.

The diffusion process is the beginning of innovation, and it is important to spread the innovation to other farms (Feder & Umali, 1993). Rogers (1983) focused on the diffusion of technological innovation that enhances its adoption rate by understanding the characteristics of innovations in terms of potential adopters' perceptions. Rogers (1983) suggested that innovation has five characteristics. The first is *the relative advantage* that reflects the level at which potential adopters perceive an innovation better than existing ideas in terms of economic aspects, prominent social factors, convenience, and pleasure. *Compatibility* reflects the level at which

Table 2 Examples of specific innovations (Summarized from Toborn, 2011)

Embodied, exogenous innovations (EEI)	Packages of disembodied agronomic and managerial innovations (PDAM)
High yielding varieties	Conservation agriculture
GM crops	Integrated soil fertility management
Fertilizers	Integrated pest management
Pesticides	Rainwater harvesting
	Agroforestry
	Low external input technologies
	Sustainable agriculture

potential adopters perceive an innovation as suitable for their current values, background, and demands. *Complexity* represents the level of difficulty in understanding and using innovation. *Trialability* represents the level of innovation that can be attempted by using a restriction base. *Observability* reflects the visibility of others in the result of innovation. Diffusion is the way in which innovations spread through market or non-market channels from their very first implementation to different consumers, countries, regions, sectors, markets, and firms. Without diffusion, innovation has no economic impact (OECD, 2005). Using this definition, it can measure the factors associated with agricultural innovation adoption that contribute to increasing agricultural productivity.

Following Rogers (1983) definition of innovation, Toborn (2011) categorized agricultural innovation into two types: embodied and exogenous innovations (EEI) that qualify as continuous or semi-discontinuous innovations, and packages of disembodied agronomic and managerial innovations (PDAM) that are discontinuous (skill-intensive). Examples of specific innovations in each category are presented in Table 2. These two categories are typically combined in practice.

Toborn (2011) also suggested that in addition to these two types of agricultural innovations, extra categories could be included, such as organic farming and integrated livestock systems.

1.3 Innovation Approaches in Agriculture: Processess and Systems

Innovation approaches in agriculture show a relationship between investments in knowledge in terms of science and technology, and agricultural development at the national level (World Bank, 2006). Along with the development of agriculture, the World Bank (2006) showed that the approaches to supporting agricultural innovation changed from the National Agricultural Research System (NARS) in the 1980s to the agricultural knowledge and information system (AKIS) in the 1990s and identified the concept of innovation systems or agricultural innovation systems (AIS). These approaches to agricultural innovation can be classified into two models: linear and non-linear models, also called innovation systems or interactive models (Botha et al., 2014; World Bank, 2006), as shown in Table 3.

Firstly, the linear model or the traditional model of innovation is propounded by Arnold and Bell (2001) which reflects that "basic science leads to applied science, which causes innovations and wealth". In this model, an innovation process was followed in one of two ways, called "science push" and "market pull" with their scheme as represented in Fig. 1. There is a linear relationship between investment in research, development of agricultural technology, and its subsequent adoption.

The major driving factor of innovation is science, which creates new knowledge and technologies. This knowledge and technology can be transferred and adopted under various conditions (World Bank, 2006). This model can also be called the 'transfer of technology' model (World Bank, 2006). Therefore, the linear model is a one-way process, from the generation of knowledge to usage (Fig. 2). This view is the foundation of the NARS, which focuses on agricultural research by transferring technologies to foster technology adoption and productivity growth (World Bank, 2006). Therefore, reaching this goal depends on the internal capacity of the actors in the public sector, which are the national agricultural research organizations, agricultural universities, and extension services (World Bank, 2006). The actors and their roles in creating and transferring the technology are shown in Fig. 2. However, the main weakness of this approach is the lack of linkages between farmers as innovation users and other actors, such as national agricultural research organizations and agricultural universities, in creating innovation (Table 3) (Arnold & Bell, 2001; World Bank, 2006).

The innovation system was also defined by the World Bank (2006) as "*a network of organizations, enterprises, and individuals focused on bringing new products, processes, and new forms of organization into economic use, together with the institutions and policies that affect their behaviors and performance*". The major components of the innovation system were adapted from those of a national innovation system, as expressed by Arnold and Bell (2001), as shown in Fig. 3.

AKIS and AIS are considered non-linear models that focus on the links among the actors in the system to develop the innovation, especially the interaction between the technology users and the technology producers (Table 3). The flow of information among actors in these systems is two-way (Figs. 4 and 5). However, the difference between them is that AKIS focuses on how the technology is created and exchanged among the actors in the rural areas only, and less attention is paid to aspects such as the role of the market and the private sector in the system (World Bank, 2006). The actors and their relationships in the AKIS are shown in Fig. 4.

Additionally, AIS not only provides ways to transfer information that farmers can access from NARS and AKIS but also extends to wider areas that include all potential actors and sectors joined in innovation (World Bank, 2006). The actors and their relationships are summarized in Fig. 5.

Although the World Bank (2006) evaluated the AIS as untested in the agricultural sector (Table 3), it has been gradually developing in understanding, and organizing support for agricultural innovation (Klerks et al., 2012). Innovation is the result of a

Table 3 Approaches in agricultural innovation (Summarized from original source of World Bank, 2006)

Model/Approach	Definition	Strength	Limitations	Purpose	Actors
1. Linear					
National agricultural research system (NARS)	Focused development effort on strengthening research supply by providing infrastructure, capacity, management, and policy support at the national level	Creating agricultural science capacity and making improved varieties of major food staples available	Research is not explicitly linked to technology users and other actors	Planning capacity for agricultural research, technology development, and technology transfer	National agricultural research organization, agricultural universities or faculties of agriculture, extension services, and farmers
2. Non-linear					
2.1 Agricultural knowledge and information systems (AKIS)	Still focused on research supply but gave much more attention to links between research, education and extension and to identifying farmers' demand for new technologies	Recognizing that multiple sources of knowledge contribute to agricultural innovation and gives attention to developing channels of communication between them. Recognizing that education improves farmers' ability to engage in innovation process	Restricting to actors and processes in the rural environment and pay limited attention to the role of markets, the private sector, the enabling policy environment, and other disciplines/sectors	Strengthening communication and knowledge delivery services to people in the rural sector	National agricultural research organization, agricultural universities or faculties of agriculture, extension services, farmers, NGOs, and entrepreneurs in rural areas

(continued)

Table 3 (continued)

Model/Approach	Definition	Strength	Limitations	Purpose	Actors
2.2 Agricultural innovation system (AIS)	A network of organization, enterprises, and individuals focused on bringing new products, new processes, and new forms of organization into economic use, together with the institutions and policies that affect their behaviors and performance	A holistic way of strengthening the capacity to create, diffuse and use knowledge. Aside from knowledge and skills, capacity development includes the attitudes and practices that influence the way organizations deal with knowledge, learning, and innovation and the patterns of relationships and interactions that exist between different organizations	Untested in the agricultural sector. Being difficult to diagnose the interactions and institutional dimensions of innovation capacity from analysis of published data sources. Less emphasis is placed on education	Strengthening the capacity to innovate throughout the agricultural production and marketing system	Potentially all actors in the public and private sectors involved in the creation, diffusion, adaption, and use of all types of knowledge relevant to agricultural production and marketing

(continued)

Table 3 (continued)

Model/Approach	Outcome	Organizing principle	Mechanism for innovation	Role of policy	Original sources
1. Linear					
National agricultural research system (NARS)	Technology invention and technology transfer	Using science to create inventions	Transfer of technology	Resource allocation, priority setting	World Bank (2006)
2. Non-linear					
2.1 Agricultural knowledge and information systems (AKIS)	Technology adoption and innovation in agricultural production	Accessing agricultural knowledge	Interactive learning	Enabling framework	World Bank (2006)
2.2 Agricultural innovation system (AIS)	Combinations of technological and institutional innovations throughout the production, marketing, policy research, and enterprise domains	New uses of knowledge for social and economic change	Interactive learning	Integrated component and enabling framework	World Bank (2006)

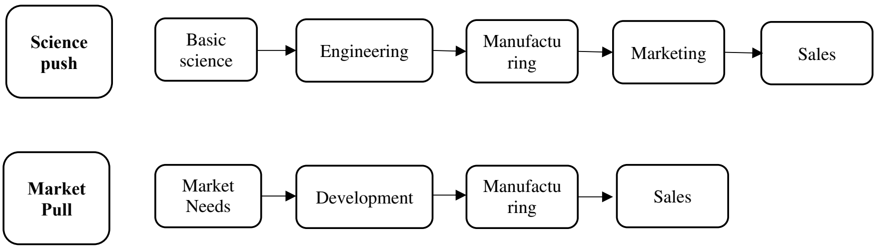

Fig. 1 Linear models of innovation (Summarized from Arnold & Bell, 2001)

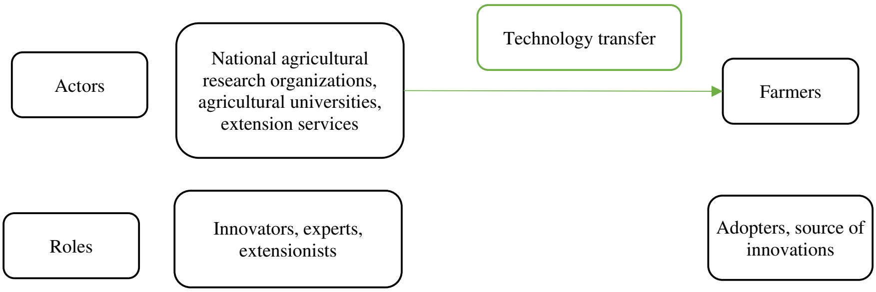

Fig. 2 Actors and their roles and relationships in NARS (Summarized from Klerks et al., 2012; World Bank, 2006)

process of networking and interactive learning among a heterogeneous set of actors, including farmers, input suppliers, processors, traders, researchers, extensionists, government officials, and civil society organizations (Botha et al., 2014; Klerkx et al., 2010). Therefore, agricultural innovation is not just about new technologies but also about institutional change, as shown in Fig. 5.

Moreover, Klerks et al. (2012) noted that these approaches are not necessarily mutually exclusive, and some are consecutively fed into each other. Moreover, in each approach, although the role of farmers was changing with them becoming more active and involved in the innovation process, the primary role of adopters of any agricultural innovation is not changing. However, to the best of our limited knowledge, we believe that discussion on the role of these approaches in agricultural innovation in developing countries is limited.

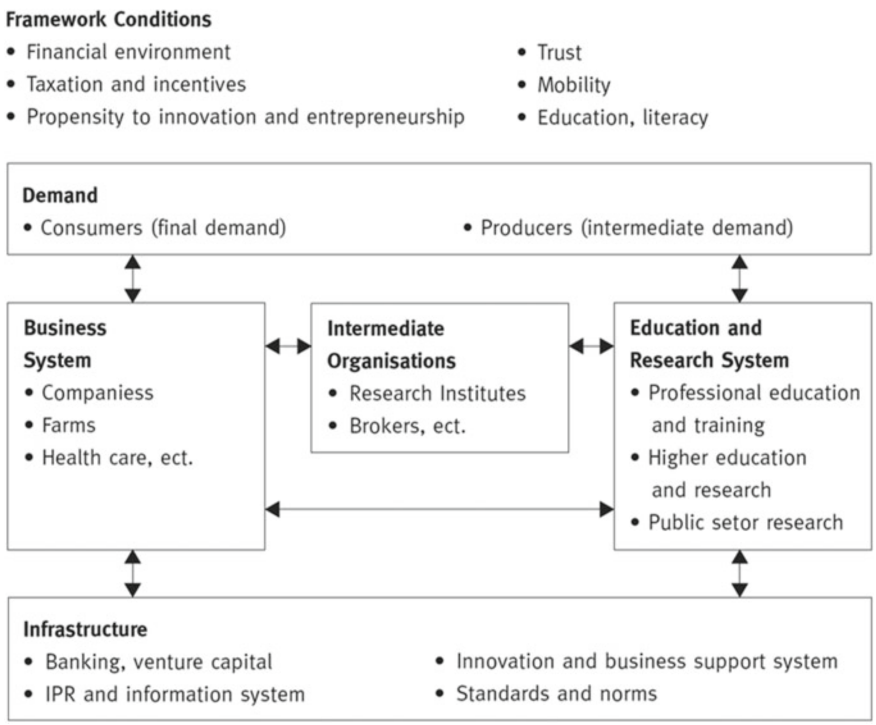

Fig. 3 Major components of a National Innovation System (Reproduced from Arnold & Bell, 2001; World Bank, 2006)

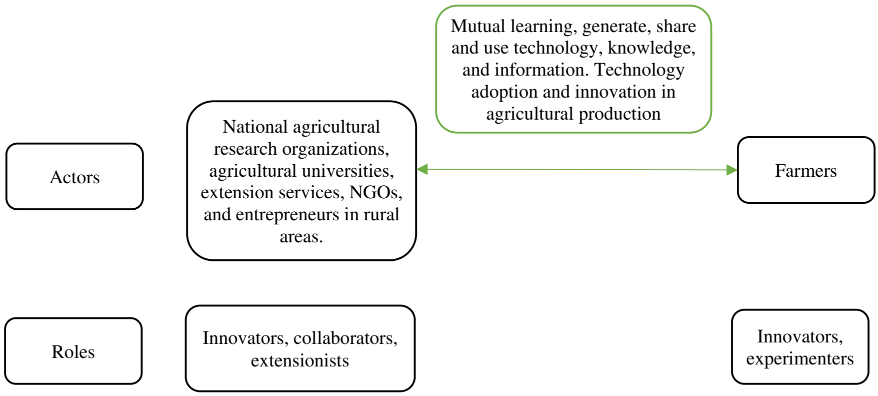

Fig. 4 Actors and their roles and relationships in AKIS (Summarized from Klerks et al., 2012; World Bank, 2006)

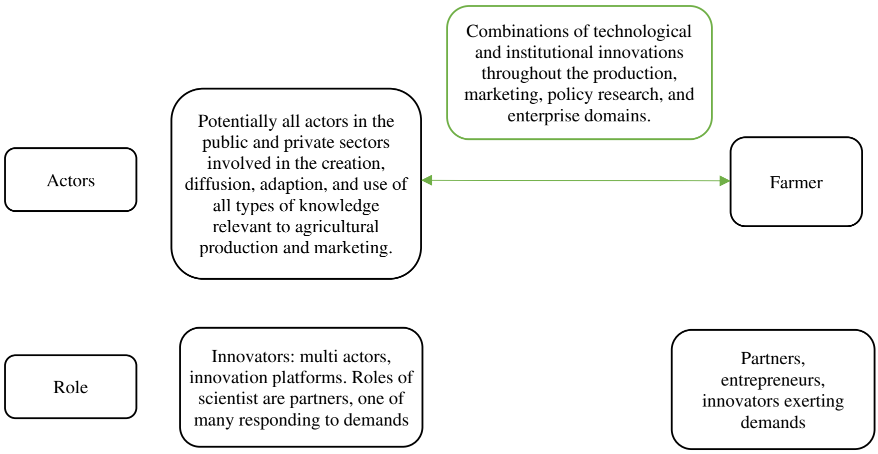

Fig. 5 Actors and their relationships in AIS (Summarized from Klerks et al., 2012; World Bank, 2006)

1.4 *Type of Agricultural Innovations and Examples in the Book*

In this book, we aimed to measure the factors associated with the types of agricultural innovations, as well as the impacts of those innovations on a variety of aspects such as production, economics, and social welfare in Asian countries, where the economies still depend heavily on agriculture. As discussed above, the OECD (2005) attempted to focus on measuring the impact of innovation on economic growth and classified innovation into four types: product, process, marketing, and organizational innovations. Therefore, in this book, we followed the definition of the OECD (2005) and its categorization. Additionally, product and process innovations are combined into technological innovation, whereas the rest are called non-technological innovations. However, along with the emergence of concepts of agricultural sustainability, the OECD (2001) supposed that technologies with a loose definition covered farm management practices. At that time, a wide range of sustainable agricultural technologies could be subsumed under this definition "*from simple to sophisticated, and from conventional farming technologies to organic, integrated, and precision farming*". These technologies are not only focused on the improvement of agricultural productivity, but also on the improvement of environments such as organics, good agriculture practices (GAP), and integrated livestock systems. Toborn (2011) suggested that these new technologies can be classified into a new category of innovation. However, in our book, with a target to know how agricultural innovations impacted agricultural performance, not only production and economics, but also the practices that farmers adopted to care for the environment were examined. The first category of agricultural innovation in this book is product and process innovation, as

Table 4 Types of agricultural innovations and examples in the book

Product and Process innovation	Marketing and organizational innovation	Social innovations by institutional changes and rural welfare
Organic rice farming	Maize Production groups	Microfinance program
GAP in crop production (tea)	Farmer groups in oil palm production	Dietary diversity on perceived food security
GAP in livestock production (Good Animal Husbandry Practices in pig production)	Traceability system of dairy product	Smart farming
Irrigation, mechanization, and subsidies in wheat production	Smart farming	
Information sources in crop production		
Smart farming		

shown in Table 4. This category covered organic rice farming, GAP in crop production (tea GAP), livestock production (good animal husbandry practices (GAHP) in pig production), irrigation, mechanization, subsidies in wheat production, and information sources in crop production. Smart farming has multidimensional impacts on farming and rural societies because of the nature of information and communication technology (ICT). Smart farming is an important driving force of all types of innovations, especially process innovation in farming. The traceability system of agricultural products can be considered part of smart farming. Thus, smart farming can also be a driving force in marketing innovation. Examples are provided in this book.

According to the OECD (2005), innovation in terms of technologies improves economic growth and innovation in terms of non-technologies. Organizations founded by farmers have shown their role in supporting farmers in improving their production. Therefore, in this book, such organizations are discussed with their special roles in marketing activities as well as organizing farmers to classify them as marketing and organizational innovations. This category focused on analyzing the maize production groups and farmer groups, as well as the traceability system of dairy products that are expected to create new market segments (Table 4).

As shown in Sect. 1.3, agricultural innovation approaches have been developed along with the development of agriculture. In this context, the development of agriculture in contexts with dramatic changes is driven by the development of agriculture, knowledge created and diffused by the private sector, and domestic agriculture developed more along with a globalized setting requiring changes in innovations (World Bank, 2006). Institutional context effects on agricultural innovation have been shown, such as Klerkx et al. (2010), who pointed out that changing institutional policy will support both technological and non- technological innovation (organizational innovation). In the book, we followed the definition of Hall et al. (2001) who defined institutions, which are a combined environment of "*the rules of the game that* *reduce uncertainty in human interaction or in other words as social rules and norms*" (North, 1990; Röling, 2009) and physical organizations and the interaction among them. The first part refers to things in terms of the sociological aspect that reflects the characteristics of behavior, including routines, norms, shared expectations, and morals (Edquist, 1997). Therefore, social innovations by institutional changes are "*the evolution and dynamic interaction between rules and norms and organizations, usually associated with the need to perform a new task or to perform an existing one differently*" (Hall et al., 2001). As a result, recent agricultural innovation is not only about new technologies but also about social and institutional change (Kilelu et al., 2013; Klerks et al., 2012; Röling, 2009; World Bank, 2006). Therefore, the third category of agricultural innovation analyzed in this book is social innovation by institutional changes and social welfare. It covered the dietary diversity on perceived food security, which showed that changes in the institutional context affected rural welfare in terms of food security and the micro finance program, which is a new institution, or a new social innovation significantly contributing to household welfare and adoption of technology innovation (Table 4). This category is expanded from the four types of innovation classified by the OECD (2005). The OECD (2005) focused on measuring the innovation of "unit" or individual farms. However, as shown above, agricultural innovation goes beyond new technologies rather than social innovations through institutional changes. Moreover, social innovations due to institutional changes have received less attention. Solis-Navarrete et al. (2021) also suggested that the definition and types of innovation of the OECD (2005) should be considered to include social, and other types of innovation. Therefore, this book attempts to cover them in the third category.

2 Measuring of Agricultural Innovation

In this book, innovation is categorized into five groups. These are product innovation, process innovation, marketing innovation, organizational innovation, and social innovations by institutional changes. How can they be measured?

Innovation is considered the main source for improving agricultural productivity, using better resource allocation, and enhancing income. The OECD (2013) indicated that the impact of innovation on firms can be measured in terms of changes in sales, market share, productivity, and efficiency. Additional indicators of innovation outcomes can be obtained through qualitative questions regarding the effects of innovation. However, in the agricultural sector, innovation at the farm level could involve specific techniques, such as new fertilizers, hybrid seeds, or production methods such as organic farming. Therefore, measuring the impact of agricultural innovation is complicated.

Ogundari and Bolarinwa (2018) reviewed the impacts of agricultural innovation globally and classified them into three groups: (1) agricultural production (farm yield, number of produced quantities, technical efficiency); (2) economic outcomes (farm income, agricultural sales amount, and farm profit); and (3) social outcomes (farm consumption, poverty, food security, child nutrition, nutrient intake, and dietary diversity). The first and second groups are considered to be the impact of innovation in terms of the agricultural economic view, and the third group is the impact of innovation in terms of the social view, as shown in this book. Moreover, the impacts on production can be listed as indicators related to changes in the amounts of physical inputs or physical outputs of a production function. The impacts on economics can be listed as outcomes in terms of value, which are due to changes in the prices of inputs and outputs.

In addition, by measuring the impact of each innovation on the outcome variables, especially product and process agricultural innovations, the determinants of these innovations are usually estimated using various approaches. For example, Nguyen et al. (2021) used the probit model to identify the determinants of product innovation implementation in Japanese agricultural corporations in Chap. 15, and Mi et al. (2021) estimated the factors associated with information and communication technologies, and smart farming technologies of agricultural corporations in Japan in Chap. 14 using a negative binomial model. Some factors have been found to increase the probability of adoption of these innovations, such as determined annual sales and the determined target in sales and profit margins (Nguyen et al., 2021). Factors contributing to an increase in the density adoption of technologies were identified, such as corporate forms, eligibility to own farmland, sales targets, profit targets, main product, self-evaluation of ICT utilization and information management, and the educational background of representatives (Mi et al., 2021).

Therefore, the analytical frameworks to measure the impacts of product and process agricultural innovation, marketing and organizational innovation, social and institutional changes, and welfare as represented in this book are shown in Figs. 6, 7, and 8, respectively. Although each agricultural innovation might have a potential impact on all three outcomes, the analytical frameworks shown here focus only on the empirical outcomes of each innovation.

As shown in Fig. 6, two approaches were used to measure the impacts of product and process innovation. The first directly measured the impacts of innovation on the outcome variables and determined the factors associated with the adoption of agricultural innovation in Chaps. 2 and 3 by using the propensity score matching method and a combination of probit and z-tests, respectively. The second approach measures the impacts of agricultural innovation indirectly via the production function to estimate technical efficiency as the outcome variable. The production function can be used in the two ways of estimating are Data Envelopment Analysis (DEA) and Stochastic Frontier Function (SFA) as in Chaps. 5 and 6, respectively. Chapter 4 combines these two approaches to test the effect of GAP adoption on tea profit efficiency. Chapter 4 uses the second approach to measure the impact of GAP adoption on profit efficiency via the production function estimated by SFA with GAP, along with other factors. Thereafter, using the first approach to measure the impact of innovation with the outcome variable, determines profit efficiency after controlling for all other observable factors that might influence GAP adoption. Furthermore, product and process innovations affect only production and economic outcomes.

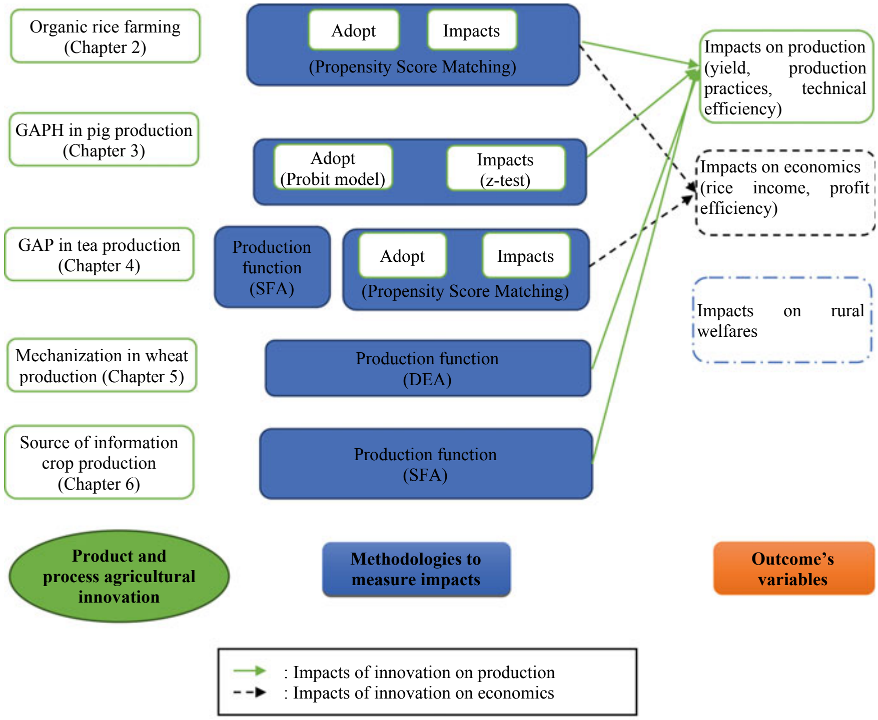

Fig. 6 Analytical framework to measure the impacts of product and process innovation in the book

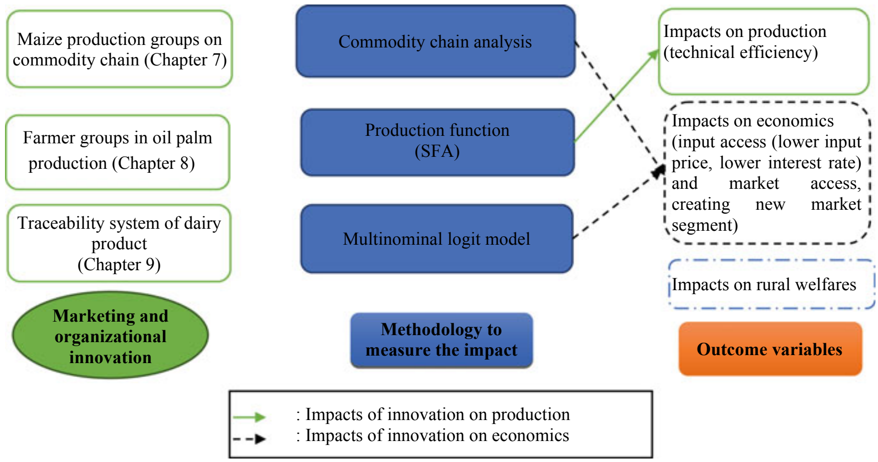

Fig. 7 Analytical framework used in the book to measure the impacts of marketing and organizational innovation

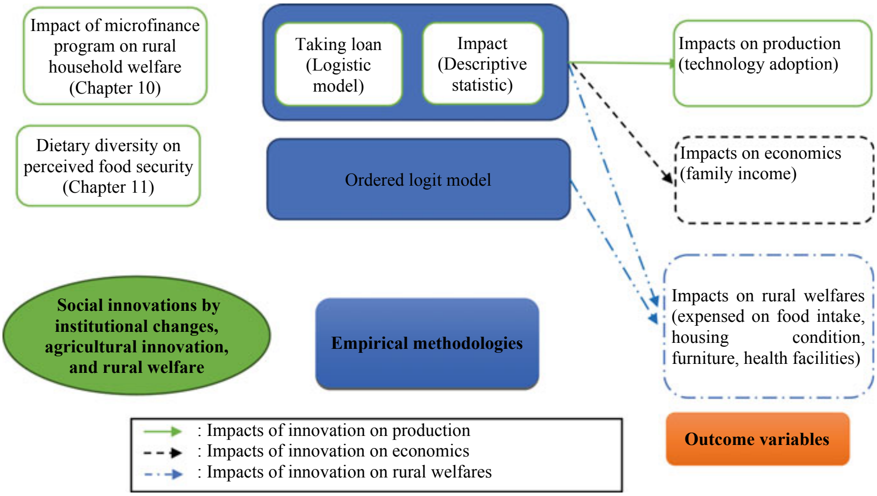

Fig. 8 Analytical framework used in the book to measure the impacts of social innovations by institutional changes and welfare

The impacts of marketing and organizational innovation are shown in Fig. 7. The direct impacts of the maize production group on the commodity chain were measured directly using commodity chain analysis. While the impact of farm groups on the outcome variable is technical efficiency, it was measured indirectly via the production function. Chapter 9 uses a multinomial logit model to clarify which attributes of dairy products will increase consumers' willingness to pay. These innovations bring better outcome variables into production and economics.

The impact of social innovations on institutional changes and social welfare is shown in Fig. 8. This shows that these impacts were measured using various logistic models. Chapter 11 used the ordered logit model, and a combination of logit model and descriptive statistics was used in Chap. 10. All of these social innovations by institutional changes seem to support agricultural innovations as well as social welfare.

3 The Structure of the Book

The structure of this book is divided into 15 chapters and an appendix (see Fig. 9, Table 5). This chapter is Agricultural Innovation and its Impact on Farming and Rural Welfare, which describes the basic background of the term innovation and its types, as well as its adaptation in agriculture. Additionally, measuring the impact of agricultural innovation is summarized in three aspects: production, economics, and social aspects, followed by the introduction of the overall structure of the book. Chapters 2–11 are divided into three categories of agricultural innovations: Parts

I, II, and III. Additionally, the book contains Part IV, from Chaps. 12–15, and the appendix as a special section that focuses on smart agriculture and smart farming. Although smart farming has become more important in managing farm resources and influencing farmers' decision-making, the literature on agricultural innovation has not yet covered the emergence of smart farming within the concept. Smart farming is a development that focuses on using information and communication technology in the cyber-physical farm management cycle, in which smart devices (i.e., those connected to the Internet) control the farm system (Wolfert et al., 2017). Knierim et al. (2019) built insights and reflections on smart-farming technology innovation in Germany. Smart farming technology refers to the technologies that contribute to a "smarter" way of farming, i.e., benefit cultivation practices, crop yield and quality, and farm work, so that these technologies are expected to reduce the impact of farming on the environment and climate, increase resilience and soil health, and reduce costs for farmers (COM, 2017; Knierim et al., 2019). Knierim et al. (2019) focused on four types of smart farming technology: recording and mapping technologies, which collect precise data for subsequent site-specific applications; tractor GPS and connected tools that use real-time kinetics to appropriately apply variable rates of inputs and accurately guide tractors; apps and farm management and information systems, which integrate and connect with mobile devices for easier monitoring and management; and autonomously operating machines (e.g., weeding and harvesting robots). Therefore, this section provides an overview of smart farming. Chapters 2–15 focus on Asian countries. The appendix discusses the role of education, institutional settings, and ICT in farming. As this topic is important for smart farming and agricultural innovation, an appendix with a non-Asian example is attached to Part IV. A summary of the relationship between the types of agricultural innovation in these chapters and the appendix is shown in Table 5, and the impacts of agricultural innovation on farming performance and rural welfare and its measuring method are shown in Table 6.

Part I is the product and process innovation covered in Chaps. 2–6.

Chapter 2 discusses the impact of organic rice farming on Cambodia's production performance. This chapter focuses on organic rice farming, which is considered a new production method that enhances sustainable agriculture. Using the propensity score matching method, the results showed that organic rice adoption was higher for two indicators of production outcomes: rice yield and rice income. Organic farmers received higher yields after they shifted to organic farming from 0.38–0.55 t/ha and organic farmers can receive a premium rice income of $US394–453/ha by shifting their farming practice, and conventional farmers would also get a higher rice income of $US468–508/ha if they shifted to organic farming because of the higher price of organic products.

Chapter 3 describes the adoption of GAP and its impact on pig production in Vietnam. This chapter showed that farmers who were male, received training on pig production, had higher household incomes, and had access to veterinary services tended to adopt Good Animal Husbandry Practices (a kind of GAP in the livestock sector) in their pig production. Among these, receiving training and access to veterinary services were the most important. Moreover, GAP in pig production significantly

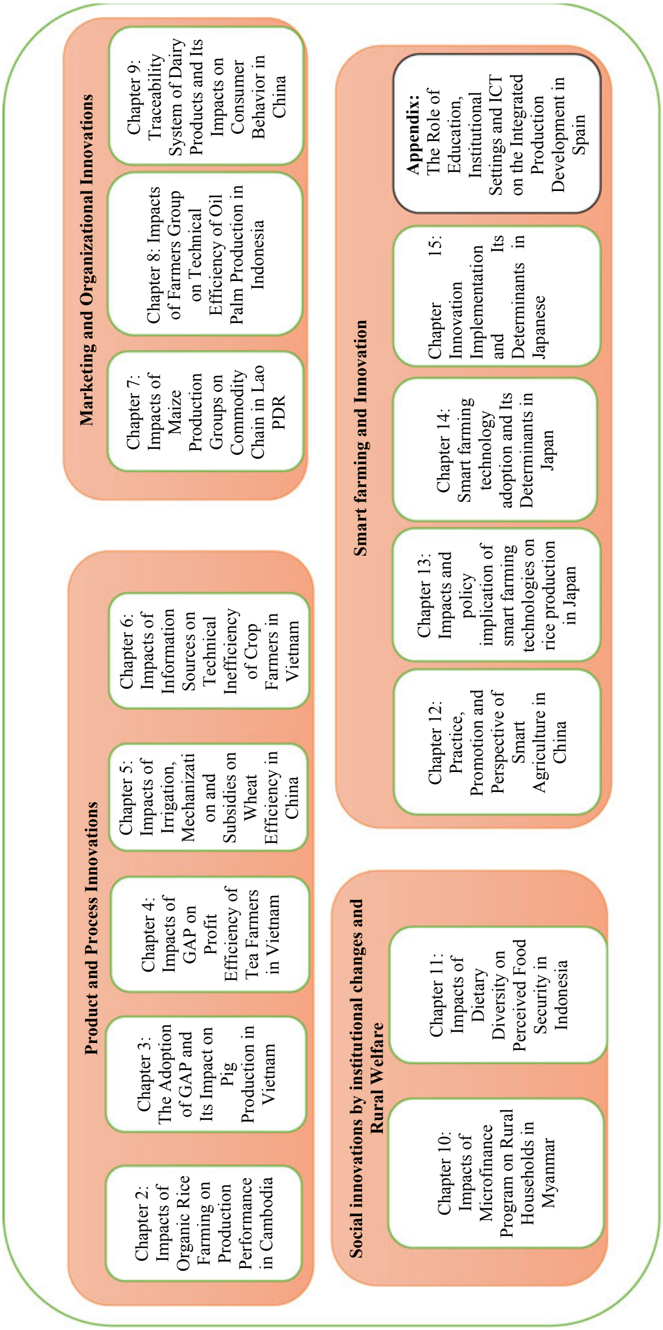

Fig. 9 The structure of the book

Table 5 The relationship between agricultural innovation types, as contained in the chapters

Chapter	Chapter title	Agricultural innovation types				
		Product and process		Marketing and organizational		Social innovations by institutional changes and rural welfare
		Product	Process	Marketing	Organizational	Institutional/social
1	Agricultural Innovation and Its Impacts on Farming and Rural Welfare	○	○	○	○	○
Part I	Product and Process Innovation					
2	Impacts of Organic Rice Farming on Production Performance in Cambodia: An Application of Propensity Score Matching	○	○			
3	The Adoption of GAP and Its Impacts on Pig Production in Vietnam: An Application of Probit Model	○	○			
4	Impacts of GAP on Profit efficiency of Tea Farmers in Vietnam: An Application of Stochastic Profit Function	○	○			
5	Impacts of Irrigation, Mechanization and Subsidies on Wheat Efficiency in China: An Application of Two-stage DEA		○			
6	Impacts of Information Sources on Technical Inefficiency of Crop Farmers in Vietnam: An Application of Stochastic Frontier Analysis		○			
Part II	Marketing and Organizational Innovation					
7	Impacts of Maize Production Groups on Commodity Chain in Lao PDR: An Application of Commodity Chain Analysis			○	○	

(continued)

Table 5 (continued)

Chapter	Chapter title	Agricultural innovation types				
		Product and process		Marketing and organizational		Social innovations by institutional changes and rural welfare
		Product	Process	Marketing	Organizational	Institutional/social
8	Impacts of Farmers Group on Technical Efficiency of Oil Palm Production in Indonesia: An Application of Stochastic Frontier Analysis				○	
9	Traceability System of Dairy Products and Its Impacts on Consumer Behavior in China: An Application of Multinominal Logit Model			○		○
Part III	Social Innovations by Institutional Changes and Rural Welfare					
10	Impacts of Microfinance Program on Rural Households in Myanmar: An Application of Logistic Regression Model					○
11	Impacts of Dietary Diversity on Perceived Food Security in Indonesia: An Application of Ordered Logit Model					○
Part IV	Smart Farming and Smart Agriculture and Innovation					
12	Practice, Promotion and Perspective of Smart Agriculture in China	○	○	○	○	○
13	Impacts and Policy Implication of Smart Farming Technologies on Rice Production in Japan	○	○			

(continued)

Table 5 (continued)

Chapter	Chapter title	Agricultural innovation types				
		Product and process		Marketing and organizational		Social innovations by institutional changes and rural welfare
		Product	Process	Marketing	Organizational	Institutional/social
14	Smart Farming Technology Adoption and Its Determinants in Japan	○	○	○		
15	Innovation Implementation and Its Determinants in Japanese Agricultural Corporations	○	○	○	○	
Appendix	The Role of Education, Institutional Settings and ICT on the Integrated Production Development in Spain	○	○	○	○	○

Table 6 Summary of the impacts of agricultural innovation on farming and rural welfare and its methods

Chapter	Outcome variables	Production	Model	Result/factor variables[a]	Country
Chapter 2: Impacts of Organic Rice Farming on Production Performance in Cambodia: An Application of Propensity Score Matching	Adoption of rice organic	**Rice**	Propensity score matching	**Age**, Gender, **Education**, Farming labor, ***House size***, No. of rice plots, total rice field size, **commercial status, other farm activities**, **no. of cows**, off-farm activity, no. of poultry, **tractor ownership,** credited use	Cambodia
	Yield (+) (Production outcome) Rice income (+) (Economic outcome)			Yield increased from 0.36–0.51t/ha Rice income increased by 439–487$/ha	
Chapter 3: The Adoption of GAP and Its Impacts on Pig Production in Vietnam: An Application of Probit Model	Adoption of VietGAHP	Pig	Probit	**Gender (male)**, education, experience, **training,** ***f armsize, pig raisers,*** pig_HH income, ***Off-farm income,*** **household income,** ***biogas,*** credit access, **veterinary access**	Vietnam
	VietGAHP practices/criteria (+) (Production outcome)		z-test	9 out of 15 compulsory criteria and 8 out of 14 optional criteria implemented by more adopter than non-adopter	

(continued)

Table 6 (continued)

Chapter	Outcome variables	Production	Model	Result/factor variables[a]	Country
Chapter 4: Impacts of GAP on Profit efficiency of Tea Farmers in Vietnam: An Application of Stochastic Profit Function	Profit efficiency via production function (+) (Economic outcome)	Tea	Cobb–Douglas	**Adoption, Farm size, *Price of chemical fertilizer, Price of organic fertilizer,* Cost for pest and disease control, *Price of labor*, other cost**	Vietnam
	Adoption of VietGAP tea		Propensity score matching	Gender, formal education, **family labor, *experience*, farm size, irrigation, tea income ratio,** credit access, **extension access, machinery use**	
	Profit efficiency (+) (Economic outcome)			VietGAP adopter was higher 3.8%	
Chapter 5: Impacts of Irrigation, Mechanization and Subsidies on Wheat Efficiency in China: An Application of Two-stage DEA	Production efficiency (+) (Production outcome)	Wheat	Data envelopment analysis	90.2% **Agro-labor per farm**, average size of farmland, **ratio of irrigable land, power of agricultural mechanization,** extension staffs of agro-tech, ***agricultural subsidies,*** water resources applicability, average schooling length of rural labor	China

(continued)

Table 6 (continued)

Chapter	Outcome variables	Production	Model	Result/factor variables[a]	Country
Chapter 6: Impacts of Information Sources on Technical Inefficiency of Crop Farmers in Vietnam: An Application of Stochastic Frontier Analysis	Technical efficiency (+) (Production outcome)	Maize	Stochastic frontier analysis	75.1% Extension services, commune cultural post office, reading printed material, **reading information**, listening to the radio, listening information, **watching television,** watching information, cell phone can access internet, visited good agricultural model, agricultural group membership	Vietnam
Chapter 7: Impact of Maize Production Groups on Commodity Chain in Lao PDR: An Application of Commodity Chain Analysis	Input's access and market access (+) bought seeds at lower prices, accessed to loan with lower interest, accessed to the markets with guarantee to selling at least at minimum output price (Economic outcome)	Maize	Commodity chain analysis	Factor analysis Functional analysis Flow analysis Technical analysis Economic impact of the chain	Laos
Chapter 8: Impact of Farmers Group on Technical Efficiency of Oil Palm Production in Indonesia: An Application of Stochastic Frontier Analysis	Technical efficiency (+) (Production outcome)	Oil palm	Stochastic frontier analysis	85% **Group**, **education,** ***age,*** **divers**, credit, farm location	Indonesia

(continued)

Table 6 (continued)

Chapter	Outcome variables	Production	Model	Result/factor variables[a]	Country
Chapter 9: Traceability System of Dairy Products and Its Impacts on Consumer Behavior in China: An Application of Multinominal Logit Model	Marginal Willingness to pay (+) (Impacts on economic outcome by creating new market segment)	Milk	Multinomial logit model	**Farm information, farm information + picture, antibiotics record, all medicine record, processing information,** processing information + picture, Gender, ***age,*** **education**, family without kids, old people**, income**	China
Chapter 10: Impacts of Microfinance Program on Rural Households in Myanmar: An Application of Logistic Regression Model	Taking loan	Micro finance program	Logistic regression model	***Family size,*** **marital status, gender,** ***age*****, education level, l*****and holding size,*** **number of crops,** Income, **technology adoption,** social activity, **establish new business**	Myanmar
	Impact of taking loan (+) (Production outcome, economic outcome, impacts on rural welfares)			Increasing in expenditure on housing, food intake expenses, expenditure on furniture, health facilities, technology adoption rate, family income, education expenses, household assets, household saving, clothing expenses	

(continued)

Table 6 (continued)

Chapter	Outcome variables	Production	Model	Result/factor variables[a]	Country
Chapter 11: Impacts of Dietary Diversity on Perceived Food Security in Indonesia: An Application of Ordered Logit Model	Subjective Food Security Status (insecure, somewhat insecure, somewhat secure, secure, and highly secure) (+) (Impacts on rural welfares)	Social innovations by institutional changes	Ordered logit model	In terms of numbers of food groups: the dietary diversity in a household had a positive influence on the perceived food security status of the household	Indonesia
				In terms of consuming food groups: **Tuber,** animal_prod, oil & fat, **oily_seed, nuts,** ***sweets,*** **fruit & vegetable**, others	
Appendix: The Role of Education, Institutional Settings and ICT on the Integrated Production Development in Spain	The development of integrated production (+) (Impacts on production that aimed to create the process innovation)	The development of integrated production		Educational programs, institutional settings and information and communication technology	Spain

Note ± refers to positive and negative impacts on outcome variables, respectively
[a]The positive significant factors are in bold; the negative significant factors are in itatic bold

improved the production practices of farmers as indicators of the impact of product and process agricultural innovation on production.

Chapter 4 focuses on the impact of GAP on the profit efficiency of Vietnamese tea farmers. This chapter showed that good agricultural practices for tea, which are considered a new agricultural management practice, significantly affected profit efficiency by using a stochastic frontier function. In addition, the positive impact of GAP on profit efficiency is tested again using propensity score matching.

Chapter 5 discusses the impacts of irrigation, mechanization, and subsidies on heat efficiency in China. Using two-stage data envelopment analysis to measure the technical efficiency of wheat production, this chapter showed that mechanization and irrigation, which are two kinds of process innovations, could result in higher production efficiency for wheat production.

Chapter 6 discusses the impact of information sources on the technical inefficiency of Vietnamese crop farmers. By defining the sources of information that farmers assessed, this chapter showed that in the era of communication and technology, reading information on agricultural production that was directly related to agricultural knowledge and seeking this information frequently via television, which was the most popular communication and technology device in the remote areas, negatively influenced technical inefficiency. In other words, they positively influence the technical efficiency of crop farmers in Vietnam.

Part II comprises marketing and organizational innovations that cover Chaps. 7–9.

Chapter 7 discusses the impact of maize production groups on commodity chains in Lao PDR. By using the commodity chain analysis approach, this chapter showed that maize production groups (MPGs) could help farmers access inputs with more benefits, such as maize seeds at lower prices and loans at low interest rates. In addition, farmers were supported to access markets with higher bargaining power by MPGs. However, the farmers were not able to earn higher prices because they had to sell maize quickly after harvesting due to a lack of storage facilities.

Chapter 8 discusses the impact of farming groups on the technical efficiency of oil palm production in Indonesia. Using the same method as in Chaps. 4 and 6, stochastic frontier analysis is used to estimate the technical inefficiency in oil palm production. In addition, this chapter provides evidence that the role of farm groups is as a kind of farmer organization that focuses on providing technical assistance for farmers with their own structure, significantly reducing the technical inefficiency of oil farmers such that farmers could retain the best management practices given by the extension service.

Chapter 9 discusses the traceability system of dairy products and its impacts on consumer behavior in China. It provides an example of the required information of consumer behavior via traceability system which might create a new market segment where farmers and other stakeholders in the food chain need to make an effort to match the consumers' demands. The results indicated that consumers have a higher willingness to pay for information with pictures than with only information. Noticeably, consumers are concerned about the use of animal medicine, especially on antibiotic records, and antibiotic usage had the highest marginal willingness to Pay 3.69RMB relative to other attributes.

Part III is social innovations by institutional changes and rural welfare, which covers Chaps. 10 and 11.

Chapter 10 is Impacts of the Microfinance Program on Rural Households in Myanmar, which is an example of the effect of the new institution on the rural household welfare. These chapters showed that those who were female, single, younger, had a middle educational level, and had a small family size, and small-scale landholding size tended to become the client of the new institution called the PACT microfinance program. The increasing number of crops has established new businesses, and higher adoption of technology is also influenced by the probability of loans being taken. As a result of joining the program, more than half of the clients could improve their livelihoods, such as housing conditions, food intake, furniture, health facilities, rate of technology adoption, and family income.

Chapter 11 discusses the impact of dietary diversity on the perceived food security in Indonesia. This chapter indicates the changes in the institutional context, that is, the diversity of food sources in terms of the number and types of food sources affecting rural welfare in terms of food security. First, the results show that dietary diversity in a household has a positive influence on the perceived food security status of the household. Second, the results also indicated that the existence of *tubers, oily seeds, nuts,* and *fruits and vegetables* in households is likely to increase the probability of a household perceiving that they are at a higher level of food security. Furthermore, this chapter showed that most households perceived that they were at a food-secure level, even though they only consumed two or three kinds of food groups. In addition, this chapter found that households that consumed starch in the tuber food group perceived higher levels of food security.

Part IV is smart farming and innovation, which includes Chaps. 12–15 and the appendix.

Chapter 12 focuses on reviewing the policy framework of smart agriculture in China that applies advanced technologies such as the Internet of Things, big data, artificial intelligence, cloud computing, and blockchain, integrating with the status, perspective, and policy suggestions. The results show that smart agriculture has played a crucial role in the national economy, but it is still in its infancy. Moreover, stimulating policies are issued to develop smart agriculture, bringing high-speed popularization and perfecting industrial chains with many large-scale enterprises involved in increasing the self-sufficiency rate of products and technology at both the national and regional levels. In addition to the positive effects of policy, the rural telecommunication industry, and technology, smart agriculture is constrained by research and development (R&D) capability, fiscal investment, farmers' capacity, and talent training. Under unified planning, taking corresponding measures for these weak sectors can accelerate agricultural and rural economic growth driven by advanced technologies.

Chapter 13 discusses the impacts and policy implications of smart farming technologies on rice production in Japan using many kinds of farming technologies from large-scale advanced rice farms to measure production efficiency determinants, production costs, and the impacts of smart farming technologies on the farm. The results indicate that smart agriculture improves agricultural production efficiency by utilizing technical support, such as data collection and mining. The results also showed that smart farming technologies have a positive impact on rice production in Japan. However, the results also show that more practical smart farming technologies may have a larger impact on actual rice production in Japan than more advanced ones. This implies that only the appropriate technologies for actual farms can contribute to agricultural innovation.

Chapter 14 provides evidence of the determining factors of information and communication technology (ICT), and smart farming (SF) technology adoption intensity by Japanese agricultural corporations. Using primary data collected from a Japanese nationwide questionnaire survey, 183 agricultural corporations in Japan were analyzed using descriptive analysis and a negative binomial model. The results showed that 175 out of 183 corporations had adopted at least one ICT & SF technology until 2019, indicating an overall adoption rate of 95.6%. The majority (84.7%) of corporations were limited companies and stock companies, and 86.9% of corporations were qualified to own farmlands. Regarding the profile of corporate representatives, over one-third graduated from universities. Based on the empirical results, corporate types, eligibility to own farmland, sales targets, profit targets, main product, and self-evaluation of ICT utilization and information management significantly affected ICT adoption of ICT&SF technology adoption. In terms of the characteristics of corporate representatives, those who graduated from specialized schools and vocational colleges tended to adopt more ICT&SF technologies.

Chapter 15 focuses on identifying the factors associated with product innovation implementation in Japanese agricultural corporations by using the probit model based on the data of 308 corporations from the national survey in 2019. The results showed that 20.5% (n = 63) of corporations were rice corporations. Most corporations (38.6%, n = 199) generated an annual sales revenue of 100 to 300 million yen. Further, 50.0% of corporations implemented product innovation, that is, these corporations started to produce and sell new or significantly improved goods or launched new or significantly improved services. The results also show that corporations that generate high annual sales, seek high number of sales, aim for profit margins of 5–15%, and believe more strongly in their ability to innovate tend to implement product innovation. Contrastingly, corporations that have a profit margin between 1 and 10% are less likely to implement product innovation than those breaking even. Corporations that mainly deal in facility vegetables or livestock products also tend to implement product innovation less than the corporations mainly selling rice. The corporations with higher self-evaluation in new product and technology development tend to implement more product innovation. Overall, the results suggest that a certain level of annual sales might be required for innovation, innovating farms seek growth and set high targets, and innovations are stimulated by hight self-evaluation in new product and technology development. Therefore, to promote product innovation in Japanese agricultural corporations, these factors should be considered.

The appendix discusses the role of education, institutional settings, and ICT in integrated production development in Spain. This section describes the successful development and transfer of an agricultural production system called integrated production (IP) via education, institutional settings, and ICT. IP uses natural methods and mechanisms of production to manage pests and diseases, considering the protection of the environment and the farm economy, with social responsibility. This type of system can be transferred to developing countries that need to solve the same challenges in terms of product quality, safety, and production requirements when exporting agricultural products. Indeed, one size cannot fit all. In addition, we discuss the institutional context at the national level. These topics are related to all types of innovations in this book, especially process and social innovations by institutional changes.

References

Arnold, E., & Bell, M. (2001). Some new ideas about research for development. In *Partnership at the leading edge: A Danish vision for knowledge, research and development* (pp. 278–316). http://www.technopolis-group.com/resources/downloads/reports/255_DANIDA.pdf

Botha, N., Klerkx, L., Small, B., & Turner, J. A. (2014). Lessons on transdisciplinary research in a co-innovation programme in the New Zealand agricultural sector. *Outlook on Agriculture, 43*(3), 219–223. https://doi.org/10.5367/oa.2014.0175

COM. (2017). The future of food and farming. In *European Commission*. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52017DC0713&from=EN

Edquist, C. (1997). *Systems of innovation: Technologies, institutions and organizations*. Routledge.

Fagerberg, J. (2009). Innovation: A guide to the literature. *The Oxford Handbook of Innovation*, 1–27.https://doi.org/10.1093/oxfordhb/9780199286805.003.0001

Feder, G., & Umali, D. L. (1993). The adoption of agricultural innovations: A review. *Technological Forecasting and Social Change*, *43*(3), 215–239. http://www.sciencedirect.com/science/article/pii/004016259390053A

Hall, A., Bockett, G., Taylor, S., Sivamohan, M. V. K., & Clark, N. (2001). Why research partnership really matter: Innovation theory, institutional arrangements and implications for developing new technology for the poor. *World Development, 29*(5), 783–797. https://doi.org/10.1016/S0305-750X(01)00004-3

Kilelu, C. W., Klerkx, L., & Leeuwis, C. (2013). Unravelling the role of innovation platforms in supporting co-evolution of innovation: Contributions and tensions in a smallholder dairy development programme. *Agricultural Systems, 118*, 65–77. https://doi.org/10.1016/j.agsy.2013.03.003

Klerkx, L., Aarts, N., & Leeuwis, C. (2010). Adaptive management in agricultural innovation systems: The interactions between innovation networks and their environment. *Agricultural Systems, 103*(6), 390–400. https://doi.org/10.1016/j.agsy.2010.03.012

Klerks, L., Mierlo, B. van, & Cess, L. (2012). Evolution of systems approaches to agricultural innovation: Concepts, analysis and interventions. In I. Darnhofer, D. Gibbon, & B. Dedieu (Eds.), *Farming systems research into the 21st century: The new dynamic* (pp. 457–483). https://doi.org/10.1007/978-94-007-4503-2

Knierim, A., Kernecker, M., Erdle, K., Kraus, T., Borges, F., & Wurbs, A. (2019). Smart farming technology innovations—Insights and reflections from the German Smart-AKIS hub. *NJAS—Wageningen Journal of Life Sciences*, *90–91*, 100314. https://doi.org/10.1016/j.njas.2019.100314

Mi, J., Nanseki, T., Chomei, Y., Uenishi, Y., & Nguyen, L. T. (2021). Determinants of ICT and smart farming technology adoption by agricultural corporations in Japan. In *The 10th Asian Society Agricultural Economist International Conference.*

Nguyen, L. T., Nanseki, T., Chomei, Y., Uenishi, Y., & Mi, J. (2021). Determinants of the product innovation implementations in Japanese agricultural corporations. *The 10th Asian Society Agricultural Economist International Conference.*

North, D. C. (1990). An introduction to institutions and institutional change. In J. Alt & N. Douglass (Eds.), *Institutions, institutional change and economic performance*. Cambridge University Press.

OECD. (1997). OECD proposed guidlines for collecting and interpreting technological innovation data—Oslo manual. In *OECD: Vol. Second edi*. OECD. https://www.oecd-ilibrary.org/science-and-technology/proposed-guidelines-for-collecting-and-interpreting-technological-innovation-data_9789264192263-en

OECD. (2001). Adoption of technologies for sustainable farming systems. In *Adoption of Technologies for Sustainbal Farming Systems Wageningen Workshop Proceedings* (pp. 1–149).

OECD. (2005). Oslo manual: Guidelines for collecting and interpreting innovation data. In *OECD and Eurostat Publication* (3rd ed.). OECD Publishing. https://doi.org/10.1787/9789264013100-en

OECD. (2009). *Innovation in firms: A microeconomic perspective*. OECD.

OECD. (2013). *Agricultural innovation systems*. OECD Publishing. https://doi.org/10.1787/9789264200593-en

OECD/Eurostat. (2018). Oslo Manual 2018: Guidelines for collecting, reporting and using data on innovation. In *The measurement of scientific, technological and innovation activities* (4th ed.). OECD. https://doi.org/10.1787/9789264304604-en

Ogundari, K., & Bolarinwa, O. D. (2018). Impact of agricultural innovation adoption: A meta-analysis. *Australian Journal of Agricultural and Resource Economics, 62*(2), 217–236. https://doi.org/10.1111/1467-8489.12247

Rogers, E. M. (1983). Diffusion of innovations. In *An integrated approach to communication theory and research* (3rd ed.). The Free Press.

Röling, N. (2009). Pathways for impact: Scientists' different perspectives on agricultural innovation. *International Journal of Agricultural Sustainability, 7*(2), 83–94. https://doi.org/10.3763/ijas.2009.0043

Schumpeter, J. A. (1939). *Business cycles: A theorical, historical, and statistical analysis of the capitalist process* (Vol. I, 1st ed.). McGraw-Hilll Book Company, Inc.

Schumpeter, J. A. (1983). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle Joseph A. Schumpeter translated from the German by Redvers Opie with a new introduction by John E. Elliott* (1983. Orig). Transaction, Inc.

Solis-Navarrete, J. A., Bucio-Mendoza, S., & Paneque-Gálvez, J. (2021). What is not social innovation. *Technological Forecasting and Social Change*, *173*, 121190. https://doi.org/10.1016/j.techfore.2021.121190

Toborn, J. (2011). *Adoption of agricultural innovations, converging narratives, and the role of Swedish agricultural research for development*. Discussion paper. https://nanopdf.com/download/adoption-of-agricultural-innovations-analysis-synthesis_pdf

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M. J. (2017). Big data in smart farming—A review. In *Agricultural systems* (Vol. 153, pp. 69–80). Elsevier Ltd. https://doi.org/10.1016/j.agsy.2017.01.023

World Bank. (2006). *Enhancing agricultural innovation: How to go beyond the strengthening of research systems*. World Bank. https://openknowledge.worldbank.org/handle/10986/24105. Accessed 1 Dec 2021.

Part I
Product and Process Innovation

Chapter 2
Impacts of Organic Rice Farming on Production Performance in Cambodia: An Application of Propensity Score Matching

Rada Khoy, Teruaki Nanseki, and Yosuke Chomei

1 Introduction

Agricultural modernization has resulted in a number of serious environmental problems over the past half-century, including water pollution and a reduction in biodiversity. To help solve these problems, it is important for the farming community to have a greater and clearer understanding of sustainable agriculture (Atsushi & Ping, 2010). Consequently, organic farming is gradually being promoted and practiced in many countries. Although organic rice farming has been introduced many years ago, Cambodia is certainly a latecomer to the international organic agriculture scene. Nevertheless, according to the Cambodian Organic Agriculture Association (2011), Cambodia has the potential to engage in organic rice farming, since many rice farmers have refused to fully embrace the intensive use of farm chemicals. In 2003, several Non-Governmental Organizations (NGOs), in conjunction with the Cambodian government, began promoting organic rice farming within farming communities. As a result, Cambodian small farmers were producing organic rice with notable success. However, in recent years, many farmers have returned to conventional farming because of certain constraints, such as the high labor input and price fluctuations in organic rice. Although some researchers have found organic rice farming to have a positive impact, some farmers are still skeptical about it because farmers tend to judge new technology based on their own needs and conditions before

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accepting it. Through a simple comparison, Taing (2008) observed that organic rice farming resulted in higher yields and income. However, according to Faltermeier and Abdulai (2009), using a simple comparison without controlling for differences in the characteristics of farmers can lead to a biased estimation. Hence, this chapter examines the impacts of organic rice farming on production performance in Cambodia by using the propensity score matching method to control for differences in farmers' characteristics.

2 Methodology

This chapter employed a two-stage sampling technique. The first stage involves purposive sampling, in which three target cooperatives in three districts in Takeo and Kompot Provinces were selected. The second stage includes random sampling, in which organic farmers from cooperatives and conventional farmers were selected. Data were collected from face-to-face interviews conducted from March to April 2014. The interviews were based on structured questionnaires that focus on rice production during rainy season in 2013. In total, we interviewed 247 farmers, but only 221 respondents (84 organic farmers and 137 conventional farmers) were included in this chapter.

According to Faltermeier and Abdulai (2009), to accurately estimate the impact produced by the adoption of a new technology, farmers should randomly be assigned to either the adoption or non-adoption group. However, the farmers surveyed in this chapter decided on their own whether or not to adopt organic rice farming. Therefore, the impact of organic rice farming might be influenced by the farmers' characteristics rather than by their organic farming practice. A simple comparison can thus lead to a biased estimation. Therefore, we employed the propensity score matching method to control for differences in farmers' characteristics.

Propensity score matching is in two-step procedure (Becker & Ichino, 2002). The first step is to determine the farmers' propensity scores by estimating the probability model (probit or logit), written as

$$Y(1; 0) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (1)$$

where Y is a dependent variable (1 = Organic farmer; 0 = Conventional farmer), β is the regression coefficient to be estimated, and X is an independent variable to be explained.

Then, we estimated the propensity score based on the following equation:

$$P_{score} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}} \quad (2)$$

In the second step, each farmer in the organic farming group is matched up to a conventional farmer with similar propensity score values to estimate the average treatment effect. Here, we used nearest neighbor matching (NNM) and kernel-based matching (KBM).

After matching, the balancing test is normally required to ascertain the quality of matching (Ali & Abdulai, 2010). We employed the mean absolute standardized bias (MASB) suggested by (Rosenbaum & Rubin, 1985), in which a standardized difference should be less than 20% to confirm success in the matching process. Additionally, to confirm the success of matching, Sianesi (2004) suggested that the pseudo R^2 should be lower, and the joint significance of covariates should be rejected, after matching.

We used rice yield and rice income as outcome variables to evaluate the impact of organic rice farming. To control for differences in outcome variables in the propensity score matching, we included as farmers' characteristics the age, gender (1 = male; 0 = female), and number of years of education of the household head, farming labor (number of laborers available for rice farming), house size (the square meters of the house owned by the farmer), the number of rice plots, total rice-field size, the farmer's commercial status (1 = farmer sells his or her rice; 0 = otherwise), the number of cows owned by the farmer, the number of poultry owned by the farmer, tractor ownership (1 = farmer owns a two-wheel tractor, 0 = otherwise), other farm activities (1 = farmer engages in other farm activities, 0 = otherwise), off-farm activities (1 = farmer has an off-farm job, 0 = otherwise), and credit use (1 = farmer took out a loan; 0 = otherwise). We believe that the above variables are the main factors influencing production performance and the farmer's decision to either adopt or reject organic rice farming practices.

3 Results and Discussion

3.1 Descriptive Results

Summary statistics and the results of the statistical significance tests for both groups are shown in Table 1. The level of the education of household's head among the organic farmers group is statistically higher than that of the conventional farmers group, which suggests that farmers with a higher level of education are more likely to adopt new farming practices because information is more accessible to them and they are better adapting the new farming practice.

In addition, most organic farmers are large-scale commercial farmers, who own more plots and have larger rice fields compared to conventional farmers. Furthermore, 96% of organic rice farmers sold their rice, whereas only 69% of conventional farmers sold their surplus rice left over from their personal consumption. Compared to conventional rice farmers, the significantly higher percentage of organic farmers who engage in other activities, and who own two-wheel tractors as well as number of cows, clearly indicates that organic farmers are generally better than conventional farmers.

Table 1 Descriptive statistics and production performance of organic and conventional farmers

Variables	Unit	Organic farmers		Conventional farmers		Difference		Test
		Mean	SD	Mean	SD			
Age	Years	47.35	9.93	45.42	11.99	1.92		1.232
Gender	Dummy	0.94	0.24	0.88	0.33	0.07		1.556
Education	Years	7.11	3.06	5.17	3.54	1.94	***	4.158
Farming labor	Person	2.85	1.05	2.76	0.94	0.09		0.635
House size	m^2	39.35	12.38	37.51	16.57	1.84		0.879
No. of rice plots	Number	2.82	1.01	2.42	1.00	0.41	***	2.921
Total rice field size	Ha	1.17	0.52	0.94	0.54	0.23	***	3.102
Commercial status	Dummy	0.96	0.19	0.69	0.46	0.27	***	4.854
Other farm activities	Dummy	0.44	0.50	0.19	0.39	0.25	***	4.007
No. of cows	Number	3.12	1.50	2.28	1.18	0.83	***	4.603
No. of poultry	Number	121.74	468.64	56.68	427.27	65.06		1.059
Off-farm activity	Dummy	0.26	0.44	0.18	0.39	0.08		1.401
Tractor ownership	Dummy	0.25	0.44	0.15	0.36	0.10	*	1.779
Credited use	Dummy	0.19	0.40	0.26	0.44	−0.07		1.230
Family labor	Man-day/ha	240.53	173.78	198.82	141.00	41.71	*	1.952
Rented labor	Man-day/ha	42.17	45.34	38.39	40.77	3.77		0.640
Total labor	Man-day/ha	282.70	154.29	237.21	124.83	45.49	**	2.400
Yield	t/ha	3.32	1.02	2.58	0.84	0.75	***	5.884
Rice revenue	$/ha	1184.59	383.94	723.89	316.11	460.70	***	9.681
Fixed cost	$/ha	24.43	29.94	32.63	33.76	−8.20	*	1.829
Variables cost	$/ha	186.39	155.32	315.38	221.84	−128.99	***	4.671
Total cost	$/ha	210.82	165.80	348.01	225.19	−137.19	***	4.836
Rice income	$/ha	973.77	415.16	374.88	303.47	597.90	***	12.326

Note *, **, *** significant at 10%, 5%, and 1%, respectively

As shown in Table 1, organic requires more labor than conventional farming. Organic farmers spent 240.53 man-day/ha of family labor, which is significantly higher than the 198.82 man-day/ha spent by conventional farmers. No significant difference was found between two groups for rental labor. In total, organic farmers statistically contributed more labor than conventional farmers did, with a 45.49 man-day/ha difference, which shows that organic farming is labor-intensive. That might be one of the main reasons why some farmers refuse to adopt this farming.

Table 1 shows the production performance of organic farmers and conventional farmers. The yield, revenue, and total rice income generated by organic farmers is 0.75 t/ha, 460.70$/ha, and 597.90$/ha higher, respectively, than those produced by conventional farmers. Furthermore, the variable cost and total cost assumed by organic farmers are significantly lower than those assumed by conventional farmers because of the high amount of chemical fertilizers used in conventional farming, whereas the lower fixed cost of organic farmers is due to the larger rice-field size they own. From this simple comparison, we cannot conclude that organic farmers might have been influenced by their more favorable characteristics than by their adoption of organic farming. Therefore, controlling for those differences in characteristics is necessary in order to assess the impacts of organic farming.

3.2 Propensity Score Matching Results

The probit estimates of the adoption propensity equation are presented in Table 2. Several variables are significantly associated with the adoption of organic rice farming. Age, education, and commercial status are positively associated with the adoption of organic rice farming, which suggests that older farmers with a higher level of education are more likely to adopt new farming practices because information is more accessible for them, and they are better skilled at adapting new farming practices for commercial purposes. The probit model also shows that farmers who engage in other farm activities, who have more cows, and who own a tractor are likely to adopt organic rice farming because engaging in other farm activities and possessing a larger number of cows allow them to produce larger amounts of organic fertilizers for the organic farm. Moreover, possessing two-wheel tractors is favorable for conducting organic farming, which requires good land preparation. On the other hand, only house size is negatively associated with the adoption of organic farming. As an indicator of the farmer's wealth, house size suggests that richer farmers are less likely to adopt organic farming, since they are interested in businesses other than rice farming.

Table 3 presents results from the covariate balancing tests before and after matching. The standardized mean difference for overall covariates used in the propensity score is 5.6–19% after matching. The p-values of the likelihood ratio tests indicate that the joint significance of covariates was consistently rejected after matching. The pseudo R^2 also dropped significantly from 26.7% before matching to 1.5–8.3% after matching. The low pseudo R^2, low mean standardized bias, and the insignificance

Table 2 Probit estimates of the propensity score to adopt organic rice farming

Variables	Coef.		Std. Err	Z	P > z
Age	0.021	**	0.010	2.080	0.037
Gender	−0.013		0.376	−0.030	0.973
Education	0.092	**	0.036	2.570	0.010
Farming labor	−0.134		0.107	−1.250	0.211
House size	−0.025	***	0.009	−2.930	0.003
No. of rice plots	−0.068		0.119	−0.570	0.566
Total rice field size	0.231		0.218	1.060	0.289
Commercial status	1.269	***	0.353	3.590	0.000
Other farm activities	0.881	***	0.250	3.520	0.000
No. of cows	0.269	***	0.088	3.050	0.000
No. of poultry	0.070		0.255	0.270	0.002
Off-farm activity	0.000		0.000	0.460	0.784
Tractor ownership	0.611	**	0.282	2.170	0.649
Credited use	−0.225		0.265	−0.850	0.030
Constant	−2.729	***	0.696	−3.920	0.000

Note *, **, *** significant at 10%, 5%, and 1%, respectively; Log likelihood = −107.584, LR Chi^2 = 78.370***, Pseudo R^2 = 0.267

Table 3 Matching quality indicators before and after matching

Matching method	Pseudo R^2		LR chi^2 (p-value)			Mean standardized bias after matching
	Before	After	Before		After	
NNM (1)[a]	0.267	0.083	78.37 (0.000)	***	19.30 (0.154)	19.0
NNM (5)[b]	0.267	0.025	78.37 (0.000)	***	5.86 (0.970)	10.6
KBM (0.06)[c]	0.267	0.015	78.37 (0.000)	***	3.52 (0.998)	5.6
KBM (0.03)[d]	0.267	0.038	78.37 (0.000)	***	8.75 (0.847)	11.0

Notes *, **, *** significant at 10%, 5% and 1%, respectively
[a]NNM (1) = single nearest neighbor matching with replacement and common support
[b]NNM (5) = five nearest neighbors matching with replacement and common support
[c]KBM (0.06) = kennel based matching with ban width 0.06 and common support
[d]KBM (0.03) = kennel based matching with band width 0.03 and common support

of the likelihood ratio test after matching suggest that the proposed specification of the propensity score is fairly successful.

The impact of organic rice farming on production performance is shown in Table 4, which presents an assessment of organic rice farming by estimating the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU), and the average treatment effect (ATE). Firstly, we examine the impact of organic rice farming on rice yield. Table 4 shows that for all matching methods, the difference in the ATT ranges from 0.38–0.55 t/ha with significant difference. It suggests that organic farmers received higher yields after they shifted to organic farming. Thus, organic farmers made the right decision by adopting organic rice farming because of their more favorable conditions, as discussed in the descriptive results. Table 4 also shows no significant differences among the four matching methods, except for five nearest neighbor matching in the ATU. Therefore, we don't have enough evidence to conclude that conventional farmers will get higher yields if they shift to organic farming. However, it suggests that conventional farmers did not adopt organic farming because most of them are subsistence farmers who prefer to increase production for personal consumption rather than seek profit from organic farming, which would require a high amount of labor. Finally, the ATE shows that if all of the farmers in the sample shifted from conventional to organic farming, they would get higher yields ranging from 0.36–0.51 t/ha. This result confirms the finding of Taing (2008), who, using a simple comparison, concluded that organic farmers were able to obtain yields that are higher than those of conventional farmers.

We also examined rice income of both rice-farming practices to confirm the benefit of organic rice farming. The result shows a significant difference in the ATT and the ATU for all four matching methods. This strongly suggests that both the organic and conventional farmer samples can earn more rice income if they shift to organic rice farming. Organic farmers can receive a premium rice income of 394–453 $/ha by shifting their farming practice, and conventional farmers would also get higher rice income, ranging from 468–508 $/ha if they shifted to organic farming. This implies that conventional farmers made a wrong decision by not adopting organic rice farming. It is contradictory between rice yield and rice income which we do not have enough evidence to conclude that organic farming will result in higher yield for conventional farmers; however, organic farming will result in higher rice income for conventional farmers because of the price premium of organic rice. The result also reports the ATE, which suggests that if all of the sampled farmers shifted to organic farming, then rice income would increase by 439–487 $/ha for all matching methods. We found similar result in the works of Setboonsarng et al. (2008) and Mansoori et al. (2012), who concluded that organic rice farmers were able to obtain increased benefits, compared to conventional farmers.

Table 4 Average treatment effects of organic rice practice on production performance

Out-come	Matching Method	ATT					ATU					ATE
		Org	Con	Dif	t-stat		Org	Con	Dif	t-stat		
Yield	NNM (1)[a]	3.32	2.77	0.55	2.54	**	2.95	2.58	0.37	1.34		0.44
	NNM (5)[b]	3.32	2.82	0.50	2.78	***	3.09	2.58	0.51	2.08	**	0.51
	KBM (0.06)[c]	3.32	2.91	0.41	2.28	**	2.95	2.58	0.37	1.44		0.39
	KBM (0.03)[d]	3.33	2.95	0.38	1.93	*	2.93	2.59	0.34	1.27		0.36
Rice income	NNM (1)[a]	973.77	549.77	424.00	4.00	***	848.65	375.88	472.77	4.62	***	454.24
	NNM (5)[b]	973.77	520.59	453.19	6.20	***	848.27	375.88	508.39	5.14	***	487.41
	KBM (0.06)[c]	973.77	548.83	424.94	6.21	***	856.95	375.88	481.07	4.61	***	459.74
	KBM (0.03)[d]	974.07	579.65	394.41	5.33	***	849.28	381.73	467.55	4.35	***	439.19

Note Same as those for Table 3; Org. is Organic Group, Con. is conventional Group, and Dif. is Difference

4 Conclusion

The result of this chapter strongly suggest that organic rice farming produces positive effects for farmers and that conventional farmers would benefit by shifting to organic farming. Although we do not have enough evidence to support the conclusion that switching to organic rice farming results in higher yields for conventional farmers, the results of our study do show that farmers can derive higher rice income if they conduct organic farming.

Finally, since Cambodia has great potential in the organic rice industry, we recommend all stakeholders should work together to improve organic rice farming in Cambodia so that more benefits and opportunities may be derived from it. Organic rice cooperatives should help expand the market to obtain suitable prices and disseminate information to conventional farmers by enhancing own management system as well as the abilities of the cooperatives' members. NGOs and the Cambodian government should also support the cooperatives in expanding the market, provide extension services, and locate technologies that can reduce the labor intensity of organic rice farming. Furthermore, all related institutions should guide subsistence farmers toward more commercially oriented practices and seek more investors to invest in organic rice trading. Lastly, to sustain the price of organic rice, we highly recommend the implementation of contract farming and farm insurance in order to secure production from organic farmers.

References

Ali, A., & Abdulai, A. (2010). The adoption of genetically modified cotton and poverty reduction in Pakistan. *Journal of Agricultural Economics, 61*(1), 175–192. https://doi.org/10.1111/j.1477-9552.2009.00227.x

Atsushi, M., & Ping, Y. (2010). Analysis of the social conditions conductive to sustainable organic rice farming around Lake Biwa in Japan. In L. L. Tolentino, L. D. Landicho, S. Wun'Gaeo, & K. Ikegami (Eds.), *4th Asian Rural Sociology Association International Conference* (pp. 284–296). Asian Rural Sociology Association. https://www.academia.edu/3660461/4th_Asian_Rural_Sociology_Association_Conference_Proceedings

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal: Promoting Communications on Statistics and Stata, 2*(4), 358–377. https://doi.org/10.1177/1536867x0200200403

Cambodian Organic Agriculture Association. (2011). *Organic agriculture and food processing in Cambodia status and potentials*. https://data.thailand.opendevelopmentmekong.net/en/library_record/organic-agriculture-and-food-processing-in-cambodia-status-and-potentials. Accessed date 10 Feb 2022.

Faltermeier, L., & Abdulai, A. (2009). The impact of water conservation and intensification technologies: Empirical evidence for rice farmers in Ghana. *Agricultural Economics, 40*(3), 365–379. https://doi.org/10.1111/j.1574-0862.2009.00383.x

Mansoori, H., Moghaddam, P. R., & Moradi, R. (2012). Energy budget and economic analysis in conventional and organic rice production systems and organic scenarios in the transition period in Iran. *Frontiers in Energy, 6*(4), 341–350. https://doi.org/10.1007/s11708-012-0206-x

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *American Statistician, 39*(1), 33–38. https://doi.org/10.1080/00031305.1985.10479383

Setboonsarng, S., Stefan, A., Leung, P. S., & Cai, J. (2008). Profitability of organic agriculture in a transition economy: The case of organic contract rice farming in Lao PDR. In *16th IFOAM Organic World Congress.* Modena, Italy.

Sianesi, B. (2004). An evaluation of the Swedish system of active labor market programs in the 1990s. *Review of Economics and Statistics, 86*(1), 133–155. https://doi.org/10.1162/003465304323023723

Taing, K. (2008). *Economic analysis of organic-culture rice in rural household economy: Case studies in Tram Kork and Chumkiri District*. Royal University of Agriculture.

Chapter 3
The Adoption of GAP and Its Impacts on Pig Production in Vietnam: An Application of Probit Model

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1 Introduction

Enhancing the economic performance and the competitiveness as well as caring the environment sustainability have been expecting to achieve through agricultural innovation, especially in the context of higher and more diverse demand from the market (OECD, 2013). As pointed out by OECD (2013), at the micro level, the agricultural innovations can be listed as the process innovations because of relating to the production techniques such as the adoption of new or improved seed. These agricultural innovations have affected positively on production performance, income (Brouder & Gomez-Macpherson, 2014; Ho et al., 2019a, 2019b; Rada et al., 2016) or even on food security, reducing poverty and consumption expenditure (Asfaw et al., 2012; Coulibaly et al., 2017; Kassie et al., 2011, 2014).

Along with the above concept, Good Agriculture Practice (GAP) has been promoted to cover the requirement of the consumer demand on food safety and remain the environmental sustainability allowing the farm productive operation (Asian Productivity Organization, 2016 on Manual on Good Agricultural Practice) by both private sector (Global GAP) and public sector (national GAP). The Vietnamese government has released a variety of GAP for vegetables, fruits, livestock, and aquaculture (MARD, 2008a, 2008b, 2008c, 2008d, 2008e, 2008f, 2010a, 2010b,

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2011a, 2011b, 2011c, 2014, 2015, 2016). Specifically, the Vietnamese Good Animal Husbandry Practices (VietGAHP) publication describes GAP for livestock (MARD, 2008c, 2008d, 2008e, 2008f, 2011b, 2011c, 2015, 2016). Specifically, the Vietnamese Good Animal Husbandry Practices (VietGAHP) publication describes GAPs for livestock (MARD, 2008c, 2008d, 2008e, 2008f, 2011b, 2011c, 2015, 2016). The VietGAHP for household (HH) pig production includes a sequence of principles and guidance to: (1) ensure and enhance the quality of pig products to meet food safety standards and improve the health of pig producers and pork consumers; (2) protect the environment; and (iii) offer product traceability (Ministry of Agriculture and Rural Development–MARD, 2016). The original VietGAHP standard for pig production in Vietnam was released in 2008 by MARD, and has been promoted since 2008 to encourage pig production by all general production units, including households, commercial farms, agricultural enterprises, cooperatives, and other organizations (MARD, 2008d). The VietGAHP for pig production has included specifications at the HH level since 2011 under the Livestock Competitiveness and Food Safety Project, or "LIFSAP" (MARD, 2011b). According to the World Bank (2009a), LIFSAP aims to "*increase the production efficiency of household-based livestock producers* and *reduce the environmental impact of livestock production.*" This project operated from 2010 to 2015 and was expanded at the end of 2018, with 12 of 63 provinces selected to promote VietGAHP standards at the HH level. As a first step, they aimed to achieve LIFSAP's objectives, and ultimately aspired to promote and deeply diffuse VietGAHP standards in HH pig production.

Although HH pig production is vital in the Vietnamese pig industry and has been promoted to produce safe pork meat based on VietGAHP criteria, VietGAHP-based pork products are limited. Further, 3.44 million Vietnamese households participated in pig-raising in 2016 (General Statistics Office of Vietnam–GSOV, 2018), while HH pig production supplied approximately 80% of Vietnamese pork (Lapar et al., 2011). Moreover, Lapar (2014) indicated that HH-based pig production will continue to dominate the Vietnamese pig sector over the next decade. Although the Vietnamese government has widely promoted VietGAHP standards for household-level pig production in particular, and among other production units in general, VietGAHP-compliant units only contributed 24.9 tons of pork in 2016, or 0.7% of total pork production (The Census Steering Committee Central, 2017).

Giang et al. (2016), Lapar et al. (2017), Nguyen (2017) and Vo (2017) have proposed various factors associated with VietGAHP adoption as well as ways in which the adoption has impacted Vietnamese pig production. While changes in farmers' behavior were also observed after VietGAHP adoption (Lapar et al., 2017), some questions on farmers' engagement and participation in the program still remain, as some VietGAHP standards are strict and difficult for farmers to adopt, and especially for farmers with limited abilities (Nguyen, 2017). Moreover, the VietGAHP for HH pig production is a package of technologies with 29 practices. Thus, two sides of farmers' VietGAHP adoption can be investigated: (1) the factors related to the HH and institutional characteristics in adopting VietGAHP; and (2) the differences between the VietGAHP and conventional HHs in implementing VietGAHP criteria. This context is particularly important as all VietGAHP households that lost their active VietGAHP status at the end of 2015 continue to implement VietGAHP criteria. Moreover, no studies have combined the determinants of VietGAHP in HH pig production and the measurement of differences in implementing VietGAHP criteria between VietGAHP and conventional households. Therefore, the objectives of this chapter are to identify the factors associated with VietGAHP adoption in HH pig production and to determine the impact of VietGAHP adoption on its criteria implementation toward fulfilling 2016 VietGAHP requirements. This chapter is an example of measuring the impacts of new production process as a package of technologies on its implementation of the smallholders.

2 Methodology

2.1 Site Selection

Hung Yen Province was 1 of 12 target provinces in LIFSAP, located in Vietnam's Red River delta. The delta is the largest pig production region in Vietnam, with 7.4 million pigs accounting for 25.5% of domestic pig production in 2016 (GSOV, 2017). Tien Lu and Khoai Chau were two of four districts promoting VietGAHP under LIFSAP support for HH pig production in Hung Yen Province. In 2017, the ratio of agricultural production land to the total land in the Tien Lu and Khoai Chau districts were the highest in four districts, at 63% and 60%, respectively. Further, these districts had the largest total land area in the province, at 7,859 and 13,098 ha, respectively (Hungyen Statistics Office, 2019).

2.2 VietGAHP Criteria and Adoption

The VietGAHP standard released in 2011 has only been applied for households registered as LIFSAP members, hereafter called "VietGAHP households" or "VietGAHP adopter households." The VietGAHP for HH pig production was updated in 2016 based on the VietGAHP for HH pig production released in 2011, with HH based-pig production defined as the total revenue received from pig production in a financial year totaling less than one billion Vietnamese dong, or 44,535 USD (MARD, 2016).[1]

The 2016 VietGAHP standard included 29 practices or criteria divided into 15 compulsory "A criteria" and 14 optional "B criteria." These were categorized into eight groups, including Group I (location, building infrastructure, and equipment, or criteria 1 to 6), Group II (breeding and breeding management, or criteria 7 to 9), Group III (feeding and feeding management, or criteria 10 to 13), Group IV (water, or criteria 14 and 15), Group V (veterinary practices and veterinary hygiene, or criteria

[1] Exchange rate: US$1 = 22,454 Vietnamese dong at the time of the survey.

16 to 23), Group VI (sales, or criteria 24 to 26), Group VII (environment, or criteria 27 and 28), and Group VIII (recording, or criterion 29). Appendix (Table 6) defines each criterion and describes its requirements in detail. Furthermore, those aspiring to become active VietGAHP households must first satisfy all 15 A criteria and at least 7 B criteria (MARD, 2016).

2.3 Data Collection

Primary data was collected in April 2018, and included 114 VietGAHP households and 116 conventional households. A VietGAHP HH is defined as a pig HH who registered as a member of their district's LIFSAP group. They were randomly chosen based on lists of VietGAHP groups. A conventional (VietGAHP non-adopting) household is a household pig producer as defined by MARD (2016) that was not registered as a member of VietGAHP groups. They have not received any training regarding VietGAHP criteria, but have basic amenities in place for their farms and pig-keeping. Conventional households were randomly selected in the same district as VietGAHP households.

2.4 Empirical Model of VietGAHP Adoption

First, the literature on agricultural technology adoption indicates that the most appropriate approach used to specify the relationship between the decisions to adopt or not adopt, with a set of explanatory variables, would be the Logit or Probit models (Feder et al., 1985). The Probit model is preferable to the Logit model in econometrics due to the normality assumption for the error term (Wooldridge, 2013). Recent empirical studies have used the Probit model to discover the factors affecting the adoption of agricultural technology (Asfaw et al., 2012; Coulibaly et al., 2017; Ghimire et al., 2015; Saiful Islam et al., 2015; Wang et al., 2012). Further, this approach has used in sustainable agricultural technology (Mariano et al., 2012; Marine et al., 2016; Srisopaporn et al., 2015). Therefore, this research uses the Probit model, based on the latent variable model (Wooldridge, 2013), to investigate the factors determining VietGAHP adoption in this research, as follows:

$$Y^* = \beta_0 + X\beta + e \tag{1}$$

$$with\ Y = 1\ if\ Y^* > 0\ and\ Y = 0\ if\ Y^* \leq 0$$

where Y^* is an unobserved or latent variable; Y is an observed variable of Y^*, with $Y = 1$ if the farmer is a VietGAHP HH, and 0 otherwise; X is the full set of explanatory variables; β is the set of parameters; and e is independent of X and has a standard normal distribution.

This chapter also estimated the average marginal effects of explanatory variables regarding the probability of becoming a VietGAHP HH to demonstrate the magnitude of these relationships, as Wooldridge (2013) proposed. This estimation is essentially based on the explanatory variables' partial effects on adoption probability. Wooldridge (2013) indicated that if x_j is a continuous variable, its marginal effect is calculated as in the below Eq. (2):

$$\frac{\partial probability(Y = 1)}{\partial x_j} = g(\beta_0 + X\beta)\beta_j \tag{2}$$

where g is a probability density function. This marginal effect always has the same sign as β_j. However, if x_l is a dichotomous explanatory variable, its marginal effect is simply the change in the predicted probability of adoption when x_l changes from zero to one given all other variables are fixed.

2.5 Variables Used in VietGAHP Adoption Model

Table 1 details the definition and expected sign of the explanatory variables used in the Probit model. The expected sign of each variable regarding VietGAHP adoption was based on an observation of the literature regarding the adoption of agricultural technology (Asfaw et al., 2012; Feder et al., 1985), sustainable agricultural practices (Baumgart-getz et al., 2012; Coulibaly et al., 2017; Ghimire et al., 2015; Mariano et al., 2012; Noltze et al., 2012; Saiful Islam et al., 2015; Souza et al., 1990; Wang et al., 2012), and public GAP adoption (Giang et al., 2016; Marine et al., 2016; Srisopaporn et al., 2015). All explanatory variables were divided into three categories: farmer characteristics, represented by *Gender, Education, Experience*, and *Training*; HH characteristics, represented by *Farm size*, *Pig raisers*, *Pig_HH income*, *Off-farm income*, *HH income*, and *Biogas*; and institutional characteristics, represented by the *Credit access* and *Veterinary access* variables.

2.6 Measuring Impact of VietGAHP Adoption on Its Criteria Implementation

The z-test was used to compare the two proportions in each VietGAHP criterion between the VietGAHP and conventional groups; P_1 is the proportion of VietGAHP group households stating that they meet all VietGAHP criteria, divided by the total

Table 1 Explanatory variables and their definitions as uded in the Probit model

Variable	Definition	Expected sign
Dependent variable		
VietGAHP HH	= 1 if HH adopted VietGAHP for their pig production and registered as a LIFSAP member, 0 otherwise	
Explanatory variables		
Farmer's characteristics		
Gender	= 1 if the respondent farmer is male, 0 otherwise	+
Education	Formal education (in years)	+
Experience	Pig production experience (in years)	±
Training	= 1 if the farmer has been trained in pig production, 0 otherwise	+
HH's characteristics		
Farm size	Pig warehouse's area (m^2)	+
Pig raisers	Number of family members joining in pig production (number of persons)	+
Pig_HH income	Ratio of pig income to total HH income (%)	+
Off-farm income	= 1 if HH has income from activities external to the farm, 0 otherwise	±
HH income	The sum of the farm's total cash income and the HH's off-farm income in 2017 (in thousands of USD)	+
Biogas	= 1 if households have a biogas system, 0 otherwise	+
Institutional characteristics		
Credit access	= 1 if households currently have loan credit for their pig production, 0 otherwise	+
Veterinary access	= 1 if household used veterinary services in their pig production, 0 otherwise	+

Note + and − indicate positive and negative signs, respectively

number of VietGAHP households; P_2 is the proportion of conventional group households stating that they fulfilled all VietGAHP criteria, divided by the total number of conventional households.

Although each VietGAHP criterion has its own assessment method (MARD, 2016; see also the Assessed Method column in Appendix, Table 7) there can be one method or a combination of methods used for each, including reviewing record books and the VietGAHP manual, or observations and interviews. However, both VietGAHP and conventional households were assessed regarding their compliance with each criterion by the same approach, specifically, interviewing farmers based on "yes or no" questions for each criterion requirement in two steps. First, farmers were asked if they comply with each criterion. If so, they were asked a subsequent question related to the intensity of that compliance. If farmers answered yes to all requirements, this was noted as full compliance with that criterion, and thus, the farmer could immediately answer about the requirement based on their current implementation. We directly asked farmers regarding criteria numbered 1–4, 6, 9–13, 16–19, 21, 22, and 24–26 using the above procedure. For the other criteria, we asked indirect questions regarding their pig production practices, and evaluated these practices against the VietGAHP requirements for each criterion as noted in the VietGAHP manual.

Another important factor for implementing VietGAHP goals involves product traceability based on farmers' record books, but most farmers were not aware of the record book format. Therefore, the implementation of criteria 7, 9, 10, 20, 21, 23, 27, and 29 was assessed only regarding the compliance of recorded information content. Farmers were asked whether they fully recorded information for these particular criteria, and we did not mention the record book format included in criteria 29. All questions regarding compliance with VietGAHP criteria were tested and revised based on the results of a pilot survey of 14 farmers to guarantee that farmers could answer them. As a result of the pilot survey, it was determined that farmers could not clearly answer "yes" or "no" when assessing the level of compliance for criteria number 5, 7, 8, 14, 15, 20, 23, 27, 28, and 29. We then added indirect questions to ask them how they practiced their pig production regarding the above criteria. All the additional questions are detailed in Appendix, Table 7, in the Assessed Method column.

3 Results and Discussion

3.1 Characteristics of Vietnamese HH Pig Production

Table 2 displays the socioeconomic characteristics of Vietnamese HH pig production, as well as the differences between VietGAHP and conventional groups. First, Vietnamese HH pig farmers only had 8.27 years of formal education, but 84.35% were trained in pig production techniques, with nearly 16 years of experience in pig production. Further, HH pig producers used only family labor, and 62.99% of their income came from pig production. On average, the pig warehouse area per HH was approximately 180 m^2, and the scale of pig production from the current survey was appropriate 34 heads of pigs per HH; 49.13% of farmers had accessed credit for their pig production, and 63.48% had access to veterinary services.

Second, differences can be noted in both groups' characteristics. It is noticeable that more farmers in the VietGAHP group were male and were trained in pig production than in the conventional group. Additionally, the VietGAHP HHs were richer and had more access to veterinary services than conventional HHs. In contrast, it is noteworthy that the conventional HH owned larger farms and operated on a larger production scale, and their pig activities contributed more to household income compared to VietGAHP HHs. Further, more HHs had built biogas systems for their pig farms and had accessed credit services in the conventional group than their counterparts.

Table 2 The differences in socioeconomic characteristics between VietGAHP and conventional farmers

Variable	All HH ($n = 230$)		VietGAHP HH ($n = 114$)		Conventional HH ($n = 116$)		Difference	
	Mean	SD	Mean	SD	Mean	SD		
Farmer's characteristics								
Gender (male %)	69.13	46.30	76.32	3.98	62.07	4.51	14.25	**
Education (years)	8.27	2.23	8.01	0.20	8.52	0.21	−0.51	*
Experience (years)	15.69	8.78	16.68	0.73	14.72	0.89	1.96	*
Training (%)	84.35	36.41	95.61	1.93	73.28	4.13	22.34	***
HH's characteristics								
Farm size (m^2)	179.79	171.31	147.94	12.29	211.10	18.46	−63.16	***
Scale (heads)	33.57	29.97	29.18	24.21	37.88	34.28	−8.70	**
Pig raisers (persons)	1.71	0.54	1.70	0.05	1.72	0.05	−0.01	
Pig_HH income (%)	62.99	24.93	58.41	25.37	67.48	23.76	−9.07	***
Off-farm income (%)	71.74	45.12	67.54	4.39	75.86	3.97	−8.32	
HH income (thousand USD)	15.64	14.24	17.23	1.36	14.08	1.28	3.15	*
Biogas (%)	78.26	41.34	69.30	46.33	87.07	33.70	−17.77	**
Institutional characteristics								
Credit access (%)	49.13	50.10	40.35	4.59	57.76	4.59	−17.41	***
Veterinary access (%)	63.48	48.25	78.95	3.82	48.28	4.64	30.67	***

Note ***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively

3.2 Determinants of VietGAHP Adoption in HH Pig Production

This chapter aims to uncover the major factors associated with VietGAHP adoption for HH pig production by including farmer, farm, and institutional characteristics. The results reveal that farmer and institutional characteristics were the most positively associated with VietGAHP adoption, while farm characteristics were the most negatively associated with this adoption.

A likelihood ratio test with 12 degrees of freedom suggests that the estimated model exhibits a good fit, with a statistically significant score of 79.42 at 1%. The correctly classified estimated model indicates that the Probit model correctly predicted 76.52% of the observations (Table 3).

First, among the positive factors associated with VietGAHP adoption in Vietnamese HH pig production, *Training* was found to be the most significant factor. As anticipated, farmers participating in training on pig production techniques were more likely to adopt VietGAHP in their farms. At the 1% significance level, the probability of adoption increases by 35% if a farmer has been involved in any training programs, which parallels results by Baumgart-getz et al. (2012), Mariano et al.

Table 3 Estimated coefficients and average marginal effects of factors associated with VietGAHP adoption

Variables	Coefficient		Std. Err	Average marginal effects		Std. Err. (delta method)
Farmer's characteristics						
Gender (dummy)	0.386	*	0.221	0.115	*	0.065
Education (years)	−0.032		0.045	−0.009		0.013
Experience (years)	0.011		0.011	0.003		0.003
Training (dummy)	1.176	***	0.316	0.350	***	0.086
HH's characteristics						
Farm size (m^2)	−0.001	**	0.001	−0.0004	**	0.000
Pig raisers (persons)	−0.406	**	0.199	−0.121	**	0.058
Pig_HH income (%)	−0.569		0.436	−0.169		0.128
Off-farm income (dummy)	−0.412	*	0.230	−0.122	*	0.067
HH income (thousand USD)	0.017	**	0.008	0.005	**	0.002
Biogas (dummy)	−0.856	***	0.249	−0.254	***	0.068
Institutional characteristics						
Credit access (dummy)	−0.194		0.198	−0.058		0.059
Veterinary access (dummy)	0.755	***	0.201	0.224	***	0.054
Constant	0.401		0.657			

Note ***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively; log likelihood = −119.703; Chi-squared likelihood ratio (12) = 79.42***; pseudo-R2 = 0.2491; correctly classified = 76.52%

(2012), and Noltze et al. (2012). These training programs aim to enhance farmers' managerial abilities in pig production; consequently, farmers gain new information on production techniques. These farmers have been trained to gain better knowledge and access to training program information. *Training* was followed by the *Veterinary access* factor, which positively affects VietGAHP adoption. As anticipated, farmers with access to veterinary services for their farms were also more likely to adopt VietGAHP. Estimating this variable's marginal effect reveals that the probability of VietGAHP adoption increases by 22.4% for farmers with access to veterinary services. This access also allowed farmers to directly receive animal health services from the government, such as animal health consulting and the latest information. This result is consistent with findings from Mariano et al. (2012) and Srisopaporn et al. (2015), who argued that rice farmers who contacted the government's farming extension tended to increase their probability of GAHP adoption. Moreover, the Vietnamese government primarily supplies not only free training programs through agricultural extension activities (Lapar, 2014), but also veterinary services for farmers (Nga et al., 2014). Thus, participation in training programs and accessing veterinary services are noteworthy in enhancing the VietGAHP adoption rates in HH pig production.

Furthermore, *Gender* and *HH income* also positively and significantly contributed to VietGAHP adoption. As anticipated, male farmers were more willing to adopt VietGAHP in their production practices, and the probability of their VietGAHP adoption increased by 11.5% compared to female farmers. This was as anticipated, as HH heads in Vietnam are typically male, and might have better access to new agricultural techniques (Saiful Islam et al., 2015). Regarding the *HH income* factor, wealthier farmers were more willing to adopt VietGAHP because target VietGAHP households had to have sufficient financial resources to satisfy high-standard VietGAHP requirements (World Bank, 2009b). Moreover, Baumgart-getz et al. (2012) indicated similar results, as wealthier farmers tend to adopt new technologies to seek higher benefits. However, this variable exhibited a small estimated marginal effect of only 0.5%. Therefore, this chapter again confirmed that *Gender* and *HH income* were still considerably significant in spreading agricultural technology adoption, and especially sustainable agricultural technology.

Second, it is also noteworthy that all factors inversely related to VietGAHP adoption belonged to the owned HH characteristics, except for *HH income*. However, it was not anticipated that households with larger pigsty areas and more family members participating in pig production were less likely to adopt VietGAHP. Although farm size had been considered an important factor in prior decades in the early diffusion of agricultural innovation in developing countries, it was no longer an important factor in the final stages of such diffusion (Feder et al., 1985). Furthermore, VietGAHP for pig production was still in an initial diffusion phase, as the Vietnamese government had anticipated that VietGAHP adopters, or the farmers who had registered with and joined VietGAHP groups, would primarily contribute to enhancing future adoption rates. As VietGAHP for pig production required significant, initial, one-time investments—such as restructuring pigsties and separating the farm from residential areas by fencing and an enclosed gate—farmers with larger farms must invest more for initial costs; Hobbs (2003) noted this as an economic deterrent to the adoption of public GAPs. Further, Feder et al. (1985) indicated that the probability of adoption would decrease with the increase in fixed costs. Thus, farmers with larger farms might have insufficient sources of capital to support simultaneous VietGAHP adoption. However, the farm size's estimated marginal effect indicated that the probability of adoption decreased only slightly, or by 0.04% per m^2 change in farm size. The HH pig producers were primarily small-scale, with pigsties of an average 180m^2/HH, and these pig farms were located in residential areas. Regarding the *Pig raisers* variable, the likelihood of adoption decreased by 12.1% for each family member joining in pig production, as households only use family members, and they seem to very carefully consider when new techniques are presented. These results imply that farm size is important in adopting sustainable agricultural technologies, even among small households that only include their family members in their agricultural activities.

Off-farm income was found to be negative and significant in influencing VietGAHP adoption; thus, households with off-farm income had a probability of VietGAHP adoption decreasing by 12.2%, with all other variables fixed. This might indicate that farmers who could earn from non-farm activities may attempt to do so, rather than investing in new, possibly risky agricultural technology (Feder et al., 1985). Furthermore, this research was conducted in 2018, when pig production in Vietnam was affected by a sharp decrease in output prices, and farmers tended to seek off-farm activities for earnings, thus retaining a constant agricultural production.

Biogas was considered a positive factor in supporting VietGAHP adoption in terms of decreasing the cost of manure waste treatment. However, this variable was unexpectedly and inversely related to adoption; the estimated marginal effects suggest that an available biogas system decreased the probability of adoption by 25.4%. The current biogas system had been in existence for many years to treat manure waste, although such a waste treatment system might not satisfy VietGAHP standards. This might result in higher investment costs for farmers adopting VietGAHP standards. Reinvestment costs were also a priority issue in pig farmers' VietGAHP adoption, which had been noted in Vietnam's Hai Duong Province (Nguyen, 2017).

Education was anticipated to positively influence VietGAHP adoption, as this requires a higher education, and the *Education* factor was observed as a means for farmers to learn new skills. This result contrasted findings by Souza et al. (1990), Asfaw et al. (2012), Mariano et al. (2012), Ghimire et al. (2015), Srisopaporn et al. (2015),and Giang et al. (2016); these authors indicated that farmers with a higher formal education tended to adopt new agricultural technology because they had a better ability to reach and process new information. However, this chapter's findings reflect those found by Noltze et al. (2012) and Saiful Islam et al. (2015), who supposed that the farmer's education simply allowed them to acquire low-level knowledge that may be insufficient or irrelevant for adopting intensive new agricultural techniques. Further, a meta-analysis on the adoption of best management practices in the USA revealed that formal education did not seem to affect adoption (Baumgart-getz et al., 2012). On average, farmers' education in this chapter area met Vietnam's universal secondary education standards, and thus, farmers' educational levels were not high enough to lead to a difference in the adoption of strict, high-standard agricultural technologies, such as VietGAHP. *Experience* also was a positively non-significant factor impacting VietGAHP adoption. Although it was anticipated that this variable would be associated with better techniques and these farmers would more easily adapt with new techniques, the results do not support this expectation, which parallels results from Asfaw et al. (2012), Srisopaporn et al. (2015), and Marine et al. (2016). Experience was perhaps highly positively associated with the farmer's age, which negatively affected their adoption of new agricultural technology.

3.3 Current Status of Implementing VietGAHP Criteria on HH Pig Production

More than 50% of the farmers surveyed had fully complied with 6 of the 15 compulsory VietGAHP practices, including (Fig. 1): having a dried floor (A2), not using banned substances (A10), pigs for sale are in good health (A12), having a waste treatment system (A3), fully vaccinating pigs intended for breeding (A5), and periodically disinfecting the pigsty (A7). Based on farmers' experience, most farmers adopting these criteria might assume that A2 and A5 were the most important practices to help maintain their pigs' health and prevent disease, although A3 and A7 were also listed as the most important practices to maintain a good environment to deter disease. Regarding A10 and A12, the farmers noted that their chosen feeds were quality-guaranteed and without banned substances, and that their pigs intended for sale were in good health.

Moreover, the smallest percentage of farmers (less than 10%) complied with the following practices: providing pig profile records (A13), recording all pig production information (A15), and following equipment disinfection rules (A8). The same results from A13 and A15 were found in work by Nguyen (2017), which revealed that no VietGAHP farmers in Hai Duong Province fully complied with such criteria, with only 7.32% of VietGAHP farmers implementing 50–80% of these criteria. One explanation for this result is that these practices did not affect pig productivity, and were not perceived as important VietGAHP criteria to ensure product traceability in the market (Nguyen, 2017). Thus, it is important to enhance farmers' awareness of the importance of each practice in VietGAHP adoption.

Regarding the rest of the compulsory criteria adopted by less than 50% of farmers, Lapar et al. (2017) found the same results for following disease-processing procedures (A11), having a protective fencing system (A1), following dead pig disposal rules (A14), and using clear breeding sources (A4). However, these contrast results for fully vaccinating fattened pigs (A9) and having clear knowledge of feed origins (A6). This contrasting results found in this chapter might be due to a decrease in the price for fattened pigs at the time of the survey, from January 2017 until March 2018, which compelled farmers to save on production costs as much as possible by decreasing vaccination costs and using less commercial feed.

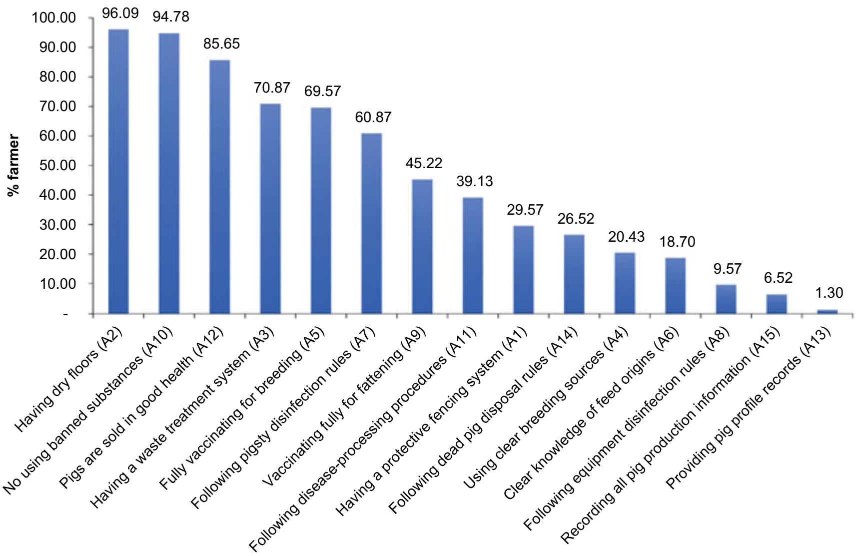

Fig. 1 Frequency of farmers adopting each compulsory VietGAHP criterion

More than half of the surveyed farmers adopted 9 of the 14 optional practices, including (Fig. 2): collecting daily waste (B10), using hygiene-guaranteed feed (B5), having an enclosed warehouse (B2), using specialized pig production equipment (B3), following feed storage rules (B7), separating newly acquired breeding stock (B4), treating wastewater (B9), using hygienic drinking water for pigs (B8), and using nutrient-guaranteed feed (B6). The results from implementing B10, B5, B2, B9, B6, and B8 paralleled findings from Lapar et al. (2017), as those practices clearly kept pigs in good health, while the authors found B3, B4, and B7 had low levels of implementation. The level of commercialization in pig production might be affected by these practices.

3.4 Impact of VietGAHP Adoption on Implementing Its Criteria

Aside from denoting the most influential factors in adopting VietGAHP, this chapter is the first to explore the impact of VietGAHP application on the implementation of each of its criteria. This impact was indicated by the difference in implementing each criterion between the VietGAHP and convention groups. To become active VietGAHP households, HHs must satisfy all 15 compulsory criteria and at least 7 optional criteria (MARD, 2016). Therefore, this chapter measured the impacts of VietGAHP adoption on implementation in the compulsory and optional criteria

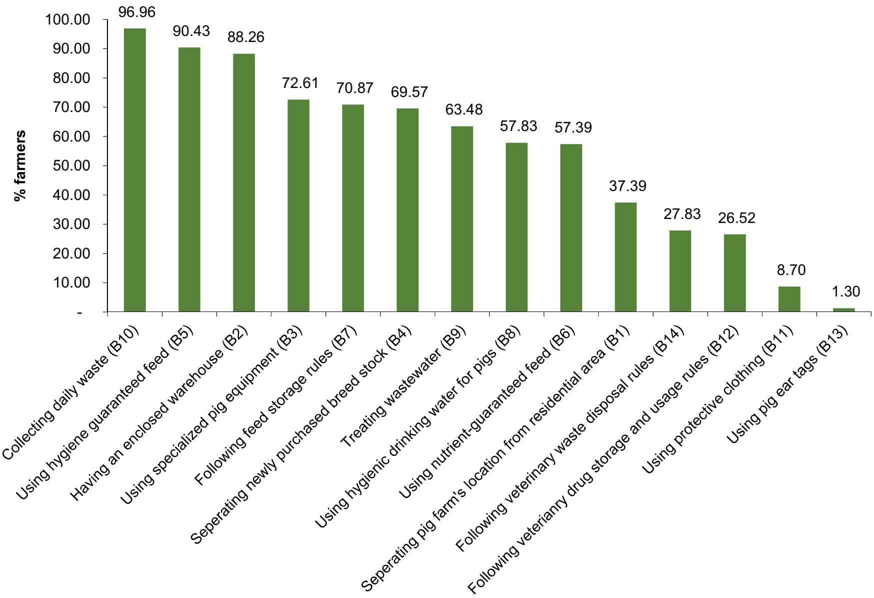

Fig. 2 Frequency of farmers adopting each optional VietGAHP criterion

groups separately. Overall, VietGAHP adoption impacted the implementing of difficult criteria and had a more substantial impact on compulsory than optional criteria implementation.

3.4.1 Compulsory "A" Criteria

Full compliance rates in 9 of the 15 "A" criteria were significantly higher within the VietGAHP group than in the conventional group; no difference was noted in the adoption rates between the two groups in 5 of the 15 "A" criteria, and only 1 of the 15 "A" criteria was fully adopted by more farmers in the conventional group than in the VietGAHP group (Table 4).

Specifically, and in order from the largest to smallest differences among the 9 of 15 A criteria implemented by more farmers in the VietGAHP group, these include: following disease-processing procedures (A11), having a protective fencing system (A1), following dead pig disposal rules (A14), periodically disinfecting pigsties (A7), following record-keeping rules (A15), fully vaccinating fattening pigs (A9), using clear breeding sources (A4), disinfecting equipment (A8), and providing pig profile records (A13), with the largest and smallest differences being 16.33% and 2.63%, respectively. First, these practices could be considered financial practices (A1, A7, A9, A4, and A8), as farmers must invest more money in adopting these criteria, and these could financially burden farmers if the resulting production does not create favorable returns on investments. These practices could be economic deterrents

Table 4 The difference in the full compliance rates for each compulsory criterion between the two groups (% farmers)

Group	Criteria	All HH (n = 230)	VietGAHP HH (n = 114)	Conventional HH (n = 116)	Difference		z-value	p-value
V	Following disease-processing procedures (A11)	39.13	47.37	31.03	16.34	**	2.54	0.011
I	Having a protective fencing system (A1)	29.57	37.72	21.55	16.17	***	2.69	0.007
VII	Following dead pig disposal rules (A14)	26.52	33.33	19.83	13.50	**	2.18	0.020
V	Periodically disinfecting pigsties (A7)	60.87	67.54	54.31	13.23	**	2.06	0.040
VIII	Recording all pig production information (A15)	6.52	12.28	0.86	11.42	***	3.51	0.001
V	Fully vaccinating fattened pigs (A9)	45.22	50.88	39.66	11.22	*	1.71	0.087
II	Using clear breeding sources (A4)	20.43	25.44	15.52	9.92	*	1.87	0.062
V	Disinfecting equipment (A8)	9.57	14.04	5.17	8.87	**	2.28	0.022
III	Clearly knowing feed origins (A6)	18.70	21.05	16.38	4.67		0.91	0.363
VI	Providing pig profile records (A13)	1.30	2.63	0.00	2.63	*	1.76	0.079
II	Fully vaccinating breeding stock (A5)	69.57	70.18	68.97	1.21		0.05	0.842
I	Having a dried floor (A2)	96.09	96.49	95.69	0.80		0.90	0.754
V	Not using banned substances (A10)	94.78	94.74	94.83	−0.09		−0.32	0.975
VI	Pigs for sale have good health (A12)	85.65	84.21	87.07	−2.86		−0.80	0.536
I	Having a waste treatment system (A3)	70.87	64.04	77.59	−13.55	**	−2.11	0.024

Note ***, **, and * statistical significance at the 1%, 5%, and 10% levels, respectively to adopting GAPs, as Hobbs (2003) noted, and especially in terms of increasing production costs and investing assets (Feder et al., 1985). Additionally, less than 50% of the farmers complied with these practices, except for A7, as these generally became barriers to VietGAHP adoption. The results reveal that VietGAHP farmers complied with these procedures more than conventional famers, possibly because VietGAHP farmers received some subsidies from LIFSAP, such as two million dong in cash, storage for veterinary medicines, disinfectants, and disinfection tools to increase adoption rates. Thus, direct-incentive economics might be an option for the government in promoting VietGAHP for HH pig production. Second, the remaining practices can be listed as practices related to empirical knowledge. Farmers with better access to VietGAHP information—and subsequently, better knowledge—might successfully implement these practices in their pig production. One reason why VietGAHP farmers might comply with these practices more than conventional farmers could be that the former received training from frequent meetings organized by LIFSAP, and they better understood and adhered to such practices. Thus, spreading empirical knowledge through training could enhance the VietGAHP adoption rate among pig producers.

The practice of having a waste treatment system (A3) was the only practice that farmers in the conventional group complied with more often than those in the VietGAHP group. This reflects findings found by Lapar et al. (2017) in Vietnam's Nghe An Province. This might be due to VietGAHP farmers using manure from their pig production for other farming activities, such as fish-feeding in their ponds instead of building a waste treatment system to save their production costs. Similarly, Giang et al. (2016) demonstrated that fish ponds were an important factor impacting households' VietGAHP adoption in the Hung Yen Province's Tien Lu district. Thus, VietGAHP adoption might have negative consequences for farmers' perceptions of its implementation.

Regarding the clear knowledge of feed origins (A6), while this did not differ among farmers' perceptions, less than 50% of the farmers complied with this criterion, as they bought feed based on their trust in the feed seller and the feed's brand; they did not know whether the feed was guaranteed as per the relevant standard. These farmers suggested that the government should clarify the feed's origin then inform them if the brand-name feed satisfied feed standards for pig production. Further, this criterion as well as four other compulsory criteria did not differ between the two groups—including: fully vaccinating pigs for breeding (A5), having a dried floor (A2), not using banned substances (A10), and selling pigs in good health (A12)—and was adopted by more than 50% of farmers. This was because these practices correlated well with pig production's basic conditions, which involved keeping pigs in good health, and could be partially controlled by the farmers themselves.

In summary, it can be concluded that VietGAHP adoption only had a positive impact by increasing the proportion of farmers implementing difficult compulsory criteria through financial and equipment support and training.

3.4.2 Optional "B" Criteria

The two groups differed in their implementation of 8 of the 14 optional "B" VietGAHP criteria, including (Table 5): using hygienic drinking water for pigs (B8), separating newly purchased breeding stock (B4), following feed storage rules (B7), using specialized pig equipment (B3), separating the pig farm's location from the residential area (B1), using protective clothing (B11), collecting daily waste (B10), and using pig ear tags (B13).

These were also practiced among groups that needed credit for investments, except for collecting daily waste (B10). Among them, farmers least often complied with the use of protective clothing (B11) and pig ear tags (B13), as farmers perceived these as unnecessary for their current contexts, and these increased production costs. However, more VietGAHP farmers complied with these criteria than conventional farmers because they received support from LIFSAP. More farmers in the VietGAHP group also followed feed storage rules and practices than in the conventional group, as the former also received training on these practices, and LIFSAP delivered some equipment to satisfy these VietGAHP standards. The above results lead to the conclusion that VietGAHP adoption positively impacted these practices, and primarily through the distribution of supporting equipment. However, these practices were soon eliminated when the equipment was no longer usable, as these required further costs to maintain and farmers did not perceive them as directly affecting pig productivity. Aside from the equipment distributed to support farmers by decreasing their short-term production costs, the long-term benefit of each VietGAHP practice should be emphasized to improve general VietGAHP adoption in pig production.

More than 50% of farmers adopted the remaining practices—except for separating the pig farm location from the residential area (B4)—as these also correlated well with a basic objective in pig production: to maintain the pigs' good health. More farmers in the VietGAHP group upheld these practices than in the conventional group, possibly because the former included wealthier farmers who were well-trained as a result of becoming VietGAHP adopters. Again, VietGAHP adoption could enhance the practices associated with maintaining pigs' good health, at least in terms of diffusing knowledge. Regarding the separating of the pig farm location from the residential area (B4), this was impacted by households' land limitations, as farmers would absorb the cost of such a project if they had to invest more to build pigsties separated from their houses. This was observed as the most difficult practice for farmers in Hai Duong Province (Nguyen, 2017). More farmers in the VietGAHP group adopted this criterion than in the conventional group, possibly because they had better land location and financial conditions. Thus, in priority order, training and financial support might be suitable to enhance these VietGAHP practices.

The same reason might be applied—in that the practices correlate well with pig production's basic objective to keep pigs in good health—as no difference could be noted for the waste water treatment (B9), using hygiene-guaranteed (B5) and nutrient-guaranteed feed (B6) practices when these were upheld by more than 50% of farmers, although more so in the conventional group than in the VietGAHP group.

Table 5 The difference in full adoption rates of each optional criterion between the two groups (% farmers)

Group	Criteria	All HH (n = 230)	VietGAHP HH (n = 114)	Conventional HH (n = 116)	Difference		z-value	p-value
IV	Using hygienic drinking water for pigs (B8)	57.83	69.30	46.55	22.75	***	3.49	0.001
II	Separating newly bought breeding stock (B4)	69.57	78.07	61.21	16.86	***	2.91	0.006
III	Following feed storage rules (B7)	70.87	78.95	62.93	16.02	***	2.67	0.008
I	Using specialized pig equipment (B3)	72.61	79.82	65.52	14.30	**	2.43	0.015
I	Separating the pig farm's location from the residential area (B1)	37.39	43.86	31.03	12.83	**	2.01	0.044
V	Using protective clothing (B11)	8.70	13.16	4.31	8.85	**	2.39	0.017
V	Following veterinary drug storage and usage rules (B12)	26.52	30.70	22.41	8.29		1.42	0.155
I	Having an enclosed warehouse (B2)	88.26	90.35	83.62	6.73		1.52	0.13
V	Collecting daily waste (B10)	96.96	100.00	93.97	6.03	***	2.66	0.008
VI	Using pig ear tags (B13)	1.30	2.63	0.00	2.63	*	1.76	0.079
VII	Following veterinary waste disposal rules (B14)	27.83	28.95	26.72	2.23		0.38	0.707
IV	Treating wastewater (B9)	63.48	63.16	63.79	−0.63		−0.10	0.92
III	Using hygiene-guaranteed feed (B5)	90.43	87.72	93.10	−5.38		−1.39	0.165
III	Using nutrient-guaranteed feed (B6)	57.39	54.39	60.34	−5.95		−0.91	0.361

Note ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively

This might also be because VietGAHP farmers were better trained and better understood the VietGAHP criteria, and they assessed their own practices as unfit compared to VietGAHP standards.

The other practices without differences among the two groups included following rules for using and storing veterinary medicines (B12) and following veterinary waste disposal rules (B14), with average compliance rates of 26.52 and 27.83, respectively. This was because farmers assumed that it was unnecessary to follow veterinary medicine storage and usage rules (B12) when they had always consulted veterinary sales and used all veterinary medicines without storage. Further, following veterinary waste disposal rules (B14) did not affect their pig production, and farmers consequently perceived this as normal HH waste. Thus, the impacts of VietGAHP adoption seem to fail in the practices related to managing farmers' knowledge without strict governmental control.

4 Conclusion and Implications

The constraints on improving livestock production are generally rooted in farmers' perceptions (Gillespie et al., 2013; Mapiye et al., 2018; Mazimpaka et al., 2018; Sitienei et al., 2015; Zander et al., 2013). Shiferaw et al. (2015) and Kebebe et al. (2017) showed that when farmers want to adopt new technologies, it is important to address the multiple constraints they face. Few studies focus on the constraints farmers face in adopting new management practices in beef and dairy production (Ali et al., 2019; Gillespie et al., 2007). Furthermore, the constraints faced by farmers involved in general production differ from those faced by farmers adopting new technologies for livestock production.

Unlike previous studies, this chapter demonstrated the factors that contributed most to VietGAHP adoption and the VietGAHP criteria with which farmers most often complied. It reveals that it would be most significant for the Vietnamese government to improve VietGAHP adoption rates for agricultural producers in general, but pig production HHs in particular. Further, our results would be valuable for other public GAP programs for small farmers in the world, such as those in ASEAN countries.

First, the significant, positive factors associated with VietGAHP adoption were gender, training, HH income, and access to veterinary services. Among these, training and the access to veterinary services were the most important, and the government is primarily responsible for cultivating these two factors. Thus, the Vietnamese government should first continue to focus on these two channels to widely promote VietGAHP and enhance its adoption rate.

Aside from these positive factors, it is noteworthy that farm size, the number of pig producers, off-farm income, and biogas were proven to significantly decrease VietGAHP adoption. All these factors are owned HH characteristics, and the biogas factor was the most influential. This indicates an economic deterrent, or what Hobbs (2003) noted as a "new capital investment" in GAP adoption, even among small households that only utilize family members in their agricultural activities. Thus, if the government wants households to develop larger-scale pig production, more family members participating in pig production should adopt VietGAHP, and the government should design a financial support system to reduce the effects of any cost deterrent.

Second, VietGAHP adoption has considerably influenced the implementing of eight difficult compulsory criteria, as these were implemented by less than 50% of all farmers. Moreover, VietGAHP had a significant, positive impact on the implementing of the eight optional criteria. Three of these criteria could be listed as difficult optional criteria, and farmers perceived these criteria and their costs as unnecessary. VietGAHP adoption clearly enabled the goal of meeting at least seven optional criteria to satisfy the condition of becoming an active VietGAHP HH (MARD, 2016). This was possible because VietGAHP farmers were supported through technical training and financial resources provided by LIFSAP (World Bank, 2009b). As the government's support has been vital in improving the implementation of VietGAHP criteria, such technical training and financial support should be delivered to all households.

Appendix

See (Table 6).

See (Table 7).

Table 6 Definition and requirements for each VietGAHP criterion for HH pig production (MARD, 2016)

No	Criterion	Adopted level[a]	Requirements
Group I. Location, building infrastructure, and equipment			
1	Separating pig farm's location from residential area (B1)	B	Farm is separated from residential areas as well as drinking water sources
2	Having a protective fence system (A1)	A	Having a walled or fenced enclosure; having a gated entrance into the pigsty; having an antiseptic system at the gated entrance
3	Having dry floors (A2)	A	Farm has no standing water on the floor
4	Having an enclosed warehouse (B2)	B	Warehouse has no leaks or drafts
5	Having a waste treatment system (A3)	A	Having a waste treatment system to collect and dispose of solid and liquid wastes
6	Using specialized pig equipment (B3)	B	Having specialized pig production tools and equipment
Group II. Breeding and breeding management			
7	Using a clear breeding source (A4)	A	Having clear breeding sources and fully recording these sources
8	Fully vaccinating for breeding (A5)	A	All pigs are fully vaccinated
9	Separating newly acquired breeding stock (B4)	B	Separating newly purchased breeding stock and maintaining their records
Group III. Feeding and feeding management			
10	Clearly knowing feed origins (A6)	A	All feed has a clear origin, including the shop address and production address, with records
11	Guaranteeing hygiene (B5)	B	Concentrated or compound feed and the ingredients for pig feed must be hygienic, with no mold; agricultural products must be well-cooked before serving

(continued)

Table 6 (continued)

No	Criterion	Adopted level[a]	Requirements
12	Using nutrient-guaranteed feed (B6)	B	Concentrated feed must have clear, suitable guidelines for each type of pig; compound feeds must be verified with a stamp; mixed feeds must have a mixed formulation
13	Following feeding storage rules (B7)	B	Store feed on shelves and packed in sealed bags; a separate storage location should protect the feed from insects and rodents
Group IV. Water			
14	Using clean drinking water for pigs (B8)	B	Use clean, sufficient drinking water sources for pig production
15	Wastewater is treated (B9)	B	Treated by a waste treatment system
Group V. Veterinary practices and veterinary hygiene			
16	Following pigsty disinfection rules (A7)		Disinfecting pigsty before raising pigs every seven days and right after selling pigs; periodic disinfection around the pigsty area
17	Collecting waste daily (B10)	B	Clean and collect daily solid and liquid wastes
18	Using protective clothing (B11)	B	Change clothes and use protective equipment when entering the pigsty area; periodically disinfect clothes and protective equipment
19	Following equipment disinfection rules (A8)	A	Disinfect shoes when entering and exiting the pigsty; tools and equipment must be disinfected before taking in and out of the pigsty area
20	Vaccinating fully for fattening (A9)	A	Fully vaccinate pigs for required diseases and maintain full vaccination records

(continued)

Table 6 (continued)

No	Criterion	Adopted level[a]	Requirements
21	Following rules for using and storing veterinary medicines (B12)	B	All veterinary medicine, including the purchase of antibiotics, must follow a veterinarian's guidance, with full records maintained; veterinary medicine should be kept in separate storage
22	Not using banned substances (A10)	A	Do not use banned substances, such as banned antibiotics
23	Following disease-processing procedures (A11)	A	Households must inform local authorities of disease occurrences; full records must be kept regarding such diseases
Group VI. Sale			
24	Pigs are sold in good health (A12)	A	Veterinary medicine is stopped after a suitable time as described on the drug label; pigs are sold as healthy
25	Providing pig profile records (A13)	A	Full records are provided to buyer when selling pigs
26	Using pig ear tags (B13)	B	Fattened pigs sold for meat must have an ear tag
Group VII. Environment			
27	Following dead pig disposal rules (A14)	A	Dead pigs must be collected as proposed in veterinary rules; Full records must be kept regarding these dead pigs
28	Following veterinary waste disposal rules (B14)	B	Needles, plastic bags, and plastic containers must be collected for separate treatment
Group VIII. Recording			
29	Recording all pig production information (A15)	A	Maintain precise and complete records based on the recording sample attached to this decision

[a] A represents compulsory criteria, and B represents optional criteria

Table 7 Assessed method of VietGAHP criteria for HH pig production (MARD, 2016)

Criterion no	Criterion	MARD verification method	This chapter's verification method[a]
1	Separating pig farm's location from residential area (B1)	VietGAHP manual and observation	Asked directly regarding each requirement
2	Having a protective fence system (A1)	VietGAHP manual and observation	Asked directly regarding each requirement
3	Having dry floors (A2)	VietGAHP manual and observation	Asked directly regarding each requirement
4	Having an enclosed warehouse (B2)	VietGAHP manual and observation	Asked directly regarding each requirement
5	Having a waste treatment system (A3)	VietGAHP manual and observation	Asked indirectly whether a biogas system or other waste treatment system exists
6	Using specialized pig equipment (B3)	VietGAHP manual and observation	Asked directly regarding each requirement
7	Using clear breeding sources (A4)	Reviewing record book and observation	Asked indirectly through separate questions. First, "What kind of breeding source is used—self-produced or purchased?" If self-produced, the breeding source is clearly known. If purchased, does the respondent know the seller and sales location? If they know, then they are assessed as fully compliant with this criterion
8	Fully vaccinating for breeding (A5)	Vaccination certificates (if any); reviewing record book and interview	Asked indirectly through the question: "What types of vaccinations are used for breeding?" If farmers injected all three compulsory vaccinations, including those for diarrhea, Pasteurella, and foot and mouth disease, and these are frequently used, then they are assessed as fully compliant with this criterion

(continued)

Table 7 (continued)

Criterion no	Criterion	MARD verification method	This chapter's verification method[a]
9	Separating newly acquired breeding stock (B4)	Observation, interview, and reviewing record book	Asked directly regarding each requirement
10	Clearly knowing feed origins (A6)	Reviewing record book and observation	Asked directly regarding each requirement
11	Guaranteeing hygiene (B5)	Observation	Asked directly regarding each requirement
12	Using nutrient-guaranteed feed (B6)	Observation, interview, and record book	Asked directly regarding each requirement
13	Following feeding storage rules (B7)	Observation	Asked directly regarding each requirement
14	Using clean drinking water for pigs (B8)	Observation	Asked indirectly for the first requirement using two questions regarding the types of drinking water sources, and whether they have been treated prior to use. Asked directly for the second requirement
15	Treating wastewater (B9)	VietGAHP manual and observation	Asked indirectly, "Do you have a biogas system or other waste treatment system?"
16	Following pigsty disinfection rules (A7)	Interview and reviewing record book	Asked directly regarding each requirement
17	Collecting waste daily (B10)	Observation	Asked directly regarding each requirement
18	Using protective clothing (B11)	Observation	Asked directly regarding each requirement
19	Following equipment disinfection rules (A8)	Observation	Asked directly regarding each requirement
20	Vaccinating fully for fattening (A9)	Reviewing record book	Asked directly, "What types of vaccinations do you use in pig fattening?" If farmers injected both compulsory vaccinations (for diarrhea and Pasteurella) and they were frequently used, then they are assessed as fully compliant with this criterion

(continued)

Table 7 (continued)

Criterion no	Criterion	MARD verification method	This chapter's verification method[a]
21	Following rules for using and storing veterinary medicines (B12)	Reviewing record book	Asked directly regarding each requirement
22	Not using banned substances (A10)	Interview	Asked directly regarding each requirement
23	Following disease-processing procedures (A11)	Reviewing record book	Asked indirectly, "When diseases occur, what do you do?" If they inform the local authorities, they are assessed as fully compliant with this criterion
24	Selling pigs in good health (A12)	Interview and reviewing record book	Asked directly regarding each requirement
25	Providing pig profile records (A13)	Reviewing record book	Asked directly regarding each requirement
26	Using pig ear tags (B13)	Reviewing record book and observation	Asked directly regarding each requirement
27	Following dead pig disposal rules (A14)	Reviewing record book	Asked indirectly, "How do you dispose of dead pigs?" and comparing their response with the rule mentioned in the VietGAHP manual
28	Following veterinary waste disposal rules (B14)	Observation	Asked indirectly using a question regarding how they dispose of their veterinary waste, and comparing their response with the rule mentioned in the VietGAHP manual
29	Recording all pig production information (A15)	Reviewing record book	Asked indirectly, "What type of content do you record?" and "Does this follow the sample record book released by the government?"

[a] The authors' own proposal

References

Ali, J., Khooharo, A. A., Mirani, Z., & Siddiqui, B. N. (2019). Farmer's perception regarding constraints faced in adoption of dairy farming practices in Sindh province Pakistan. *Tropical Animal Health and Production, 51*(6), 1707–1715. https://doi.org/10.1007/s11250-019-01867-5

Asfaw, S., Shiferaw, B., Simtowe, F., & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy, 37*(3), 283–295. https://doi.org/10.1016/j.foodpol.2012.02.013

Asian Productivity Organization. (2016). *Manual on good agricultural practices (GAP).*

Baumgart-Getz, A., Prokopy, L. S., & Floress, K. (2012). Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. *Journal of Environmental Management, 96*(1), 17–25. https://doi.org/10.1016/j.jenvman.2011.10.006

Brouder, S. M., & Gomez-Macpherson, H. (2014). The impact of conservation agriculture on smallholder agricultural yields: A scoping review of the evidence. *Agriculture, Ecosystems and Environment, 187*, 11–12. https://doi.org/10.1016/j.agee.2013.08.010

Coulibaly, J. Y., Chiputwa, B., Nakelse, T., & Kundhlande, G. (2017). Adoption of agroforestry and the impact on household food security among farmers in Malawi. *Agricultural Systems, 155*(April), 52–69. https://doi.org/10.1016/j.agsy.2017.03.017

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: a survery. *Economic Development and Cultural Change*, *33*(2), 255–298. http://www.jstor.org/stable/1153228

Ghimire, R., Huang, W. C., & Shrestha, R. B. (2015). Factors affecting adoption of improved rice varieties among rural farm households in Central Nepal. *Rice Science, 22*(1), 35–43. https://doi.org/10.1016/j.rsci.2015.05.006

Giang, H., Tran, T. C., Nguyen, T. H. T., & Ninh, X. T. (2016). Evaluation of smallholders ' VietGAHP adoption in pig farms in Tien Lu, Hung Yen. *Journal of Economics and Developments*, *12*(229(II)), 91–98.

Gillespie, J., Kim, S. A., & Paudel, K. (2007). Why don't producers adopt best management practices? An analysis of the beef cattle industry. *Agricultural Economics, 36*(1), 89–102. https://doi.org/10.1111/j.1574-0862.2007.00179.x

Gillespie, J., Nyaupane, N., & McMillin, K. (2013). Producer perceptions of important challenges currently facing the United States meat-goat industry. *Professional Animal Scientist*, *29*(4), 333–344. https://doi.org/10.15232/S1080-7446(15)30246-1

GSOV. (2017). *Statistical yearbook of Vietnam 2016*. Statistical Publishing House. https://www.gso.gov.vn/default.aspx?tabid=512&idmid=5&ItemID=18531

GSOV. (2018). *Results of the rural, agricultural and fishery census 2016*. Statistical Publishing House.

Ho, V. B., Nanseki, T., & Chomei, Y. (2019a). Impact of VietGAP tea production on farmers' income in Northern Vietnam. *Japanese Journal of Farm Management, 56*(4), 100–105.

Ho, B. V., Nanseki, T., & Chomei, Y. (2019b). Profit efficiency of tea farmers: Case study of safe and conventional farms in Northern Vietnam. *Environment, Development and Sustainability, 21*(4), 1695–1713. https://doi.org/10.1007/s10668-017-0073-z

Hobbs, J. (2003). *Incentives for the adoption of good agricultural practices* (p. 34).

Hungyen Statistics Office, H. (2019). *Hungyen statistical yearbook 2018*. Statistical Publishing House. http://niengiam.thongkehungyen.gov.vn/mobile/index.html#p=44. Accessed 9 Mar 2020.

Kassie, M., Shiferaw, B., & Muricho, G. (2011). Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development, 39*(10), 1784–1795. https://doi.org/10.1016/j.worlddev.2011.04.023

Kassie, M., Ndiritu, S. W., & Stage, J. (2014). What determines gender inequality in household food security in Kenya? Application of exogenous switching treatment regression. *World Development, 56*, 153–171. https://doi.org/10.1016/j.worlddev.2013.10.025

Kebebe, E. G., Oosting, S. J., Baltenweck, I., & Duncan, A. J. (2017). Characterisation of adopters and non-adopters of dairy technologies in Ethiopia and Kenya. *Tropical Animal Health and Production, 49*(4), 681–690. https://doi.org/10.1007/s11250-017-1241-8

Lapar, L., Nga, N. T. D., Thinh, N. T., Huyen, N. T. T., Unger, F., Grace, D., Lapar, M. L., Nga, N. T. D., Thinh, N. T., Huyen, N. T. T., Unger, F., Grace, D., Lapar, L., Nga, N. T. D., Thinh, N. T., Huyen, N. T. T., Unger, F., & Grace, D. (2017). Adoption and impact of gaps in pig value chains: Implications for institutional policy and practice change. In *The 9th ASAE International*

Conference: Transformation in Agricultural and Food Economy in Asia 11–13 January 2017 Bangkok, Thailand, *January* (pp. 1025–1037). https://cgspace.cgiar.org/handle/10568/80372

Lapar, M. L. A. (2014). *Review of the pig sector in Vietnam.* https://cgspace.cgiar.org/handle/10568/72682. Accessed 16 Oct 2019.

Lapar, M. L. A., Nguyen, N. T., Staal, S., Nguyen, N. Q., & Nguyen, D. A. T. (2011). The pork value chain in Vietnam: Emerging trends and implications for smallholder competitiveness. In *Presentation at the 55th Annual Conference of the Australian Agricultural and Resource Economics Society (AARES), Melbourne, Australia, 9–11 February 2011. Nairobi, Kenya: ILRI*. https://hdl.handle.net/10568/12596

Mapiye, O., Makombe, G., Mapiye, C., & Dzama, K. (2018). Limitations and prospects of improving beef cattle production in the smallholder sector: A case of Limpopo Province, South Africa. *Tropical Animal Health and Production, 50*(7), 1711–1725. https://doi.org/10.1007/s11250-018-1632-5

MARD. (2008a). *Decision No. 1121/QĐ-BNN-KHCN dated 14 April 2008a of Minister of Agriculture and Rural Development on Issuing the prodedure of Good Agricultural Practices for production of fresh tea in Vietnam.* http://www.vinacert.vn/pic/news/FileOfNews/1121-qd-bnn-khcn-vietgap-cho-che_(21-1-2015-947).pdf

MARD. (2008b). *Decision No. 379/QD-BNN-KHCN dated 28 January 2008b of Minister of Agriculture and Rural Development on Issuing the prodedure of good agricultural practices for safe vegetables and fruits.* http://nafiqad5.gov.vn/vanban/detail/Quyet-dinh-379-QD-BNN-KHCN-8/

MARD. (2008c). *Decision No.1504 dated 15 May 2008c of Minister of Agriculture and Rural Development on issuing the prodedure of Good Animal Husbandry Practices for Poultry in Vietnam.* http://vbpl.vn/bonongnghiep/Pages/vbpq-toanvan.aspx?ItemID=87965&Keyword=

MARD. (2008d). *Decision No.1506/QĐ-BNN-KHCN dated 15 May 2008d of Minister of Agriculture and Rural Development on issuing the prodedure of Good Animal Husbandry Practices for Swine in Vietnam.* http://vbpl.vn/bocongan/Pages/vbpq-luocdo.aspx?ItemID=87966. Accessed 5 Nov 2018.

MARD. (2008e). *Decision No.1579 QĐ-BNN-KHCN dated 26 May 2008e of Minister of Agriculture and Rural Development on issuing the prodedure of Good Animal Husbandry Practices for safe Dairy in Vietnam.* http://nafiqad1.vn/wp-content/uploads/2018/01/VietGAHP_cho_bo_sua.pdf

MARD. (2008f). *Decision No.1580 QĐ-BNN-KHCN dated 26 May 2008f of Minister of Agriculture and Rural Development on issuing the prodedure of Good Animal Husbandry Practices for Bee in Vietnam.* https://thuvienphapluat.vn/van-ban/Linh-vuc-khac/Quyet-dinh-1580-QD-BNN-KHCN-Quy-trinh-thuc-hanh-chan-nuoi-tot-111259.aspx

MARD. (2010a). *Decision No. 2998/QĐ-BNN-TT dated 09 November 2010a of Minister of Agriculture and Rural Development on Issuing the prodedure of Good Agricultural Practices for rice.* http://www.vietgap.com/pic/files/2998-qd-bnn-tt-vietgap-cho-lua.pdf

MARD. (2010b). *Decision No. 2999/QĐ-BNN-TT dated 09 November 2010b of Minister of Agriculture and Rural Development on Issuing the prodedure of Good Agricultural Practices for coffee.* http://www.vietgap.com/pic/files/2999-qd-bnn-tt-vietgap-cho-ca-phe.pdf

MARD. (2011a). *Decision No. 1947/QD-BNN-CN dated 23 August 2011a of Minister of Agriculture and Rural Development on Issuing the prodedure of Good Animal Husbandry Practices for Household Based Swine Production.* https://thukyluat.vn/vb/quyet-dinh-1947-qd-bnn-cn-quy-trinh-thuc-hanh-chan-nuoi-tot-chan-nuoi-lon-an-toan-nong-ho-2115c.html

MARD. (2011b). *Decision No.1503 QĐ-BNN-TCTS dated 05 July 2011b of Minister of Agriculture and Rural Development on issuing the code of Vietnamese Good Aquaculture Practices.* http://vbpl.vn/bonongnghiep/Pages/vbpq-toanvan.aspx?ItemID=79715&Keyword=

MARD. (2011c). *Decision No.1948 QĐ-BNN-CN dated 23 August 2011c of Minister of Agriculture and Rural Development on issuing the prodedure of Good Animal Husbandry Practices for chicken in Vietnam.* https://thuvienphapluat.vn/van-ban/Linh-vuc-khac/Quyet-dinh-1948-QD-BNN-CN-Quy-trinh-thuc-hanh-chan-nuoi-tot-131497.aspx

MARD. (2014). *Decision No.3824/QĐ-BNN-TCTS dated 06 September 2014 of Minister of Agriculture and Rural Development on issuing the code of Vietnamese Good Aquaculture Practices (Vietgap).* http://vbpl.vn/backan/Pages/vbpq-toanvan.aspx?ItemID=76191&Keyword=

MARD. (2015). *Decision No. 4653/QĐ-BNN-CN dated 10 November 2015 of Minister of Agriculture and Rural Development on issuing the prodedure of Good Animal Husbandry Practices (VietGAHP).* http://www.vietgap.com/huong-dan-ap-dung/1047_5490/quyet-dinh-so-4653qd-bnn-cn-ban-hanh-08-quy-trinh-thuc-hanh-chan-nuoi-tot-vietgahp-cho-bo-sua-bo-thit-de-sua-de-thit-lon-ga-ngan-vit-va-ong.html

MARD. (2016). *Decision No.2509/QĐ-BNN-CN dated 22 June 2016 of Minister of Agriculture and Rural Development on issuing the certification regulations and the prodedure of Good Animal Husbandry Practices for pig and chicken production at households.* https://www.mard.gov.vn/VanBan/VanBan/2509cn.pdf

Mariano, M. J., Villano, R., & Fleming, E. (2012). Factors influencing farmers' adoption of modern rice technologies and good management practices in the Philippines. *Agricultural Systems, 110*, 41–53. https://doi.org/10.1016/j.agsy.2012.03.010

Marine, S. C., Martin, D. A., Adalja, A., Mathew, S., & Everts, K. L. (2016). Effect of market channel, farm scale, and years in production on mid-Atlantic vegetable producers' knowledge and implementation of Good Agricultural Practices. *Food Control, 59*, 128–138. https://doi.org/10.1016/j.foodcont.2015.05.024

Mazimpaka, E., Tukei, M., Shyaka, A., & Gatari, E. N. (2018). Poultry production and constraints in Eastern Province of Rwanda: Case study of Rukomo sector, Nyagatare district. *Tropical Animal Health and Production, 50*(4), 753–759. https://doi.org/10.1007/s11250-017-1491-5

Nga, N. T. D., Ninh, H. N., Hung, P. Van, & Lapar, M. L. (2014). Smallholder pig value chain development in Vietnam : Situation analysis and trends. In *ILRI project report*. https://cgspace.cgiar.org/bitstream/handle/10568/53935/pr_situation_analysis_vietnam_web.pdf?sequence=7&isAllowed=y

Nguyen, T. D. N. (2017). Development of VietGAHP pig production in Cam Giang district, Hai Duong province (in Vietnamese: Phát triển chăn nuôi lợn VietGAHP ở huyện Cẩm Giàng, tỉnh Hải Dương). *Vietnam Journal of Agricultural Science, 15*(6), 844–851.

Noltze, M., Schwarze, S., & Qaim, M. (2012). Understanding the adoption of system technologies in smallholder agriculture: The system of rice intensification (SRI) in Timor Leste. *Agricultural Systems, 108*, 64–73. https://doi.org/10.1016/j.agsy.2012.01.003

OECD. (2013). *Agricultural innovation systems.* OECD Publishing.https://doi.org/10.1787/9789264200593-en

Rada, K., Nanseki, T., & Chomei, Y. (2016). Profit efficiency of rice farmers in Cambodia the differences between organic and conventional farming. *Journal of Sustainable Development, 9*(6), 34. https://doi.org/10.5539/jsd.v9n6p34

Saiful Islam, A. H. M., Barman, B. K., & Murshed-e-jahan, K. (2015). Adoption and impact of integrated rice – fish farming system in Bangladesh. *Aquaculture, 447*, 76–85. https://doi.org/10.1016/j.aquaculture.2015.01.006

Shiferaw, B., Kebede, T., Kassie, M., & Fisher, M. (2015). Market imperfections, access to information and technology adoption in Uganda: Challenges of overcoming multiple constraints. *Agricultural Economics (united Kingdom), 46*(4), 475–488. https://doi.org/10.1111/agec.12175

Sitienei, I., Gillespie, J., & Scaglia, G. (2015). Producer perceptions of the importance of challenges currently facing the United States grass-finished beef industry. *The Professional Animal Scientist, 31*(4), 315–323. https://doi.org/10.15232/pas.2014-01375

Souza, G. D., Cyphers, D., & Phipps, T. (1990). Factors affecting the adoption of sustainable agricultural practices. *Agricultural and Resource Economics Review, 22*(2), 159–165. https://doi.org/10.1017/S1068280500004743

Srisopaporn, S., Jourdain, D., Perret, S. R., & Shivakoti, G. (2015). Adoption and continued participation in a public Good Agricultural Practices program: The case of rice farmers in the Central Plains of Thailand. *Technological Forecasting and Social Change, 96*, 242–253. https://doi.org/10.1016/j.techfore.2015.03.016

The Census Steering Committee Central. (2017). *Report summary of the formal results of the 2016 rural, agricultural and fishery census (in Vietnamese).* https://www.gso.gov.vn/wp-content/uploads/2019/03/01.-BAO-CAO-TOM-TAT.pdf

Vo, T. S. (2017). *Vietnam livestock competitiveness and food safety : P090723 - Implementation status results report : Sequence 12 (English).* http://documents.worldbank.org/curated/en/524791495137773273/pdf/ISR-Disclosable-P090723-05-18-2017-1495137758824.pdf

Wang, H., Pandey, S., & Velarde, O. (2012). Pattern of adoption of improved rice varieties and its determinants in Cambodia. *Procedia Economics and Finance*, *2*(Qqe), 335–343. https://doi.org/10.1016/S2212-5671(12)00095-0

Wooldridge, J. M. (2013). *Introductory econometrics a modern* (5th Intern). South-Western Cengage Learning.

World Bank. (2009a). *Livestock Competitiveness and Food Safety Project (LIFSAP): Environmental Management Framework (EMF)* (Issue April). http://documents.worldbank.org/curated/en/819281468130184142/pdf/E21440P09072301LIC10EAP1EMF1P090723.pdf. Accessed 15 Oct 2018.

World Bank. (2009b). *Vietnam-Livestock Competitiveness and food safety project (English).* http://documents.worldbank.org/curated/en/276741468328186419/pdf/501610PAD0P0901ly10IDA1R2009b1024411.pdf

Zander, K. K., Mwacharo, J. M., Drucker, A. G., & Garnett, S. T. (2013). Constraints to effective adoption of innovative livestock production technologies in the Rift Valley (Kenya). *Journal of Arid Environments, 96*, 9–18. https://doi.org/10.1016/j.jaridenv.2013.03.017

Chapter 4
Impacts of GAP on Profit Efficiency of Tea Farmers in Vietnam: An Application of Stochastic Profit Function

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1 Introduction

Tea plays an important role in Vietnam, in terms of the culture and economy. In Vietnam, tea plantation has a long history, dating back over 3000 years, and tea drinking is an integral part of Vietnamese culture (ADB, 2004; Tran, 2008). From an economic point of view, tea is an important cash crop for farmers in the northern provinces of Vietnam. In 2012, about 146,700 tons of tea products were exported, valued about USD 224.6 million (FAO, 2012). With a gross planting area over 130,000 ha, tea contributes significantly to job generation. According to the Centre for Research on Multinational Corporations (SOMO, 2007), about 400,000 households are involved in tea production for their income and livelihood. The tea industry supplies about 1.5 million jobs for Vietnamese people.

Conventional tea production has been facing many challenges. Although the tea consumption and export volume have been increasing steadily since 1990s, tea has been mainly exported to the traditional markets with low requirements, such as China, Russia, Taiwan, and Iran (ADB, 2004). Besides, chemical components and pesticide have been widely used by tea farmers for protecting tea farms. Improper use of pesticides and chemical fertilizers has led to detrimental consequences for human health and the environment (Aktar et al., 2009; Hong & Yabe, 2015; Tran &

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Yanagida, 2015). This, combined with domestic consumers' increasing concerns on food safety, led to the conversion from conventional to "safe or clean" tea production in Vietnam. Since 2008, the Vietnamese government has promoted the implementation of a voluntary standard package, called the Vietnamese Good Agricultural Practices (VietGAP), which is established on hazard analysis and critical control points, ASEAN Good Agricultural Practices, Global Good Agricultural Practices, and Freshcare. This standard package is designed to provide basic criteria for controlling agricultural production and must be applied in all stages including field selection, pre-plant field preparation, production, harvest, and post-harvest (MARD, 2008). VietGAP tea production is certified by authorities for non-chemical residue. This is also considered as eco-friendly production practices due to maximal use of organic components in cultivation and protection (Ha, 2014b).

Although there have been many studies on Good Agricultural Practices (GAPs) from various aspects, the findings are not consistent. For instance, the adoption of GAPs was identified as having a positive impact on the technical efficiency (Ha, 2014b; Taraka et al. 2012), while some studies stated that farmers adopting GAPs do not receive a higher price (Calvin et al., 2004; Pongvinyoo et al., 2015; Subervie & Vagneron, 2012), and others have found a positive impact on price, yield, or income (Islam et al., 2012; Kariuki et al., 2012). In Vietnam, data on the production efficiency of VietGAP adoption are limited due to the relatively late implementation of VietGAP. Ha (2014a) indicated that applying VietGAP in agricultural production would be a conversion period toward organic production, aiming to address relative challenges. Several works have focused on tea production. Tran (2008) estimated the economic efficiency of organic tea farmers in Thai Nguyen province. Saigenji (2010) determined the impact of contract farming on production efficiency and household income in the northwest region of Vietnam. Hong and Yabe (2015) investigated the profit efficiency of conventional tea farmers. According to Tran (2009), analyzing and comparing different tea production practices is an important element of understanding farmers' decision-making. Nguyen et al. (2015) concluded that tea production adopting VietGAP had achieved significantly higher yields than those using organic methods. Although profit efficiency of tea farmers was also investigated by Hong and Yabe (2015), her study did not consider VietGAP tea practices. Tran (2008) confirmed that the production and profit efficiency of organic tea farming are higher than those of clean tea farming and conventional tea farming. This means that production practices can create different production efficiency, and thus, it is necessary that we study the production efficiency of VietGAP tea farmers.

There are several approaches of impact evaluation and various econometric methods have been used over the decade (Khandker et al., 2010). The choice of a particular method in a specific context is always argued for empirical economic analysis in the different fields (Wang et al., 2014). For instance, the effect of treatment can be estimated as the coefficients of covariates for treatment in the regression (Imbens, 2004), while other studies also assessed the impact by including a dummy variable whether the farmer cultivated a certain crop or improved technology (Walker et al., 2004). In standard context, impact evaluation can provide most precise results if same farmers are compared with each others before and after the adoption takes place. This will ensure that there are not original differences in evaluation that may lead to bias results. In other words, baseline data on probable adopters would be needed before the adoption takes place. This might be possible in research trial with a small sample scale, but it is unfeasible at the regional scale. Imbens and Wooldridge (2009) found that better performance of some farmers might be the result of the characteristics of individuals rather than being an adopter or non-adopter. It is notable that in literature, the data is often obtained from non-randomized observational studies rather than from randomized trial (Becker & Ichino, 2002). This implies that a selection bias among farmers might have a significant impact on their decisions and production performance. Thus, comparing the profit efficiency of tea practices could be biased if we do not control for these factors. To address this gap, this study investigated the profit efficiency of VietGAP and conventional tea farms. Then, we assessed the difference in profit efficiency between the two farmer groups, using propensity score matching to the control selection bias.

2 Methodology and Data Collection

2.1 Measurement of Production and Profit Efficiency

Over last two decades, most of the empirical studies in agricultural production efficiency have focused on two major groups. One category of the literature estimated efficiency concerning price response of input demand. The other trend considered production inefficiency ignoring price responses (Arnade & Trueblood, 2002). Of which cost minimization and profit maximization hypotheses are often considered in modeling production inefficiency. The difference here is that under cost minimization hypothesis, outputs are not included, and inputs are the endogenous variables, while both input and outputs are endogenous under profit maximization hypothesis. The estimation method using profit function was developed to deal with both production inefficiency and response price (Kumbhakar, 1996). Production inefficiency is usually analyzed by its three components, namely technical, allocative, and scale inefficiency. In general context, if output level of a production unit lies below the maximum feasible output (the frontier output), then it is said to be technically inefficient, for a given set of inputs. Similarly, if a production unit is not using inputs in optimal proportion given the observed input prices and output level, then it cannot also be allocatively efficient. In a framework of profit maximization, a production unit cannot also be of scale efficiency if it is not producing an output level by utilizing the product price with the marginal cost (Kumbhakar et al., 1989). Recent developments of econometrics combined three measurements into one system, which enables more efficient estimation to be obtained by simultaneous estimates of the system using a profit function framework (Ali & Flinn, 1989; Kumbhakar et al., 1989; Wang et al., 1996). A frontier production function is a widely used approach to measure efficiency, its components (Battese & Coelli, 1995). However, measuring efficiency using a production function approach may be inappropriate when farmers face various prices and have different factor endowments (Ali & Flinn, 1989). As a result, the stochastic profit function is directly applied to estimate a firm-specific efficiency (Ali & Flinn, 1989; Kumbhakar et al., 1989; Wang et al., 1996). The profit function approach combines these three concepts (technical, allocative and scale inefficiency) into the profit relationship and any errors in the production decision are assumed to be lower profit for production units. According to the production analysis literature, two primary frontier methods are widely used to analyze production efficiency—the econometric approach and the mathematical programming approach (Lovell, 1994). The stochastic frontier model is included two components. The first is a symmetric component that captures random variations of the frontier across firms and the effects of measurement errors. The second is a one-sided component that captures the effects of inefficiency relative to the stochastic frontier and incorporates an error term (Aigner et al., 1977). The stochastic frontier approach (SFA) is an econometric stochastic model that can separate the effects of noise from technical inefficiency.

The stochastic profit function is defined as follows:

$$\pi_i = f(P_i, Z_i).\exp(\xi_i), \tag{1}$$

where π is the normalized profit for the i th farm, defined as revenue less total variable costs, divided by firm-specific output price; P_i is a vector of the input price variables of i th farm, divided by the output price; Z_i is a vector of the fixed factors of the i th farm; i is the number of tea farms in the sample; and ξ_i is an error term, consisting of two components, ν_i and μ_i (Ali & Flinn, 1989). Then,

$$\xi_i = \nu_i - \mu_i, \tag{2}$$

where ν_i is assumed to be independently and identically distributed $N(0, \sigma_v^2)$; μ_i denotes non-negative random variables associated with production inefficiency, and ν_i and μ_i are independent of each other.

The profit efficiency (PE) of farm i th in the context of the stochastic frontier profit function is defined as

$$PE = E\left[\exp(-\mu_i)|\xi_i\right], \tag{3}$$

where E is an expectation operator that can be estimated by obtaining the expressions for the conditional expectation μ_i upon the observed value of $\xi_i (0 \le PE \le 1)$.

2.2 Empirical Model

Tea growers have many options for selecting inputs and selling their products as well. This leads to variations in the vector of actual prices faced by farmers. The price variation can be different in locations and product quality. Thus, a tea farmer can be assumed to allocate the inputs in optimal proportion by equating their ratios to the marginal productivity. In economic theory of profit efficiency analyses, a farm operation is assumed to maximize its profit in the given condition of perfectly competitive input and output markets, and a given output technology. Profit efficiency is defined as the ability of a farm to achieve the highest possible profit, with given the prices and fixed factors used. Then, profit inefficiency in this context is defined as the loss of profit resulting from not operating on the frontier (Ali & Flinn, 1989). In other words, the profit efficiency of a tea farmer in this study is defined as the profit achieved from operating on the profit frontier, taking into consideration the variable input prices and quasi-fixed input quantities. According to Rahman (2003) and Kolawole (2006), the profit of a specific farm is equal to total revenue less total variable costs.

Taking the Cobb–Douglas production form for production frontier, the production frontier function in an Eq. (1) can be written in logarithmic form as:

$$\ln vn/p = \alpha_0 + \Sigma \propto_i \ln P_i/p + \Sigma \alpha_q \ln z_q + v_i - \mu_i, \tag{4}$$

where vn/p is a normalized variable of the profit frontier, P_i/p is a normalized variable of input prices, z_q denotes the quasi-fixed input quantities, and α_i and α_q are unknown parameters.

Then, P_i is the price of the ith input variable used by ith tea farm, normalized by dividing the tea price of the farm (p), including chemical fertilizers (equivalently converted to NPK), organic compounds, pesticide costs, labor costs, and the other costs. In addition, z_q is the quantity of fixed inputs used by a tea farm, including the tea farm size (ha), v_i is the statistical noise, μ_i is the effect of profit inefficiency, and α is the unknown parameter needs to be estimated.

The technique of maximum likelihood estimation is used to estimate the unknown parameters. The likelihood function is expressed in terms of variance parameters, $\sigma_v^2 + \sigma_u^2$ and $y = \sigma_u^2/\sigma_v^2$ (Battese & Coelli, 1995). Then, the profit efficiency level of specific tea farms was predicted using specified statistic software. Finally, the regression model was deployed to determine the factors that affect the levels of profit efficiency of tea farmers. The regression model is given as follows:

$$PE = \beta_0 + \Sigma \beta_j Z_j + \omega, \tag{5}$$

where PE is the profit efficiency level of the ith tea farmer; Z_j denotes the variables of socioeconomic and farm characteristics that can affect the profit efficiency of a tea farmer, including gender, formal education, family labor, farming experience, irrigation access, credit access, ratio of tea income, membership of cooperatives, and machine status; and ω is an error term representing factors outside the model.

2.3 Propensity Score Matching

In case of randomized experiment context, the mean impact of a treatment on the treated group can be easily determined by measuring the difference between mean values of the outcome variable for both treatment and control groups. However, this approach could not be applied in the case because VietGAP tea farmers are not random. In other words, an appropriate method for impact evaluation in non-experimental case should be applied in the present case. Thus, we applied a propensity score matching (PSM) method to quantify the impact of VietGAP adoption on farmer using cross-sectional data.

The PSM was used to compare groups by matching individuals with similar characteristics or features. Theoretically, a PSM model attempts to create an experimental condition in which adopters and non-adopters are selected randomly. According to Becker and Ichino (2002), PSM is a two-step mathematical procedure. The first step estimated a farmer's propensity score using logit or probit models as follows:

$$Y(1,0) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{6}$$

where Y is the dependent variable (1 = VietGAP farmer, 0 = conventional farmer), β denotes the estimated coefficients, and X_n denotes covariates. The choice of the covariates in X should be guided by economic theory, a sound knowledge of previous research (Sianesi, 2004; Smith & Todd, 2005). The omission of important variables can seriously increase bias in estimating results (Dehejia & Wahba, 1999). In the study, we used the same covariates "number of family labors, formal education of household's head, credit access, extension access" as Noltze et al. (2012). We added the variables "irrigation status, machinery use" as indicators of mechanization in tea production (Tran, 2008). The variables as gender, farming experience, farm size can also affect the adoption of agricultural innovations or production standards. Thus, they were also included in the model as Kersting and Wollni (2012). Finally, we incorporated a variable "ratio of tea income" to account for importance of tea income in the study area.

Then, the propensity score was estimated using the following equation:

$$P_{score} = 1/1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)} \tag{7}$$

In the second step, farmers with similar propensity scores between the groups were matched to estimate the average treatment effect for the treated (ATET), denoted as

$$ATET = E(Y_1 - Y_0 | x, D = 1) = E(Y_1 | x, D = 1) - E(Y_0 | x, D = 1), \tag{8}$$

where D is an indicator equal to one if the farmer applies VietGAP, and zero is otherwise, Y_1 is the outcome for a VietGAP adopter, Y_0 is the outcome for a non-adopter, and x is a vector of control variables. Then, single nearest neighbor matching (NNM) was used to match similar observations.

The estimator that provides the statistically identical variable means for treatment and control groups is preferable. Propensity score matching works under conditional independence assumption and common support. In fact, there might also be unobservable variables that affect both adoption of VietGAP production and its outcome variables. A hidden bias might arise if matching estimators are not robust (Rosenbaum, 1995). These hidden biases may lead to both positive and negative unobserved adoption decision. As a result, the treatment effect would be overestimated if a farmer adopted the VietGAP production is also more likely to adopt VietGAP standards. Conversely, if negative unobserved selection exists, the treatment effect would be underestimated, because that the conditional independence assumption could not be directly tested. Thus, balancing test should be tested instead of first one. In previous studies, several indicators were used to check whether the matching procedure can balance the distribution of the relevant variables in both groups. Significant differences should not be systematically existed after conditioning on the propensity score (Caliendo & Kopeinig, 2008). Adequate matching quality should create significantly lower standardized bias (Rosenbaum & Rubin, 1985). They include statistically insignificant likelihood ratio test on the joint significance of all regressors (Smith & Todd, 2005), and fairly low pseudo-R2 (Sianesi, 2004) after matching. Finally, common support should be accomplished by using visual inspection of the densities of propensity scores of treatment and control groups. Also, another way could be done via comparison test such as the Kolmogorov–Smirnov nonparametric test. If sizeable differences existed between the maxima and minima of the density distribution, cases lying outside the support of other distribution should be removed (Caliendo & Kopeinig, 2008).

2.4 Description of Used Variables

All variables used in the model were selected on the basis of economic theory, the findings of previous studies, and the actual status of agricultural production in the study area. The dummy variable was used to assess the adoption of VietGAP among farmers instead of adoption index. This was derived from the fact that VietGAP certification is only certified for tea farmers who strictly follow all requirements of the organization as stipulated. Previous analysts have shown that a farmer's behavior can be affected by socioeconomic characteristics, such as education level and income, among others (Coady, 1995; OECD, 2008). Other dummy variables include machinery use, extension, credit access, as also used in recent studies (Coelli et al., 2002; Hong & Yabe, 2015). At the same time, features of crops and agricultural products, such as input cost, output price, yield, irrigation pattern, and others, are also believed to have strong relationships with new crop management practices. The definitions of the variables are presented in Table 1.

Table 1 Variable definition of used models

Variable	Definition	Unit
Used in the profit model		
Profit	Net return per hectare	K.vnd[1]/ha/year
Adop	Adoption of production practices (1-VietGAP; 0-CON)[2]	dummy
Pchem	Price of chemical fertilizer (converted NPK)	K.vnd/kg
Porg	Price of organic fertilizer	K.vnd/kg
Pescost	Cost for pest & disease control	K.vnd/ha/year
Plabor	Price of hired labor using in farm	K.vnd/day
Ocost	Other costs (fuel, fee…)	K.vnd/ha/year
Farm size	Tea farm size	ha
Used in the Tobit model		
PE score	Profit efficiency score of tea farmer	percent
Gender	Gender of household head (1-male; 0-female)	dummy
Formal education	Formal education (1-primary, 2-secondary, 3-high school, 4-upper)	category
Family labor	Number of family labors (aged 16–65 s) involving in tea production	number
Experience	Tea production experience of household head	year
Irrigation	Investing active irrigation system serving for tea farm (1-yes; 0-no)	dummy
Credit access	Accessing to credit loan invested for tea production (1-yes, 0-no)	dummy
Tea income ratio	Ratio of tea income over total family income	percent
Cooperative	Status of joining in tea production cooperative or group (1-yes; 0-no)	dummy
Extension access	Accessing trained service that meets farmer's demand (1-yes; 0-no)	dummy
Machinery use	Status of machinery application in tea processing (1-yes; 0-no)	dummy

Note [1] K.vnd: monetary unit of Vietnam measured in thousand dong; 1 usd * 21 K.vnd; [2]VietGAP farm: Tea farm under Good Agricultural Practices; CON: conventional tea farm

2.5 Study Site and Data Collection

The northern Vietnam is a major tea production region, accounting for 64.7% of total tea output and 71.6% of the country's tea production land. The field survey was conducted in Thai Nguyen province locating in the region that is very well known for tea production. According to GSO (2013), the province is the first position in tea production. We used a two-stage sampling technique for data collection. First, large number of farmers adopted VietGAP and conventional tea-producing districts in the region were sampled in three districts of the province, including Thai Nguyen city, Dai Tu and Dong Hy. Second, a random sampling technique was adopted to select representative VietGAP and conventional tea farmers belonging to the same study site. In other words, the survey did not make any prior stratification by gender, education level, assets marital status of household head or any other attribute of tea farmers in the study area, which is believed to have ensured equal chances of inclusion of VietGAP and conventional tea farmers. The farm-level data, essential to this study, was gathered by interviewing tea farmers using structured questionnaires constructed specifically for this purpose. The questionnaire set was designed with the support and aid of consultants and colleagues who have much experience in field surveys. Prior to the interviews, we translated the questionnaire, initially designed in English, into Vietnamese. Then, the questionnaire was pre-tested on 10 tea farmers in the study site. Based on the feedback, the questionnaire was updated and modified. Finally, the completed version was used to gather the data, including information on input use, costs, yields and output prices, farm-level characteristics as well as socioeconomic characteristics of the households. The data was collected through questionnaire interviews by enumerators who were trained prior to the exercise, between July and August 2016. After field survey, total dataset of 116 VietGAP and 210 tea farmers was used for analysis in this study. Besides, secondary data was also obtained from the General Statistic Office of Vietnam and communal reports during the field survey.

3 Results and Discussion

3.1 Socioeconomic Characteristics of Tea Farmers in Study Area

The descriptive statistic method was used to describe the current status of tea farms in the study area. Table 2 illustrates the descriptive features of important variables used in the model, as well as specific farm characteristics. A statistical index of VietGAP and conventional tea farmers were compared using t statistics. Moreover, as multicollinearity of variables may lead to an estimation bias in the regression model, an index of variance inflation factors (VIF) was used to test for collinearity. The estimated mean VIF index is 1.43, suggesting that there is no collinearity in the model.

Table 2 Result statistics of tea production comparing between two models

Variables	All samples ($n = 326$)	VietGAP ($n = 116$)	CON ($n = 210$)	Diff.	t stat
Yield (kg/ha)	8116.8	8555.6	7874.4	681.17**	2.3935
Profit (K.vnd/ha)	147,588.4	172,683.8	133,726.2	38,957.59***	5.4041
Total cost (K.vnd/ha)	117,663.5	129,559.7	111,092.2	18,467.35**	2.1251
Chemical (kg/ha)	2628.6	2494.5	2702.6	−208.16	−1.3458
Organic (kg/ha)	2012.6	2557.3	1711.7	845.54***	3.8978
Pescost (l/ha)	176.5	157.2	187.1	−29.97**	−2.2390
Labor (man-day)	1105.1	1236.3	1032.6	203.74***	3.1915
Ocost (K.vnd)	26,193.3	24,839.7	26,941.1	−2101.41	−1.4385
Variables		Mean	SD	Min	Max
Input variables of profit function					
Pchem (K.vnd/kg)		6.88	1.72	4.5	13.5
Porg (K.vnd/kg)		4.89	1.94	2.4	15.6
Pescost (K.vnd/ha/year)		453.42	281.46	0	2650
Plabor (K.vnd/day)		135.73	36.80	50	210
Ocost (K.vnd/ha/year)		25,771.4	11,094.61	2364	81,538
Farm size (ha)		0.35	0.16	0.11	1.3

Note K.vnd: monetary unit of Vietnam measured in thousand dong; 1 usd * 21 K.vnd; *** and ** significance at the 1 and 5% levels, respectively

Besides, we also tested the relationship among variables using a correlation matrix. The coefficient of "age" and "experience" was high. Thus, only "experience" variable was retained in regression. The results indicated that the average tea yield is about 8100 kg per hectare. Tea farmers using VietGAP production obtained significantly higher yields compared with conventional tea farmers, at the 5% significance level. On average, a farmer earned about VND 147,500 thousand per hectare. The VietGAP tea farmers also earned a higher profit than the conventional tea farmers, and the difference was statistically significant at 1% level.

Similarly, the VietGAP tea farmers spend more in terms of total cost per ha than do conventional farmers. Notably, tea farms under VietGAP production apply more organic fertilizer than do conventional tea farms. One of the reasons VietGAP tea farmers use more organic fertilizers is that they understand the sustainable benefits of using organic inputs for their tea products and farmland. In addition, VietGAP tea farmers have significantly lower pesticide costs than the conventional tea farmers. However, the variability might be the result of other factors, such as farm size, annual pest attacks, and the farmer's attitude and perception to the effects of pesticide. Technical training courses on pesticide use under the VietGAP program are largely considered as a major positive contributor to changing farmers' attitudes and perceptions on the use of pesticides and chemical compounds in tea farming. Furthermore, tea farms using VietGAP production require more labor-days than the conventional tea farms. This is largely the result of the strict control requirements for VietGAP tea products, in particular, following all the steps necessary for tea production. On average, the labor time required for tea production per hectare/year is around 1100 days, indicating that farming activities are highly labor intensive, particularly in the harvesting season when hand labor is still widely used. The tea production under VietGAP requires more working days than those under conventional practices. The estimation also indicated that the average size of a tea farm is around 0.35 ha per farmer, with no significant difference between VietGAP and conventional tea farms. This farm size is generally characterized as small-scale agricultural production in northern Vietnam.

Table 3 shows the comparative statistics of the major variables used in the regression model. The difference (diff.) between the groups is equal to the mean of VietGAP tea farmers less the mean of conventional tea farmers. The t statistic value indicates the significant level of difference between the groups.

Most of the tea farmers (85%) received a basic education at a secondary or high school level. A very small proportion of the tea farmers received a higher level of education, indicating that tea production has not yet attracted educated people, particularly among young labors. This may be a barrier to applying technology or using marketing to access high-value tea markets. The results also show that farmers have much experience in tea cultivation (about 22 years) and that they earn about 62% of total tea income, suggesting that the study area is dominated by tea production.

The comparative results indicated that farmers adopting VietGAP standards have more family labor available than do conventional tea farmers and that the difference was statistically significant at the 1% level. Although VietGAP farms are not intensive agriculture, they require more labor than conventional farming practices do.

Table 3 Comparative statistics of model variables

Variables	All samples ($n = 326$)	VietGAP ($n = 116$)	CON ($n = 210$)	Diff.[1]	t stat
Gender	0.59	0.603	0.59	0.008	0.1443
Formal education					
Primary	0.075	0.060	0.090	0.030	0.9614
Secondary	0.475	0.465	0.481	0.015	0.2672
High school	0.377	0.379	0.376	0.003	0.0556
Upper level	0.064	0.094	0.048	0.047	1.6623
Family labor	2.90	3.078	2.800	0.278***	2.6291
Experience	22.30	21.293	22.862	−1.569	−1.5559
Irrigation	0.68	0.879	0.571	0.308***	6.005
Tea income ratio	0.62	0.665	0.596	0.068***	3.4485
Credit access	0.15	0.163	0.142	0.021	0.5051
Cooperative	0.51	0.879	0.314	0.565***	9.770
Machinery use	0.62	0.810	0.509	0.301***	5.582

Note ***Significance at 1% level

[1]Diff. is the difference between the adopter and non-adopter of VietGAP and equals the mean of the adopter minus the mean of the non-adopter

Labor time in tea cultivation is mostly spent during harvesting. Furthermore, the strict requirements of VietGAP certified tea farm means that farmers often invest more in production system including irrigation systems in order to control water quality. Water source and other input factors relevant to tea farms are regularly verified by certified organizations. Only when practices of the tea farmers meet all regulated standards, their tea products are certified with Viet-GAP trademark. In other words, availability of active irrigation system would be one of favorable factors for adopting new practices. Thus, VietGAP tea farms have been actively irrigated than conventional tea farms. Then, the results indicated a significant difference in the tea income ratio between the two groups. A positive coefficient of the tea income ratio implied that farmers following VietGAP earned a higher income from tea production than the conventional tea farmers. In other words, conventional tea farmers are less dependent on tea production for their income than are VietGAP farmers. A significant difference between the VietGAP and conventional tea farms was also evidenced by the variables denoting the status of whether have joint any local agricultural cooperative and machinery application. Tea farmers adopted VietGAP tend to invest more capital in machinery and become members of a cooperative. Lastly, statistically insignificant differences were observed between the groups on other features, such as gender, formal education, farming experience, and credit access.

3.2 Estimated Result of Profit Frontier Function

Economic efficiency is of interest to both farmers and policymakers. The dual method was used to analyze the profit efficiency of tea farmers. The difference between VietGAP and conventional farms was assessed using the dummy variable "adop". The estimated results are presented in Table 4.

The positive and significant effect of the dummy variable "adop" in the profit frontier function reflected that tea farmers participated in the VietGAP program operate at higher profit efficiency than other tea farmers. The question here is whether the VietGAP program has a positive impact on profit efficiency. The higher profit efficiency of VietGAP tea farmers might be the result of better farm/farmer characteristics or the effect of participating in the VietGAP program. To answer this question, we conducted a more in-depth analysis in the next section, controlling for bias selection. The positive and significant effect of farm size implied that families with larger tea farms operate at a higher profit efficiency than do smaller tea farms. This finding was consistent with the results of Ali and Byerlee (1991), Kolawole (2006), Abdulai and Huffman (2000), and Tran and Yanagida (2015). Tea-producing farms using the VietGAP standard are not organic farms. Thus, chemical fertilizers and pesticides are still applied. The difference is that VietGAP tea farmers minimize the use of such compounds, following strict harvesting intervals after spraying, and increase the adoption of organic fertilizers and biological compounds for pest and disease control. The tea products obtained from VietGAP production are free of pesticides

Table 4 Estimation result of profit efficiency among tea farmers

Variables	Coefficient	*SD*	*z* stat	$p > \|z\|$
Adop	0.193***	0.046	4.12	0.000
Farm size	0.200***	0.059	3.36	0.001
Pchem	−0.318***	0.110	−2.89	0.004
Porg	−0.344***	0.069	−4.95	0.000
Pescost	−0.013	0.388	−0.33	0.740
Plabor	−0.325***	0.076	−4.19	0.000
Ocost	0.213***	0.044	4.82	0.000
Constant	8.151***	0.453	18.00	0.000
Log-likehood	−138.0769			
Lamda	1.478303			
Variance_u	0.4110226			
Variance_v	0.2780368			

Note ***Significance at the 1% level

and chemical residues and certified by authorized agencies in Vietnam. The estimated results showed that increasing prices of chemical and organic fertilizers have a negative and significant effect on profit efficiency. Thus, as the price of fertilizer inputs increase, the profit efficiency of tea production will decrease. These results were similar to those of Ali and Flinn (1989), Kolawole (2006), Tran and Yanagida (2015), and Abdulai and Huffman (2000). The large coefficients of fertilizer prices implied a strong dependence on fertilizer inputs in both tea production practices. While the coefficient of pesticide cost was negative and statistically insignificant, the price of hired labor (man-days) was highly significant. The negative sign of the coefficient of labor price suggested that as the price of labor increases, the profit efficiency of tea farmers will decrease. This is reasonable, because labor is one of most important inputs of agricultural production such as tea. Thus, labor-related cost changes have a strong impact on profit efficiency. Note that other costs include hired irrigation, machine-related costs, and processing steps. The positive and significant coefficient of these costs implied that increasing these costs will increase profit efficiency. This result also suggested that farmers using machines during the production and post-harvest stages would obtain higher profit efficiency than other farmers.

3.3 Factors Explaining the Profit Efficiency of Tea Farmers

Factors explaining the profit efficiency of tea farmers would be useful for policy purposes. Thus, we determine the factors affecting profit efficiency of tea farmers separately using a Tobit model, with a dependent variable of profit efficiency score. Then, important features of farms and farmers were used as explanatory variables in the model. The detailed results are shown in Table 5. Notably, joining cooperatives or production groups has a positive and significant impact on profit efficiency for both farmer groups, while other coefficients are relatively different. For farmers following the VietGAP standard, the coefficient of accessing an irrigation system is positive and significant. This suggests that tea farms irrigated by farmers achieve higher profit efficiency. Regular irrigation reduces loss of a tea yield, especially in the dry season and for high-yield tea varieties. This finding is consistent that of Hong and Yabe (2015). Participating in production cooperatives or groups contributes to increasing profit efficiency for tea farmers under the VietGAP program. In general, farmers have a greater chance of accessing new information, technical training through experience exchange, and information sharing when they participate in production cooperatives or groups (Hong & Yabe, 2015). Moreover, joining the cooperatives is more attractive to VietGAP tea farmers in terms of saving production costs on machinery investment for processing/packaging, trademark registration, and VietGAP certification. In addition, cooperatives make it easier to access credit facilities from agencies and to sign consumption contracts with collectors/distributors. In the case of individual tea producers, borrowing large amounts as loans from agencies and working with large wholesalers/companies seems to not be possible.

For conventional tea farmers, as in the case of VietGAP tea farmers, participating in production groups or cooperatives has a positive effect on profit efficiency, for much the same reason. Although these farmers do not incur higher production costs for VietGAP certification and product testing fees, they benefit from cooperatives or production groups through experience exchange, marketing information, and cost savings. Irrigation system is positive for profit efficiency improvement, but it is insignificant. The difference between two groups may be derived from the fact that

Table 5 Factors affecting profit efficiency of tea farmers

Variables	PE (VietGAP)	*t* stat	PE (CON)	*t* stat
Gender	0.014	1.24	0.026	1.58
Formal education				
Secondary	−0.018	−0.75	−0.027	−0.92
High school	−0.002	−0.07	−0.029	−0.93
Upper level	0.022	0.74	−0.066	−1.15
Family labor	−0.004	−0.58	−0.006	−0.70
Experience	0.0007	1.04	0.002	0.27
Irrigation	0.041**	2.25	0.003	0.12
Credit access	−0.008	−0.60	−0.015	−0.66
Tea income ratio	0.029	0.85	0.176***	3.68
Cooperative	0.089***	4.68	0.048***	2.68
Machinery use	0.011	−0.76	0.006	0.22
Constant	0.633***	19.32	0.561***	14.60

Note *** and ** significance at the 1 and 5% levels, respectively various types of tea plantation have been growing in the study area. While most conventional farmers prefer local tea varieties to new ones that have often better resistant ability to dry weather condition, VietGAP farmers with better advantages of labor and investment capital often grow highly yield varieties. In turn, these new tea types also require strictly cared conditions including more regularly irrigated water, fertilizer input. The ratio of tea income "RItea" has a significant effect on profit efficiency. The positive sign of the estimated coefficient showed that farmers who are able to earn more income from tea farms pay more attention to their tea farms than do other tea farmers. Directly, this finding suggested that farmers show depend heavily on the income of tea production achieve greater profit efficiency. The underlying reason may be that this is the main source of income for the family. In this case, farmers often invest more of their time and attention. As a result, they achieve better performance than other farmers do. This result is similar to that of Ali and Flinn (1989), Wang et al. (1996), and Rahman (2003), who reported that farmers who earn a greater share of their income from off-farm activities operate at lower levels of efficiency. Other variables in the model do not have statistically significant impacts on profit efficiency. These variables include gender, education level, labor size, and farming experience. As expected, a higher level of education increases profit efficiency, but in the study area, most farmers have a basic education, with simple knowledge that is not relevant to farming. Thus, it is no surprise that formal education level does not have a significant effect on profit efficiency. This result did not differ from that of Coelli et al. (2002), who concluded that a higher level of education has not a large influence on efficiency levels. Similarly, the coefficients of credit access and machinery status have the same effects on profit efficiency for both types of farms. The negative sign of credit access seems to be irregular. However, it is not statistically significant. In the study area, a very small ratio of tea farmers borrowed funds from credit agencies (15%, on average). This may also lead to the statistically insignificant effect of the variable.

3.4 Distribution of Profit Efficiency and Estimation of Average Treatment Effect Index

Table 6 compares the frequency distribution of the profit efficiency among tea farmers. Most farmers (72%) operate their tea farms with profit efficiency scores between 0.70 and 0.89. The average profit efficiency of tea farmers is about 74%, with a wide range, from 29 to 94%. There is a slight difference in the average profit efficiency scores between VietGAP and conventional tea farmers. VietGAP tea farmers achieve higher mean profit efficiency (76.4%), whereas conventional tea farmers obtain an average profit efficiency of 73.4%. This result suggests there is still room to improve the profit efficiency of tea production (26%).

Table 6 Frequency distribution of profit efficiency (PE)

Profit efficiency (%)	Frequency			Percentage		
	All samples	VietGAP	CON	All samples	VietGAP	CON
≤50	13	1	12	3.98	0.86	5.71
50–59	21	3	18	6.44	2.58	8.57
60–69	51	13	38	15.64	11.21	18.10
70–79	135	63	72	41.41	54.32	34.28
80–89	99	35	64	30.37	30.17	30.48
90–99	7	1	6	2.16	0.86	2.86
Mean	74.38	76.3	73.4	–	–	–
Min	28.7	44.3	28.7			
Max	93.6	90.8	93.6			

3.5 Propensity Score for VietGAP Tea Adoption

The logit estimates for the VietGAP tea propensity equation are presented in Table 7. Several variables were statistically significantly associated with adopting VietGAP tea production. Farmers with more farming experience are less likely to adopt conventional tea farms. On the other hand, farmers with more family labor participating in farm activities are more likely to convert from conventional to VietGAP tea farms. As expected, farms that have access to better irrigation systems, extension services, and larger farm area are likely to be VietGAP tea farms. The use of machinery in farm activities has a positive impact on adopting VietGAP standards. Other variables, such as gender, formal education, and credit access, are not strongly associated with the choice of production method.

As discussed in Sect. 3.2, the higher profit efficiency of VietGAP tea farmers could be the result of adopting the new production method, but may also be the result of a selection bias. The estimated effect of the treatment may be biased by the existence of confounding factors. Using propensity score matching is a good way to "correct" for confounding factors, based on the idea that the bias is reduced when the outcomes are compared using treated and control subjects who are as similar as possible (Rosenbaum & Rubin, 1983). Eliminating the effect of self-selection would be meaningful when comparing the profit efficiency of the two farmer groups. Thus, we use the average treatment effect on the treated (ATET) index here.

In the study, data analysis results in statistically insignificant likelihood ratio test on the joint significance of all regressors, and fairly low pseudo-R2 after matching process. This suggested that there is no systematical and significant difference after matching. The matching quality was successful in the study (Sianesi, 2004; Smith & Todd, 2005). Besides, there is substantial overlap in the distribution of the estimated probability of tea farmers (of both VietGAP and conventional growers). Figure 1 indicates the presence of sufficient common support between two farm groups.

Table 7 Logit estimates of the propensity to adopt VietGAP tea production

Variables	Coefficient	Standard error
Gender	−0.137	0.028
Formal education		
Secondary	−0.378	0.543
High school	0.368	0.571
Upper level	−0.321	0.571
Family labor	0.551	0.174***
Experience	−0.062	0.018***
Irrigation	1.215	0.770***
Credit access	1.228	0.421***
Tea income ratio	2.036	0.866***
Credit access	0.467	0.367
Extension access	0.542	0.328***
Machinery use	0.797	0.358***
Constant	−2.647	0.917***

Note *** and ** significance at the 1 and 5% levels, respectively

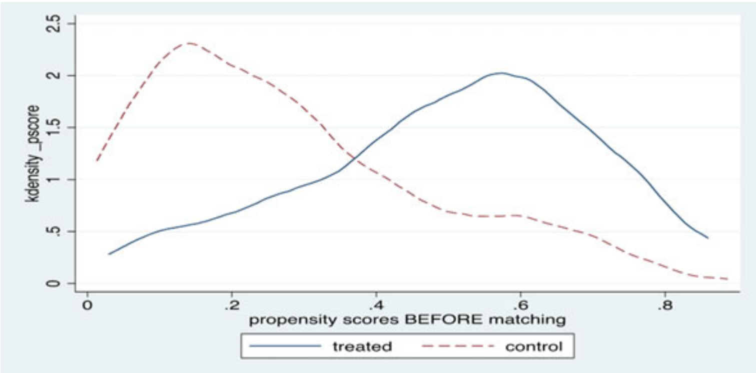

Fig. 1 Density distribution of propensity scores for treated and comparison groups

Before matching, a simple comparison indicates that the profit efficiency of VietGAP tea farmers was significantly higher than that of conventional tea farmers, at the 1% level. After matching, the estimated result of the ATET index indicates that the difference was also statistically significant (see Table 8). In other words, employing propensity score matching approach reassures that safe tea production practice has positively been contributed to improve profit efficiency for tea farmers.

Table 8 Estimation of average treatment effects on the treated

Index	Coeff.		AI robust SE	z stat
ATET (VietGAP and CON)	0.038*		0.020	1.91
Matching method	Pseudo R^2		LR $\chi^2(pvalue)$	
	Before	After	Before	After
Test of matching quality				
NNM	0.1876	0.0379	79.87**	6.88

Note ATET average treatment effects on the treated, Coeff. coefficient, NNM nearest neighbor matching; *** and * significance at the 1 and 10% levels, respectively

4 Conclusion

Tea production is generally characterized by small-scale agricultural production in northern Vietnam, with an average tea farm being 0.35 ha in size. Tea production plays an important role in generating household income and is a major income source of family income in the study area. This study investigated the profit efficiency of tea production in the northern mountainous region of Vietnam using a stochastic profit frontier function. Then, the propensity score matching approach was used to control for possible self-selection when assessing the difference between the profit efficiency of the two practices. The results showed that tea farmers are not operating at full profit efficiency. VietGAP tea producing farmers have the potential to improve their profit efficiency by about 24%, while conventional tea farmers could increase their profit efficiency by about 27%. The results also confirmed that tea farmers benefit higher profit efficiency from switching to safe tea production practice. Several policy implications are suggested by the findings of the study. The profit efficiency of tea farms can be improved significantly by supporting irrigation system development and the operational efficiency of cooperatives. Moreover, larger production scale is major important factor to promote the adoption of VietGAP standards among farmers because they can utilize machinery and other production tools. Thus, public policies aimed at diffusing adoption for eco-friendly production practices should support innovations that may minimize negative impact of small production scale. Lastly, supporting suitable labor-saving machinery, improvement of extension service might also be good incentives for the conversion in study area.

This chapter has several limitations and additional studies are required. The issue of unobservable characteristics should be further investigated. Further studies should be sought as regards the relationship between yield and used labor, the information flow among actors, policy and institutions for VietGAP product marketing, market channel or value chain. Moreover, it is also worthwhile to do similar studies with larger samples which imply to extend the research to other regions of Vietnam. It would be very useful to carry out some researches on the direction of consumer's demand such as willing to pay for VietGAP product. Besides, it would be more useful to do further studies using time-series data and different methods for checking results. Finally, more indicators for impact evaluation, such as household income, household consumption expenditure, and yield, should be investigated.

References

Abdulai, A., & Huffman, W. (2000). Structural adjustment and economic efficiency of rice farmers in Northern Ghana. *Economic Development and Cultural Change, 48*(3), 503–520. https://doi.org/10.1086/452608

ADB. (2004). *Making markets work better for the poor: The value chain for tea in Vietnam: Prospects for participation of the poor*. http://www.valuechains.org/dyn/bds/docs/484/M4P%20Poor%20in%20the%20Tea%20VC%20Vietnam%202004.pdf. Accessed 6 Feb 2018, issue 01.

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics, 6*(1), 21–37. https://doi.org/10.1016/0304-4076(77)90052-5

Aktar, W., Sengupta, D., & Chowdhury, A. (2009). Impact of pesticides use in agriculture: Their benefits and hazards. *Interdisciplinary Toxicology, 2*(1), 1–12. https://doi.org/10.2478/v10102-009-0001-7

Ali, M., & Byerlee, D. (1991). Economic efficiency of small farmers in a changing world: A survey of recent evidence. *Journal of International Development, 3*(1), 1–27. https://doi.org/10.1002/jid.4010030102

Ali, M., & Flinn, J. C. (1989). Profit efficiency among Basmati rice producers in Pakistan Punjab. *American Journal of Agricultural Economics, 71*(2), 303–310. https://doi.org/10.2307/1241587

Arnade, C., & Trueblood, M. A. (2002). Estimating a profit function in the presence of inefficiency: An application to Russian agriculture. *Journal of Agricultural and Resource Economics, 27*(1), 94–113. https://doi.org/10.2307/40987137

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Journal of Empirical Economics, 20*, 325–332.

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal: Promoting Communications on Statistics and Stata, 2*(4), 358–377. https://doi.org/10.1177/1536867x0200200403

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys, 22*(1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Calvin, L., Avendaño, B., & Schwentesius, R. (2004). The economics of food safety and produce: The case of green onions and hepatitis a outbreaks. In *Electronic outlook report from the economic research service*. https://www.ers.usda.gov/webdocs/outlooks/39501/30244_vgs30501_002.pdf?v=2298.9. Accessed 27 Oct 2021.

Coady, D. P. (1995). An empirical analysis of fertilizer use in Pakistan. *Economica, 62*(246), 213–234.

Coelli, T., Rahman, S., & Thirtle, C. (2002). Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: A non-parametric approach. *Journal of Agricultural Economics, 53*(3), 607–626. https://doi.org/10.1111/j.1477-9552.2002.tb00040.x

Dehejia, R. H., & Wahba, S. (1999). Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American Statistical Association, 94*(448), 1053–1062. https://doi.org/10.1080/01621459.1999.10473858

FAO. (2012). *Yearly crops and livestock database of Vietnam*. Food and Agriculture Organization of the United Nations, USA. http://www.fao.org/faostat/en/#data/TP

GSO. (2013). *Statistic report on agriculture, forestry and fishery*. https://www.gso.gov.vn/default_en.aspx?tabid=778.

Ha, T. M. (2014a). Effectiveness of the Vietnamese Good Agricultural Practice (VietGAP) on plant growth and quality of Choy Sum (Brassica rapa var. Parachinensis) in Northern Vietnam. *Aceh International Journal of Science and Technology, 3*(3), 80–87. https://doi.org/10.13170/aijst.3.3.2023

Ha, T. M. (2014b). Establishing a transformative learning framework for promoting organic farming in Northern Vietnam: A case study on organic tea production in Thai Nguyen province establishing a transformative learning framework for promoting organic farming in Northern. *Asian Journal of Business and Management, 2*(3), 202–211.

Hong, N. B., & Yabe, M. (2015). Profit efficiency of tea production in the northern mountainous region of Vietnam. *Journal of International Society for Southeast Asian Agricultural Sciences, 21*(1), 1–17.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics, 86*(1), 4–29. https://doi.org/10.1162/003465304323023651

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature, 47*(1), 5–86. https://doi.org/10.1257/jel.47.1.5

Islam, G. M. N., Arshad, F. M., Radam, A., & Emmy, A. (2012). Good agricultural practices (GAP) of tomatoes in Malaysia: Evidences from Cameron Highlands. *African Journal of Business Management, 6*(27), 7969–7976. https://doi.org/10.5897/ajbm10.1304

Kariuki, I. M., Loy, J.-P., & Herzfeld, T. (2012). Farmgate private standards and price premium: Evidence from the GlobalGAP scheme in Kenya's French Beans Marketing. *Agribusiness, 28*(2), 42–53. https://doi.org/10.1002/agr.20286

Kersting, S., & Wollni, M. (2012). New institutional arrangements and standard adoption: Evidence from small-scale fruit and vegetable farmers in Thailand. *Food Policy, 37*(4), 452–462. https://doi.org/10.1016/j.foodpol.2012.04.005

Khandker, Sa. R., Samad, H. A., & Samad, H. A. (2010). Handbook on impact evaluation: Quantitative methods and practices (Vol. 1, Issue 1, pp. 115–125). The World Bank. http://documents.worldbank.org/curated/en.pdf

Kolawole, O. (2006). Determinants of profit efficiency among small scale rice farmers in Nigeria: A profit function approach. *Research Journal of Applied Science, 1*(1–4), 116–122.

Kumbhakar, S. C. (1996). Efficiency measurement with multiple outputs and multiple inputs. *Journal of Productivity Analysis, 7*(2–3), 225–255. https://doi.org/10.1007/BF00157043

Kumbhakar, S. C., Biswas, B., & Bailey, D. (1989). A study of economic efficiency of Utah dairy farmers: A system approach. *The Review of Economics and Statistics, 71*(4), 595–604.

Lovell, C. A. K. (1994). Linear programming approaches to the measurement and analysis of productive efficiency. *Top, 2*(2), 175–248. https://doi.org/10.1007/BF02574810

MARD. (2008). *Decision on the procedure of good agricultural practices for safe vegetables and fruits*. http://www.vietgap.com/pic/files/379-qd-bnn-khcn-vietgap-cho-rau-qua.pdf

Nguyen, H. P., Wattanachai, P., Kasem, S., Nguyen, T. Q., Dang, V. T., Nguyen, X. C., & Van Luong, T. N. (2015). Comparison among Chemical, GAP and Organic method for tea cultivation in Vietnam. *Journal of Agricultural Technology, 11*(8), 1713–1730.

Noltze, M., Schwarze, S., & Qaim, M. (2012). Understanding the adoption of system technologies in smallholder agriculture: The system of rice intensification (SRI) in Timor Leste. *Agricultural Systems, 108*, 64–73. https://doi.org/10.1016/j.agsy.2012.01.003

OECD. (2008). *Household behaviour and the environment – Reviewing the evidence*. Organization for Economic Co-operation and Development. http://www.oecd.org/greengrowth/consumption-innovation/42183878.pdf

Pongvinyoo, P., Yamao, M., & Hosono, K. (2015). Cost efficiency of Thai National GAP (QGAP) and Mangosteen Farmers' understanding in Chanthaburi province. *American Journal of Rural Development, 3*(2), 15–23. https://doi.org/10.12691/ajrd-3-2-1

Rahman, S. (2003). Profit efficiency among Bangladeshi rice farmers. *Food Policy, 28*, 487–503. https://doi.org/10.1016/j.foodpol.2003.10.001

Rosenbaum, P. R. (1995). Constructing matched sets and strata. In *Observational studies* (pp. 200–224). http://www.springerlink.com/index/D7X7KX6772HQ2135.pdf
Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika, 70*(1), 41–55.
Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician, 39*(1), 33–38. https://doi.org/10.1080/00031305.1985.10479383
Saigenji, Y. (2010). *Contract farming and its impact on production efficiency and rural household income in the vietnamese tea sector*. PhD Dissertation, 1–175. http://opus.uni-hohenheim.de/volltexte/2012/728/pdf/Dissertation_Yoshiko_Saigenji.pdf
Sianesi, B. (2004). An evaluation of the Swedish system of active labor market programs in the 1990s. *The Review of Economics and Statistics, 86*(1), 133–155. https://doi.org/10.1162/003465304323023723
Smith, J. A., & Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics, 125*, 305–353. https://doi.org/10.1016/j.jeconom.2004.04.011
SOMO. (2007). *Report on comparative international research on the tea sector in Vietnam.* https://www.somo.nl/wpcontent/uploads/2007/01/Comparative-international-research-on-the-tea-sector-in-Vietnam.pdf. Accessed 30 Jan 2018.
Subervie, J., & Vagneron, I. (2012). *Can fresh produce farmers benefit from Global Gap Certification? The case of lychee producers in Madagascar*. International Association of Agricultural Economists (IAAE) Triennial Conference, 1–28. http://ageconsearch.umn.edu/bitstream/126704/2/SUBERVIE.pdf
Taraka, K., Shamsudin, M. N., Latif, I. A., & Sidique, S. A. (2012). Estimation of technical efficiency for rice farms in central Thailand using stochastic frontier approach. *Asian Journal of Agriculture and Development, 9*(2), 1–11.
Tran, N. D. (2008). *An analysis of economic and environmental impacts for the transition to organic tea production in the Thai Nguyen province of Vietnam.* University of Hawaii, USA. https://scholarspace.manoa.hawaii.edu/bitstream/10125/20757/1/HAWN_AC1.H3_5132_r.pdf. Accessed 10 Feb 2018
Tran, N. D. (2009). *Transition to organic tea production in the Thai Nguyen province, Vietnam: Economic and Environmental Impacts.* http://www.eepsea.net/index.php?option=com_k2&view=item&id=202:transition-to-organic-tea-production-in-the-thai-nguyen-province-vietnam&Itemid=192. Accessed 6 Feb 2018
Tran, N. D., & Yanagida, J. F. (2015). Stochastic frontier analysis with price risk: An application to organic tea production in Vietnam. *Asian Journal of Agricultural Extension, Economics & Sociology, 4*(2), 146–157. https://doi.org/10.9734/ajaees/2015/13095
Walker, T., Tschirley, D., Low, J., Pequenino Tanque, M., Boughton, D., Payongayong, E., & Weber, M. (2004). *Determinants of rural income, poverty, and perceived well-being in Mozambique in 2001–2002.* Issue Research Report No 57E.
Wang, H., Moustier, P., & Loc, N. T. T. (2014). Economic impact of direct marketing and contracts: The case of safe vegetable chains in northern Vietnam. *Food Policy, 47*, 13–23. https://doi.org/10.1016/j.foodpol.2014.04.001
Wang, J., Cramer, G. L., & Wailes, E. J. (1996). Production efficiency of Chinese agriculture: Evidence from rural household survey data. *Agricultural Economics, 15*(1), 17–28. https://doi.org/10.1111/j.1574-0862.1996.tb00417.x

Chapter 5
Impacts of Irrigation, Mechanization and Subsidies on Wheat Efficiency in China: An Application of Two-Stage DEA

Dongpo Li and Teruaki Nanseki

1 Introduction

Agricultural production, especially sufficient and efficient supply of the grain crops, plays an extremely important role in Chinese history. According to the data released by the National Bureau of Statistics on December 10, the total grain output of China in 2020 was 669.49 billion kg, an increase of 56.5 billion kg or 0.9% over 2019. The output remained above 650 billion kg for six consecutive years. In 2020, China's grain output hit a record high and achieved a 17-year consecutive increasing, which provided a solid support for ensuring national food security. In the future, it necessary to ensure grain production capacity and national food security, adhering to the strictest cultivated land protection. Hebei is one of the 13 main grain-growing provincial regions in China, and wheat is an important grain crop. By 2019, the sown area of wheat in Hebei Province was 2.32 million hm^2, accounting for 9.79% of the national figure. As the third level of Chinese local administrative hierarchy, a county is the lowest level having complete government divisions and economic industries. Until 2020, Hebei province has 121 counties including 21 county-level cities, 94 counties and 9 autonomous counties. For thousands of years, agriculture has been the main source of national tax. In December 2005, the 19th meeting of the Standing Committee of the Tenth National People's Congress adopted a decision to abolish the regulations on agricultural tax as of January 1, 2006. At the same time, an agricultural subsidy policy system has been gradually established. In 2006, the state allocated 31.05 billion yuan in various agricultural subsidies, which benefited about 720 million farmers across the country. In China, the amount of funds to subsidize

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agriculture is identified in units of counties. Therefore, we intend to study wheat production efficiency from the perspective of county-level regions in Hebei.

Since the pioneering work of Farrell (1957), literature devoted to estimate efficiency mainly embraced two approaches: the parametric function symbolized by Stochastic Frontier Production (SFP, Aigner et al., 1977), and the nonparametric Data Envelopment Analysis (DEA, Charnes et al., 1978). Requirement of a specified function is the main weakness of SFP. In contrast, the DEA embraces the advantage that multiple inputs and outputs can be considered simultaneously, even in different units. Moreover, this approach avoids the parametric specification of technology as well as the distributional assumption (Coelli et al., 2005).

In agriculture, land, labor, fertilizer, water, and other inputs are used, thus needs a multiple input model is necessary to measure the efficiency. A variety of output variables should be adopted to measure not only the physical yield, but also the market value. Both the input and output variables are in different units, without any parameters can be assumed accurately beforehand. Moreover, what the farmers can control relatively freely would be the quantity of inputs, rather than the outputs. Meanwhile, natural and marketing risks, government regulations, constraints on finance, etc., may cause a farm cannot operate at optimal scale. Therefore, we will adopt input-oriented DEA model with the assumption of VRS,[1] although many prior studies took CRS assumption.

To estimate the DEA scores and relevant determinants in the second stage, there are three major approaches that have been used, including *Tobit* regression (Tobin, 1958), the Papke-Wooldridge (PW) model and the unit-inflated beta (Beta) model. However, as proved by Hoff (2007), Tobit regression performs better that the other two and have adopted by many studies as Javed et al. (2008), Dhungana et al. (2010), etc.

We intend to fulfill the following targets in this chapter: (1) formulating a DEA model appropriate to analyze wheat production efficiencies taking Chinese counties as the DMUs, (2) revealing the overall attributes of wheat production efficiencies, (3) finding out the theoretical margin for the increasing of yields and saving inputs, (4) identifying the significant social and natural factors through the application of Tobit regression, and (5) putting forward referential recommendation for policy makers.

[1] There are two orientations in DEA model, the input-oriented model seeks to reduce in inputs, with outputs hold constant, while the output-oriented model aims to increase outputs, keeping inputs fixed. As to the assumption of return to scale, Constant Return to Scale (CRS) is appropriate when all firms are operating at an optimal scale, while Variable Return to Scale (VRS) is without this limitation.

2 Model and Data

2.1 Defining the Variables

Output variables Yields of main product refers to net weight of raw wheat in standard moisture content, which is the percentage of water and varies in different regions. In most of the cases, it is around 12–13% in Heibei Province. It implicates the physical productivity of wheat, thus the capability to fulfill the food demand and guarantee food safety. *Net profit* is the balance of the minus costs[2] in wheat farming. Generally, this variable reveals the profitability of wheat farming, under a variety of certain technical, marketing and political institutions. Therefore, the former is a technical variable, while the latter is a socio-economic one.

Input variables (1) *Labor inputted* is the standard days of labor needed by wheat farming. To calculate this variable, the farming hours of both family members and hired labors should be standardized, referring to a moderate agricultural labors,[3] and them divided by 8 h. (2) *Land rent inputted* included rent of land circulated from individuals or the collectives, and theoretical rent of own-farming land. (3) Physical amount of seeds used in wheat farming, including the bought, self-produced and donated for free, form the variable of *Seeds inputted.* (4) *Fertilizer inputted* is the amount of fertilizer, which has been standardized according to its contents of active principles. (5) *Machine service rent* is the expenditure for the mechanical operation including plough, sowing, harvest, threshing and transportation. (6) *Water fee inputted* includes the expenditure for the rent of irrigating equipment, and the costs occurred in irrigating. (7) Depreciated value of fixed assets covers assets valued more than 100 yuan, with the durance of no less than one year. To calculate depreciation of the fixed assets, the annual depreciating rate for water channel and motor-pumped well is 10%, mechanical installations with 12.5%, while large and medium farm implements with 20%.

Determinants of efficiency Input variables affect the production directly, that is, wheat cannot be properly produced without any of the variables listed as input in Table 1 (in Chap. 3). By contrast, a determinant usually does not directly determine, but has an indirect impact on technical efficiency (Audibert et al., 2003).

(1) Basic productive factors, including *Agro-labor per farm* and *Average size of farmland*. We set the hypotheses that the more agro-labor and land per farm, the more efficient of wheat production. (2) Basic farming conditions included *Ratio of irrigable land* and *Power of agricultural mechanization*, as irrigation and machinery operations are indispensable guarantees of modern agriculture. (3) Basic political

[2] Costs consist of (1) inputted material and service, including seeds, fertilizer, pesticides, and hired machinery for irrigation, plough, sowing, etc.; (2) value of hired labors and converted value of family labors; (3) value of rented lands and converted value of family-owned farming land allocated by the Household Contract Responsibility System.

[3] A moderate agricultural labor means (1) 18-50 year old male and 18-45 year old female, being able to adapt common labor intensity; (2) labors aged out of the interval stipulated above, but can undertake equivalent labor intensity; or (3) the employed labors.

factors embrace *Extension staffs of agro-tech* and *Agricultural subsidies*. We assume that positive relationships exist amongst the two variables and production efficiency. (4) Basic potential resources include Water resources applicability and *Average schooling length of rural labors*. We introduced water reserves per capita, rather than per hectare, to show the water use efficiency in the whole society. It should be hypothesized that the more plenty in water supply and well-educated farmers, the more efficient that wheat production will be.

2.2 Sample and Data

The data of inputs and outputs were got from the agricultural product survey, conducted by *Price and Cost Inspection Bureau* of Hebei in 2008. The data of this year was selected due to fact that the agricultural tax had just been exempted and the new agricultural subsidy policy system had just begun. On this basis, the main determinants of wheat production efficiency were analyzed, thus to evaluate the accuracy and rationality of following policies promoting agricultural innovations. Wheat production was sampled in 36 counties and the summary statistics were listed in Table 1. In addition, we got some other data from the Bureau of Statistics, Department of Agriculture and Department of Water Resources of Hebei.

3 Efficiency Analysis with DEA

3.1 Expression of the Used DEA Model

The DEA used in this chapter can expressed as the following linear programming (Coelli, 2005):

$$Min_{\theta,\lambda}\,\theta$$

$$st{-}y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0$$

$$\lambda \geq 0, i = 1, 2, \ldots, 36 \tag{1}$$

where θ is the efficiency score and λ is a vector of constants; $y_i and x_1$ and $y_i and x_1$ is the output and input vectors of county I; Y and X are the output and input matrices, respectively. With the assumption of VRS, three kinds of efficiency scores can be outputted through the software of DEAP 2.1, where

Table 1 Variables and the summary statistics of wheat production efficiency mainly based on the Agricultural Product Survey, 2008 conducted by Price and Cost Inspection Bureau of Hebei

Variable		Description of the variables	Unit	Maximum	Minimum	Mean	Std. D
Output	y_1	Yields of main product	Kg/mu[1]	508.90	308.30	417.84	45.94
	y_2	Net profit	Yuan/mu	319.25	6.21	160.08	81.29
Input	x_1	Labor inputted	Day/mu	8.74	2.77	5.67	1.37
	x_2	Land rent inputted	Yuan/mu	141.67	60.00	101.87	22.76
	x_3	Seeds inputted	Kg/mu	27.33	10.83	17.21	4.01
	x_4	Fertilizer inputted	Kg/mu	39.44	21.13	28.11	4.30
	x_5	Machine service rent	Yuan/mu	115.50	64.44	91.88	12.31
	x_6	Water fee inputted	Yuan/mu	83.15	14.26	45.25	16.28
	x_7	Depreciated value of fixed assets	Yuan/mu	12.17	0.93	5.64	2.86
Determinant	d_1	Agro-labor per farm	Person	153	0.41	0.91	0.29
	d_2	Average size of farmland	Mu	10.16	4.00	6.15	1.43
	d_3	Ratio of irrigated land	%	100.00	54.46	90.67	11.93
	d_4	Power of agricultural mechanization	Kw/ha	78.55	6.72	20.25	13.05
	d_5	Extension staffs of agro-tech	Person/km^2	13.22	0.13	1.97	2.66
	d_6	Agricultural subsidies	Yuan/mu	50.00	21.95	36.91	5.64
	d_7	Water resources applicability	Ton/person	196.08	55.14	92.08	30.81
	d_8	Average schooling length of rural labors	year	9.96	6.78	7.48	0.55

Note [1]as a main unit of land measurement in China 1 mu = 666.67m^2

Table 2 Summary of wheat production efficiency

Type	Number of counties	Means			Number of counties with		
		Total efficiency	Technical efficiency	Scale efficiency	*crs*	*irs*	*drs*
I	11	1.000	1.000	1.000	11	0	0
II	11	0.883	1.000	0.883	0	11	0
III	14	0.842	0.902	0.934	0	12	2
Total	36	0.902	0.959	0.940	11	23	2

Note crs = constant returns to scale; irs = increasing returns to scale; drs = decreasing returns to scale

$$Total efficiency = Technical efficiency \times Scale efficiency \tag{2}$$

3.2 Total, Technical and Scale Efficiencies

From the efficiency summary shown in Table 2, 11 counties as Type I were scored in Total efficiency as 1, thus in full efficiency and can be benchmarks for the other counties. Furthermore, within the rest 25 counties with Total efficiency less than 1, 11 counties, adjustment of any input will not change the efficiency, and it makes adjusting farm scales the only solution to improve efficiency. Meanwhile, there were still 14 counties, referred as Type III, having Technical efficiency less than 1. It means that in these counties, with given farm scales, production efficiency can still be improved through reducing some of the inputs.

Moreover, all the 11 counties in Type I were in the status of constant returns to scale, while all the 11 counties in Type II were in the status of increasing returns to scale. In Type III, 12 counties were being increasing returns to scale, and two counties were in the status of decreasing returns to scale. Therefore, in altogether 23 counties, efficiencies can be improved by enlarging the farm scales, and 2 by contraction.

3.3 Slack Analysis of the Outputs

Slack of an output shows the margin that firm can improve its output through the adjustment by DEA. The output slacks summarized in Table 3 showed that in the *Type* III counties, yields of main product can be increased by 3.08%. Meanwhile, the net profit can be increased by 82.01%. It indicates that comparing with technical improvement, much more margin lies in the socio-economic optimization including

Table 3 Slack analysis of the outputs per *mu*

Type	Number of counties	Mean of main product (kg)			Mean of net profit (yuan)		
		Origin1	Target1	Slack1	Origin2	Target2	Slack2
I	11	459.34	459.34	0.00	245.65	245.65	0.00
II	11	373.87	373.87	0.00	114.95	114.95	0.00
III	14	416.71	429.53	12.81	127.43	231.92	104.05
Total	36	417.84	423.18	5.34	160.08	203.63	43.54
Percent of slack in Type III		100.00	103.08	3.08	100.00	182.01	82.01

marketing regulation, integration of agro-aiding funds, etc., so as to improve the profitability of wheat farming.

3.4 Radial and Slack Analysis of the Inputs

As implicated by Audibert et al. (2003), the slacks provide an indication of the inputs in excess supply, and number of DMS shows the capacity of each variable that constraining production efficiency, the smaller the higher. Within Type III, *fertilizer inputted* was the first constraint limiting output as it was supplied in the excess with only one county. Fixed assets were the least constraining inputs, since 11 counties were supplied with surplus (Table 4). The summary of radial and slack movement means the total amount needs to be adjusted, so as to reach a target input while keeping output unchanged. Fixed assets can be decreased by the largest margin of 37.76%, showing the relatively redundant and inefficient usage of this input. Meanwhile, the input amount of fertilizer shows the most efficient usage with the margin of only 10.97%.

4 Effects of the Determinants

4.1 Tobit Regression and the Results

Effects of the determinants will be evaluated with Tobit regression (Dhungana et al., 2010; Tobin, 1958):

$$\theta_i = \beta_0 + \beta_1 d_{i1} + \beta_2 d_{i2} + \beta_3 d_{i3} + \beta_4 d_{i4} + \beta_5 d_{i5} + \beta_6 d_{i6} + \beta_7 d_{i7} + \varepsilon_i \quad (3)$$

where β_i are parameters to be estimated and ε_i are error terms assumed to be distributed with $N(0, \delta^2)$.

Table 4 Radial and slack analysis of the inputs per mu

		Labor (day)	Land rent (yuan)	Seed (kg)	Fertilizer (kg)	Machinery (yuan)	Irrigation (yuan)	Fixed assets (yuan)
Mean movements	Radial	0.67	11.74	1.83	3.12	10.13	10.13	0.80
	Slack	0.20	2.12	0.77	0.14	5.05	11.37	2.29
	Total	0.87	13.86	2.60	3.26	15.148	17.10	3.10
Percent of movements (%)	Radial	10.51	10.51	10.51	10.51	10.51	10.51	10.51
	Slack	2.49	1.59	4.11	0.46	4.86	18.69	27.25
	Total	13.00	12.10	14.62	10.97	15.37	29.19	37.76
Number of counties	Radial	14	14	14	14	14	14	14
	Slack	3	3	6	1	7	10	11

Through the application of EViews 7.0, maximum likelihood estimations were conducted. The effects of each determinant to the total efficiencies were evaluated and presented in Table 5. Meanwhile, for each determinant, the value of t-Ratio and the statistical significance in the level of 1, 5 and 10% were listed respectively.

Table 5 Effect of the determinants on total production efficiency of wheat

	Determinant	Coefficient	*t*-Ratio
Basic productive factors	Agro-labor per farm	0.112*	1.965
	Average size of farmland	−0.002	−0.146
Basic productive conditions	Ratio of irrigable land	0.003**	2.210
	Power of agricultural mechanization	0.004**	2.282
Basic political factors	Extension staffs of agro-tech	0.011	1.312
	Agricultural subsidies	−0.010***	−3.302
Basic potential resources	Water resources applicability	0.000	0.278
	Average schooling length of rural labor	0.048	1.234
Constant		0.441	1.111
S.E. of regression		0.071	
Log likelihood		17.492	

Note ***, **, and * represent statistical significance in the level of 1, 5 and 10% respectively

4.2 Analysis of Determinants

(1) Effects of basic productive factors. As hypothesized, *agro-labor per farm* has a significant and positive coefficient of 0.112, indicating that the more agricultural labors a farm embraces, the more efficient its production will be. However, our hypothesis on the significant and positive contribution of land size was not supported by the result. It may be explained by the fact that the surveyed farms only embraced farmland less than 10.16 *mu* (0.68 ha), which is not large enough to make scale economy. For most of the farmers, arable land is still basic means of production and taking the role of fundamental social insurance to some extent. Therefore, especially after the agricultural taxes were rescinded, they would prefer to farm by themselves rather than lending out, even if it may lead into larger scale and more efficient production. With the improved land-use policy in China, allocation of land resources and scale management are constantly optimized during recent years. According to the *Measures for the circulation of rural land management rights* released by Ministry of Agriculture and Rural Affairs in 2021, the contracted management of land registration system is established and improved to protect farmers' legitimate rights and interests. Under a principle of voluntariness and compensation by law, famers are more confident to participate in land circulative activities, enlarge cultivated scale moderately and become the real beneficiaries in the land circulation and sale management. Meanwhile, the government is committed to strengthening the vocational education for farmers by operating diversified training activities over the years, which acts an effective power in raising wheat production.

(2) Effects of basic productive conditions. The two factors of *Ratio of irrigable land* and *Power of agricultural mechanization* were both significant and positive to the total efficiency. As hypothesized, it indicates that the irrigation and machinery condition is really indispensable to wheat farming. In terms of irrigable land, the government has put efforts to increase the investment in water infrastructure and conservancy in recent years, aimed to achieve high yield and efficiency in grain production. It makes great extension of the irrigable land and plays a key role in improving the technical efficiency of grain production. According to the data released by the Ministry of Water Resources, the irrigated farmland reached 1.037 billion mu, accounting for more than half of the total cultivated area, producing 75% of grain products in China by 2020 (State Council Information Office, 2021). At the same time, with a higher level of agricultural mechanization and sufficient support for precision agriculture from the government, autonomous agricultural machinery has gradually been used in farmland. At present, the ownership of large and medium-sized agricultural machinery applied in agricultural operations has exceeded 5 million units. In this context, it is easier to adopt an autonomous agricultural machinery system, and hence improve the technical efficiency greatly with combination of automatic and intelligent control systems.

(3) Effects of basic political factors. *Agricultural Sci-tech extension staff* per km^2 was insignificant, indicating that the staff and agencies were inactive and not completely fulfilling with their duty of spreading advanced sciences and technologies. It may due to less educational background of the staff and lack of funds as surveyed by Shi et al. (2007) in some countries of Hebei. Meanwhile, the effect of agricultural subsidy is significant by negative, which maybe against the traditional imagination but interpretable with further analysis. One funding source of subsidy is the transfer payments from higher governments, which is often in favor of the less developed counties. At the same time, subsidy is funded by local fiscal revenue, which may endow superiority to the developed counties. In other words, the best funded farmers are not necessarily most efficient in wheat farming. Another important reason is that although the subsidies are aiming to encourage grain farming, they are usually granted simply according to the land area, rather than the sown area of grain, thus making some non-grain farms be subsided as well and reducing efficiency of the subsidies (Yang et al., 2010). In recent years, with the application of modern information technology in agriculture and the innovation of agricultural engineering technology, the government has strengthened the construction of agricultural database and agricultural information network system, including the collection and sorting of agricultural information, as well as data construction of environmental resources and market information. In addition, the development of agricultural information application software, such as agricultural decision support systems, ecological and biological system modeling, equipment and automation control software, have greatly increased the contribution of agricultural scientific and technological progress. By 2021, in the major grain producing areas of China, 800 million mu of high-standard farmland and ditches have been formed into a network, with the main grain crops being fully covered with quality seeds, and the contribution rate of agricultural science and technology has exceeded 60% (Ministry of Agriculture & Rural Affairs, 2021).

(4) Effects of basic potential resources. Both the two variables were proved to be insignificant. As to water resources applicability, it may be because of the inefficient usage of water in both farming and other sectors. The insignificance of average schooling length of rural labor indicated that most farmers are lack of getting new know-how with their knowledge, and they are just farming according to tradition or imitating the others. To address the issue of inefficient water resources, water-saving irrigation technologies are being developed and popularized in agricultural production. As an integrated technical system, water-saving irrigation concerns water resources, engineering, agriculture, management among other sectors. For instance, sprinkler irrigation and trickle irrigation help to reduce the evapotranspiration and increase water use efficiency. As a new technology of combination with irrigation and fertilizer, trickle irrigation promotes the process of fertilizer entering to the field with water, which increases the nutrients and rainfall use efficiency simultaneously. Meanwhile, to alleviate severe water shortages in Northern China, the major strategic infrastructure, South-to-North Water Diversion Project, diverting water from wet South to dry

North, greatly optimized the allocation of water resources. On the other hand, the government has increased the investment in rural education, which has greatly improved the educational environment of farmers in recent years.

5 Policy Recommendation

(1) To deal with the insignificant size of farmland, circulation of farmland should be accelerated, as larger farm scale can generate more penitential for efficient farming modes. In China, land will perform as self-insurance of subsistence for a period. The governments should encourage the concentration of land on farm's own willing, through favorite subsidies, financial and technological aiding. The application of the blockchain platform should be promoted to give full play to its openness, intelligence, traceability, and anti-tampering, so as to stimulate agricultural land circulation, issue agricultural subsidies intelligently, manage agricultural machinery and equipment, as well as strengthen the promotion and application of technologies for agricultural production (Li & Luo, 2021).

(2) Considering the significant productive conditions, inefficient agricultural subsidies and water application, the improvement of subsidizing efficiency should be integrated with the construction of public agricultural facilities. Funds could be pooled from part of the money aimed to subsidize the farms, and make it exclusive for the public construction of irrigating facilities and extension of agricultural mechanization, etc. Meanwhile, the government should invest more on agricultural innovation, deeply integrate agriculture production and information technology, encourage the development of smart agriculture. Strengthen the application of Internet of things (IoT) in agricultural machinery and equipment, promote agricultural automation and intelligence. Popularize the irrigation system with IoT sensing, so as to build up a multi-functional agricultural water-saving irrigation platform.

(3) To tackle with the inactive agricultural technology extension system, insignificant education background but significant number of agricultural labors, concerning institutional reforms should be deepened to accelerate the extension of agricultural technology. It includes the faster introduction of market-driven mechanism to the agencies and staffs. Moreover, individuals and commercial organizations should be encouraged to farm with advanced techniques and ways of management. Thus, attracting more educated people into farming and improve the contribution of science and education to modern agriculture.

References

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics, 6*(1), 21–37. https://doi.org/10.1016/0304-4076(77)90052-5

Audibert, M., Mathonnat, J., & Henry, M. C. (2003). Social and health determinants of the efficiency of cotton farmers in Northern Côte d'Ivoire. *Social Science and Medicine, 56*(8), 1705–1717. https://doi.org/10.1016/S0277-9536(02)00164-8

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battes, G. E. (2005). An introduction to efficiency and productivity analysis Second Edition. In *Springer* (2nd ed.). Springer.

Dhungana, B., Yasuhiro, S., Yamamoto, N., & Kano, H. (2010). Technical efficiency analysis of vegetable farms in the mid-hill region of Nepal: An approach using data envelopment analysis. *Japanese Journal of Food, Agricultural and Resource Economics, 60*, 27–38.

Farrell, M. (1957). The measurement of productive efficiency author (s): M . J . Farrell source: Journal of the Royal Statistical Society . Series A (General), Vol. 120, No. 3 (1957), Published by : Wiley for the Royal Statistical Society Stable URL : http://www.js. *Journal of the Royal Statistical Society*, *120*(3), 253–290.

Hoff, A. (2007). Second stage DEA: Comparison of approaches for modelling the DEA score. *European Journal of Operational Research, 181*(1), 425–435. https://doi.org/10.1016/j.ejor.2006.05.019

Javed, M. I., Adil, S. A., Javed, M. S., & Hassan, S. (2008). Efficiency analysis of rice-wheat system in Punjab, Pakistan. *Pakistan Journal of Agricultural Sciences*, *45*(3), 95–100. http://inis.iaea.org/search/search.aspx?orig_q=RN:40059090

Li, D., & Lou, J. (2021). Blockchain boosts digital poverty alleviation and agricultural modernization: Framework and application (in Chinese). *Journal of Dongbei University of Finance and Economics, 133*(1), 86–96.

Ministry of Agriculture and Rural Affairs. (2021). *China's autumn grain harvest started in large areas, with accelerating modernization of agricultural science and technology*. http://www.moa.gov.cn/xw/shipin/xwzx/202110/t20211011_6379097.htm. Accessed 27 Oct 2021.

Shi, H., Zong Y., & Zhao, B. (2007). Investigation on primary agricultural technology extension team in Hebei Province at the new situation (in Chinese). *Management of Agricultural Science and Technology*, *26*, 76–78.

State Council Information Office. (2021). *Hina has basically completed a system of water conservancy infrastructure with river flood control, urban and rural water supply, and farmland irrigation*. http://www.scio.gov.cn/video/42502/42511/Document/1713337/1713337.htm. Accessed 27 Oct 2021.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica, 26*(1), 24–36.

Yang X., Leng Y., & Zong, Y. (2010). Analysis on the factors influencing effects of agricultural subsidies: Based on survey of 376 household in Hebei Province (in Chinese). *Chinese Journal of Rural Economy*, *1*, 20–22.

Chapter 6
Impacts of Information Sources on Technical Inefficiency of Crop Farmers in Vietnam: An Application of Stochastic Frontier Analysis

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1 Introduction

Over the past years, although Vietnam's economic and labor structure has changed, its rural population still accounts for 67,81% in 2012 and 62.66% in 2020 of the total and the main livelihood of rural dwellers is agricultural production. Rice and maize are the largest crops by planted area and comprise the biggest cereal crop production proportion (GSO, 2013, 2021). The National Assembly of Vietnam approved plans to grow gross domestic product (GDP) for the 2011–2015 period by on averages approximately 6.5–7% a year (National Assembly of Vietnam, 2011). The Resolution No. 16/2021/QH15 on the 2021–2025 five-year socio-economic development plan proposes targeting growth of 6.5–7% also (National Assembly of Vietnam, 2021). In addition, poor households will be reduced in a fast and sustainable manner, by 2% a year on average and by 4% a year in districts and communities stricken by poverty and extreme difficulties. Furthermore, the proportion of high-tech products will account for around 30% of total industrial production by value with a technological innovation rate of 13% per year. However, GDP in 2011, 2012, and 2013 was 6.2, 5.2, and 5.4%, respectively; the poverty headcount ratio at the national poverty line was 17.2% of the population in 2012 (World Bank, 2015); and technology application remains low, especially in the agricultural field (Vietnam Trade Promotion Agency, 2014). One

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of the reasons for the low adoption technology is that farmers lack skill, experience, and knowledge to receive and generate information sources.

Now a day, we cannot deny the important role of information in life activities. Information sources are needed for agriculture because of agriculture's importance for socio-economic development, especially in developing countries; food security and welfare issues; improving the quality and quantity of agricultural products; and reducing agricultural product costs (Kaaya, 1999). Adequate quality of information is the required condition to improve all areas of agriculture, especially in countries with increasingly larger markets (Milovanovic, 2014).

As the Vietnamese government has become aware of the importance of information and communication technology (ICT), it has put in place policies to promote ICT. These include Decision No. 1755/QD-TTg of September 22, 2010, which approved a national strategy for "Transforming Vietnam into an advanced ICT country"; Decision No. 698/QD-TTg of June 1, 2009, which approved general plan on information technology (IT) human resources development up to 2020; and Decision No. 1605/QĐ-TTg of August 27, 2010, which approved a national program of IT usage for government bodies for 2011–2015. In particular, on July 12, 2011, the Prime Minister of Vietnam wrote an official letter No. 1138/TTg-QHQT allowing the Ministry of Information and Communications to establish and deploy the expanded project "Improved computer usage and public internet access ability in Vietnam" in 2011–2016 period. With a total value of 50.5 million USD, of which more than 33.6 million USD is funded by the Bill and Melinda Gates Foundation (BMGF) and Microsoft Corporation, this project aims to plug the digital gap between rural and urban areas, improve the livelihoods of people through the use of modern technology, and provide opportunities for people in rural areas to benefit from ICT services. The project has been deployed only in three provinces of Vietnam, namely, Thai Nguyen, Nghe An, and Tra Vinh.

The Prime Minister on June 3, 2020 issued Decision No.749/QD-TTg approving the National Digital Transformation Programme by 2025, with orientations toward 2030. The decision aims to acquire the dual goal of forming a digital Government, a digital economy, and a digital society, while simultaneously establishing digital businesses which have a competitive capacity in Southeast Asia and global as well. Digital transformation has also been emphasized in eight sectors which include finance and banking, healthcare, education, agriculture, transport, logistics, energy, natural resources, and environment and manufacturing (Prime Minister of Vietnam 2020).

Based on the report of FAO et al. (2021) Vietnam is ranked the third in the world in terms of affordability of information and communication, 90% of famers own a mobile phone and 42% of them have 3G or 4G connections, 10% of famers use broadband internet. Recently, Viet Nam is going to creating a more suitable environment for digital agriculture through infrastructure development and financial support. The agriculture sector is demonstrating its role as "the backbone of the economy" and one of the industries and fields that need to be prioritized for digital transformation. Over the years, Vietnam's agricultural sector has been hit hard by climate change and the COVID-19 pandemic has had a marked more negative impact. Facing of many challenges, it is important for the agricultural sector to accelerate the digital transformation process. However, the adoption of ICT rate is much lower for agriculture households. Only one in every five agriculture households have access to digital technologies, compared to around 70% for agriculture enterprises (Binh & Phuong, 2020).

Moreover, the status of information and communication use in Vietnam remain backward, especially in the agricultural sector and rural areas. Most ICT programs and projects are focused on urban areas and local officers. Compared to other regions and countries, progress has been very slow and there are many difficulties and challenges, especially for farmers in the highland area.

In the literature, some researches have studied technical efficiency (TE) and the factors that influence the TE of rice and coffee products in Vietnam, such as Rios and Shively (2005), Khai and Yabe (2011), Linh (2012), and Bac et al. (2013). Nevertheless, none of them have studied both main cereal crops (rice and maize) and the impact of information sources on TE. Therefore, this chapter has two objectives. First, it estimates the TE of crop farmers in Son La province, Vietnam using stochastic frontier analysis (SFA). Second, we determine the information sources that influence technical inefficiency using farm-level data. The rest of the chapter is organized as follows. Section 2 explains the methodology. Section 3 outlines the data used and the empirical model. The results and discussion are provided in Sect. 4. Lastly, Sect. 5 concludes and presents some recommendations.

2 Materials and Methods

TE is the indicator reflecting the capacity of a farmer to achieve maximal output with a given set of inputs (Coelli et al., 2005; Farell, 1957). Stochastic frontier analysis (SFA) and Data envelopment analysis (DEA) are the two methods that are applied widely by many researches so far. Each method has different strengths and weaknesses. DEA is a deterministic and non-parametric method while SFA is a parametric method and can separate the effects of noise from technical inefficiency. This chapter is more interested in the SFA method. Following the work of Farell (1957), the stochastic production frontier was proposed by Aigner et al. (1977); Meeusen and Van den Broeck (1977). It can be written as

$$Y_i = X_i\beta + \varepsilon_i, i = 1, 2, \ldots, N \tag{1}$$

where Y_i is the scalar output of the ith farm; X_i is the vector of input quantities of the ith farm; β is a vector of parameters to be estimated; and ε_i is a “composed” error term and can be represented as

$$\varepsilon_i = V_i - U_i, \tag{2}$$

where V_i is a two-sided random error ($V \sim N\left[0, \sigma_v^2\right]$) that captures the stochastic effects beyond farmers' control (e.g.,measurement errors, disease outbreaks and weather). The term U_i is a non-negative random variable that represents the technical inefficiency of production (Coelli et al., 2005). The one-sided term U_i can follow some distribution as half-normal, truncated-normal, exponential, or gamma (Aigner et al., 1977; Meeusen and Van den Broeck, 1977). This chapter assumes that U_i follows truncated-normal distribution with mean μ and variance ($U \sim N\left[\mu, \sigma_u^2\right]$), which is used widely in many research. It also assumes that U_i and V_i are independent of each other. The different frontier models are based on the different specification of technical inefficiency effects U_i. Some authors, like Bravo-Ureta and Pinheiro (1997), Khai and Yabe (2011), estimated stochastic frontiers to obtain farm-level efficiencies, then regressed these predicted efficiencies upon firm-specific factors, such as farmer characteristics, farm conditions, and production conditions, in an attempt to explain the different output between firms. However, Battese and Coelli (1995) revealed that these firm specific factors might impact on efficiency if they were used directly in the estimation of the production frontier. This is inconsistent with the assumption of independence between inefficiency effects and noise in this two-stage estimation procedure. To overcome this problem, Battese and Coelli (1995) proposed a one-stage simultaneous estimation approach in which the technical inefficiency effects are stochastic and expressed as an explicit function of a vector of farm-specific variables. The technical inefficiency effects can be written as

$$\mu_i = Z_i\delta + \omega_i, \tag{3}$$

where μ_i is the mean of technical inefficiency that can be estimated by one-stage simultaneous estimation. Z_i is a vector of variables that can influence the inefficiency of a farm. δ is a vector of unknown parameter to be estimated. ω_i is an error term (unobservable random variable).

The stochastic frontier production (1) and technical inefficiency model (3) are estimated simultaneously using maximum likelihood method. We choose the widely applied computer program FRONTIER 4.1c (Coelli, 1996) for estimation. This program allows us to present the coefficients of variance parameters

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 \tag{4}$$

$$\gamma = \frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}, 0 \le \gamma \le 1 \tag{5}$$

where gamma parameter (γ) indicates the share of inefficiency in the overall residual variance and must lie between zero and one. If $\gamma = 0$, the deviations from the frontier are due to noise, and if $\gamma = 1$, all deviations are due to technical inefficiencies (Battese & Corra, 1977; Battese & Coelli, 1995).

3 Data and Empirical Model

3.1 Data

The data used in this chapter are based on a direct interview survey of 358 randomly selected crop-farm households in 12 villages of three districts in Son La province in the northwest highland of Vietnam. The data cover 2014. All the output and input variables are summaries of rice and maize crops. In the study area, maize products are used for both selling and self-consumption while rice products are mostly for self consumption, therefore, using profit or income from the rice and maize product index does not display technical efficiency accurately. Therefore, the total gross income of rice and maize production is measured as output. The inputs chosen for the stochastic production frontier function are planted land, family and hired labor, seed, fertilizer (including organic, nitrogen-phosphorus-potassium, nitrogenous, and phosphate fertilizer), chemicals (including herbicide and pesticide) and other expenses (such as irrigation and transportation fees) (Bac et al., 2013; Hasnah et al., 2004; Khai & Yabe, 2011; Linh et al., 2015). Information is a vital resource for farmers. The information on generated technologies from research systems are important for farmer to apply to agricultural activities. Moreover, farmers need marketing information to make suitable decisions on how, when, and where to buy inputs or sell their products (Kaaya, 1999). In the literature, several studies have researched the importance and effects of information technology sources on agriculture, such as Ford and Babb (1989), Ortmann et al. (1993), Patrick et al. (1993), Folz et al. (1996), Kaaya (1999), Gloy et al. (2000), Gloy and Akridge (2000), and Milovanovic (2014). However, most of this research has taken place in the United States, as well as in such countries as Tanzania, and Serbia; none has occurred in Vietnam. Therefore, to our knowledge, this is the first study that evaluates the influence of information sources on technical inefficiency in Vietnam. Based on the literature and survey conditions, some information source variables are chosen and presented in Table 1 (Boz & Akbay, 2005; Füsun Tatlıdil et al., 2009; Gloy et al., 2000). Table 1 shows that total gross income of rice and maize products in 2013 was 67.4 million VND. Total rice and maize cultivated land was 1.65 ha of which most is maize. Because maize and rice are cultivated mostly on highland and sloping land, these crops demand much more seed, labor, and fertilizer. All cultivation is based strongly on human power, and thus, the total amount of chemicals and other expenses are less than other inputs. In the survey, 22% of farmers received extension services. Farmers may not have the time or inclination to read printed materials and listen to the radio. Only 25% and 13% of respondents read printed materials every month and listen to the radio at least five times per week, respectively. Of this total, only one fourth and one sixth were interested in reading and listening to agricultural information, respectively. On the other hand, 89% of respondents said they usually watched television at least five times per week and 60% of them usually watched agricultural programs. Most farmers owned cell-phones but only 1% had tried to access the internet through their smart-phones.

In addition, 77% respondents were members of at least one farm group and only a small proportion of farmers had visited good agricultural models.

3.2 Empirical Model

There are several production functions in econometric estimation, such as the Cobb–Douglas function, translog function, and constant elasticity of substitution (CES). Based on Hanley and Spash (1993), Khai and Yabe (2011) proposed that the Cobb–Douglas functional form is suitable if the model has three or more independent variables. Our study has six independent variables, and therefore, the Cobb–Douglas production function is chosen; it can be written as

$$lnY_i = \beta_0 + \sum\nolimits_{j=1}^{6} \beta_{ji} lnX_{ji} + V_i - U_i \tag{6}$$

where Y_i is the output of I farmer, X_{ji} are the j input variables presented in Table 1, and β_{ji} are parameters to be estimated.

The inefficiency model is estimated from

$$\mu_i = \delta_0 + \sum\nolimits_{k}^{11} \delta_{ji} Z_{ji} + \omega_i \tag{7}$$

where μ_i represents the mean technical inefficiency effects. Z represents various information source variables presented in Table 1.

3.3 Hypotheses Tests

It is noted that several tests are needed to test the presence of inefficiency in the model and whether the efficiency parameters are significantly different from zero (Coelli & Battese, 1996). Therefore, the following hypotheses tests are of interest:

H_{01}:$\mu = 0$, the null hypothesis specifies that the inefficiency effects are half-normal distribution;

H_{02}:$\gamma = \delta_0 = \cdots = \delta_{11} = 0$, the null hypothesis specifies that the inefficiency effects are not present;

H_{03}:$\gamma = 0$, the null hypothesis specifies that the inefficiency effects are not stochastic; and

H_{04}:$\delta_1 = \cdots = \delta_{11} = 0$, the null hypothesis specifies that the coefficients of the variables in the model for the effects are zero.

Since the model is estimated using maximum likelihood, these null hypotheses can be tested using the general likelihood-ratio statistic, λ, given by

$$\lambda = -2[L(H_0) - L(H_1)] \tag{8}$$

Table 1 Descriptive statistics of variables in the empirical model

Variable	Description	Mean	Std. Dev	Min	Max
Y	Gross income (1000 VND)	67,400.99	50,358.66	840	238,500
X_1	Cultivated land (ha)	1.65	1.27	0.05	10.00
X_2	Total amount of seed (1000 VND)	10,953.42	7,750.732	192	40,220
X_3	Total amount of fertilizer (1000 VND)	1,947.28	1,481.87	80	9,630
X_4	Total amount of chemicals (1000 VND)	132.80	104.70	2.8	750,27,900
X_5	Total labor, including family labor and hired labor (Man-days)	6,320.94	4,522.813	300	10,400
X_6	Other expenses (1000 VND)	319.01	1,129.62	0	1
Z_1	Extension services. Takes 1 if farmers received information about extension services, 0 = otherwise	0.22 lePara>	0.41	0	1
Z_2	CCPO. Takes 1 if farmers usually visit CCPO, 0 = otherwise	0.29	0.46	0	1
Z_3	Reading printed materials. Takes 1 if farmers read several times a month, 0 = otherwise	0.25	0.43	0	1
Z_4	Reading information. Take 1 if farmers read the agricultural information, 0 = otherwise	0.24	0.43	0	1
Z_5	Listening to the radio. Takes 1 if farmers listen at least 5 times per week, 0 = otherwise	0.13	0.33	0	1
Z_6	Listening information. Takes 1 if farmers usually listen the agricultural information, 0 = otherwise	0.14	0.35	0	1
Z_7	Watching TV. Takes 1 if farmers watch at least 5 times per week, 0 = otherwise	0.89	0.30	0	1
Z_8	Watching information. Takes 1 if farmers usually watch agricultural programs, 0 = otherwise	0.59	0.49	0	1
Z_9	Takes 1 if farmers' cell-phones can access the internet, 0 = otherwise	0.01	0.11	0	1
Z_{10}	Takes 1 if the farmer has visited a good agricultural model, 0 = otherwise	0.16	0.36	0	1
Z_{11}	Takes 1 if the farmer has agricultural group membership, 0 = otherwise	0.77	0.42	0	1

Note 1 USD = 21,125.00 VND (March 2014) where $L(H_0)$ and $L(H_1)$ present the value of the likelihood function under the null (H_0) and alternative (H_1), respectively.

The critical values for each of these tests are derived from Kodde and Palm (1986), as they are adjusted Chi-square (X_J^2) values to take into account the mixed nature of the likelihood ratio test (Coelli & Battese, 1996), where J is the number of restrictions under H_0.

4 Results and Discussion

4.1 Parameter Estimates

The maximum likelihood estimates (MLE) of the parameters of the stochastic frontier production function and the inefficiency model are estimated simultaneously and reported in Table 2. The signs of the coefficients of the stochastic frontier are as expected, except the negative of land for cultivation and chemical variables. The negative sign of land for cultivation, which is significant at 5% level, may be due to the fact that most cultivated land is fragmented and located in the highland. Thus, the more cultivated land is, the lower is productivity efficiency. Hung et al. (2007) indicated that land fragmentation is very common in the north of Vietnam. In addition, they found that land fragmentation increased family labor use and other expenses and had negative influence on crop productivity (Hung et al., 2007). This also explains our results when the coefficients of seed, fertilizer, and labor are positive and highly significant at the 1% level. The insignificance of the coefficients of chemicals and other expenses indicate that they are not important factors and rarely used by farmers. Chemical prices are quite high and famers know that chemicals are very harmful. Farmers use mostly human power; transportation is mostly by human and animal and lower levels of technology are applied. Thus, other expenses are very small and do not effect crop productivity.

4.2 Hypothesis Testing

Generalized likelihood tests are conducted to test the null hypothesis that the technical inefficiency effects are absent or that they have simpler normal distribution. The results are shown in Table 3. The first null hypothesis (H_{01}) inefficiency effects are half-normal distribution is rejected at the 10% level of significance, indicating that our assumption of truncated-normal distribution is adequate. The second null hypothesis (H_{02}), which specifies that the inefficiency effects are absent from the model, is rejected. The third null hypothesis (H_{03}), which specifies that the inefficiency effects are not stochastic, is strongly rejected at the 1% level. Thus, it can be said that the inefficiency effects are both stochastic and present. The γ- parameter associated with

Table 2 Parameter estimates of stochastics production frontier and technical inefficiency models

Variable	Parameter	Coefficients	SE
Stochastic production frontier			
Constant	β_0	2.53***	0.96
Log(land)	β_1	−0.45**	0.22
Log (seed)	β_2	0.35***	0.05
Log (fertilizer)	β_3	0.21***	0.04
Log (chemical)	β_4	−0.03	0.04
Log (labor)	β_5	0.87***	0.20
Log (other)	β_6	5.4E−06	0.01
Technical inefficiency model			
Constant	δ_0	0.37*	0.20
Extension services	δ_1	−0.04	0.11
CCPO	δ_2	0.02	0.11
Reading printed material	δ_3	0.23	0.16
Reading information	δ_4	−0.32*	0.19
Listening to the radio	δ_5	−0.39	0.27
Listening information	δ_6	0.39	0.26
Watching television	δ_7	−0.29*	0.16
Watching information	δ_8	−0.18	0.11
Cell phone can access internet	δ_9	−2.82	3.43
Visited good agricultural model	δ_{10}	0.09	0.14
Agricultural group membership	δ_{11}	0.05	0.12
Variance parameter			
Sigma squared	σ_v	0.21***	0.05
Gama	λ	0.64***	0.12
Log-likelihood		−137.701	

Note ***, ** and * are significant at 1, 5 and 10% levels, respectively

the variance in the stochastic frontier is 0.64 and significant at the 1% level. This can explain as 64% of the variation of gross income from maize and rice being due to technical inefficiency. The last null hypothesis (H_{04}), in which the coefficients of the variables in the model for the inefficiency effects are zero or have no effect, is rejected. This suggests that even the individual effects of 1 or more of 11 explanatory variables of inefficiencies of production may not be statically significant but, in general, the joint effects of all variables are significant.

Table 3 Results of hypothesis tests (Own survey, 2014)

Null hypothesis	Test statistic	d.f	Critical value (χ^2)	Decision
$H_{01}: \mu = 0$	2.216	1	1.642	Reject H_0
$H_{02}: \gamma = \delta_0 = \cdots = \delta_{11} = 0$	21.598	13	19.216	Reject H_0
$H_{03}: \gamma = 0$	25.448	1	6.635	Reject H_0
$H_{04}: \delta_1 = \cdots = \delta_{11} = 0$	18.932	11	16.67	Reject H_0

4.3 Technical Efficiency Estimates

The distribution of technical efficiency (TE) is shown in Fig. 1. We can see that most crop farms have TE of higher than 0.7 but no farm is fully technically efficient. The mean TE of crop farmers is estimated to be 0.751 with the range from 0.332 to 0.967. This indicates that farmers could improve TE by 24.9% with a given set of inputs and technology at that time. This mean value is smaller than the finding of Khai and Yabe (2011) and Bac et al. (2013). However, Khai and Yabe (2011) estimated TE for rice production of farmers in all Vietnam using The Vietnam Household Living Standard Survey 2005–2006 and Bac et al. (2013) estimated TE for two rice seasons in the northern highland of Vietnam while our study calculates crop production, including rice and maize throughout the year.

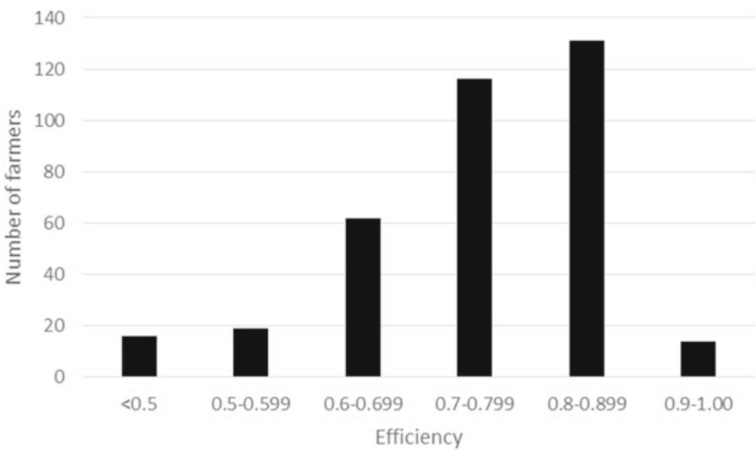

Fig. 1 Distribution of technical efficiency

4.4 Factors Influencing Technical Inefficiency

The most interesting finding of this chapter is the determination of information technology sources that affect the technical inefficiency of crop farmers. The estimation of an inefficiency model was performed simultaneously with the stochastic frontier model and the results are also presented in Table 2. The results show that the estimated coefficients of reading agricultural information through printed material and frequent watching of television are negatively significant with technical inefficiency. In other words, they had positive relationships with TE of crop farms. This indicates the importance of information from printed materials and television for improving farmers' perceptions, knowledge, and increasing crop efficiency.

Agricultural extension services in Vietnam are run by the Ministry of Agriculture and Rural Development. These services extend from the government to villages. They are expected to have a significantly negative impact on decreasing technical inefficiency, but the results indicate that they do not significantly influence even the negative sign with technical inefficiency. This is inconsistent with the finding of Linh et al. (2015). They found that extension services were positively significant with the TE of maize crops but not rice crops. However, this research uses the sum of both rice and maize crops. The Commune Cultural Post Office (CCPO) is an important and significant program of the Vietnamese government to support information and improve knowledge for citizens, especially in difficult and remote areas. Another study used it to evaluate the economic returns to farmers of participating in the CCPO (Linh et al., 2014). The results indicated that despite its many investments so far, the CCPO has many disadvantages and it does not affect the economic return of farmers (Linh et al., 2014). This is confirmed by our result that the CCPO is not statically significant on TE. Even the coefficient of frequent reading of printed materials by farmers was not significant, although the agricultural information that farmers read is negatively significant with technical inefficiency. This proves the importance of the information that influences TE. Printed materials can be read by own buying, borrowing, or going to the CCPO. However, the extent of reading printed materials was found to be far less in the study area. These printed materials are quite out of date and are not sufficient. This is in line with the results of Boz and Akbay (2005), who studied factors influencing the adoption of maize in Turkey.

Radio and television are extensively used in the study area, but the main purpose of utilizing these mass media is for news and entertainment, and the programs on television or radio lack agricultural information. Out of 9,071 communes in the whole country, there were 7,380 communes with loudspeaker systems linked to villages in 2011 (GSO, 2012). This system is built to spread information and knowledge for residents. Thus, the number of radios that farmers owned in the research area is 0.06%. However, the loudspeaker system was used mostly twice per day (morning and evening), and each time was for only around 30 min. In addition, the information is used to spread government policy and is not related entirely to agriculture and farm life. The results show that 91.1% of households in the study area have their own television and some families have more than one television. In this area, the television program is transmitted using analog signals. Most television programs are for entertainment and a few programs or channels are for farmers, like VTV1, VTV2, and VTV5. Most respondent stated that television programs did not supply sufficient agricultural information, and this may explain why the coefficient of agricultural information watching is not statistically significant. When cell-phones are used widely in Vietnam, the numbers of people who used fixed phones decreases gradually. In the study area, 99% farmers have cellphones but all of them stated that they use it only to communicate with each other for social life and not for agriculture. Now a day, the power of computers and the internet for information transmission and daily life is known widely. However, in the study area, no respondents used or owned computers, although some accessed the internet through their cell-phones. However, smart-phones, which can access the internet, are priced highly. Farmers do not have experience in and are not trained to use the internet. The two carriers that have good networks for remote areas are Viettel and Vinaphone. However, 3G is expensive and its speed is slow. The survey results indicate that 1% of respondents can use the internet though their cell-phones but do so for entertainment and not for agricultural purposes.

A good way for farmers to obtain information and improve farm efficiency is to visit a good farm model. Of the 358 respondents, only 16% had visited good agricultural models and all of them stated that this was very helpful; in addition, 298 farmers stated they wanted to visit good agricultural models for free at least once. While there are some agricultural groups to help farmers with agricultural activities, such as farmers' groups, women's groups, credit groups, and veteran groups, they do not perform as expected. According to the field survey, 275 households (77%) are members of groups but 264 (96%) said their group was ineffective and should improve to become more appropriate to farmers' lives. This explains why membership of a farm group does not necessarily help farmers.

5 Conclusion and Recommendations

The purpose of this chapter was to estimate technical efficiency (TE) levels and identify the information factors that influence the technical inefficiency of crop farmers in the northwest highland of Vietnam. We chose 358 respondents randomly based on a multi-stage procedure. The stochastic frontier production function and the inefficiency model were estimated simultaneously using maximum likelihood estimates (MLE). Several tests were undertaken to test the null hypothesis that technical inefficiency effects are absent or that they have simpler normal distribution. The results show that there is significant room for technical inefficiency and no farm is fully technically efficient. Because of land fragmentation and highland location, labor, seed, and fertilizer are the most important factors for enhancing TE of these crop farms. This chapter found some interesting results with regard to information sources that have impacted on technical inefficiency. Agricultural information from printed materials and frequent watching of television were two negatively significant factors for technical inefficiency. This indicates that if farmers read more agricultural information from printed materials and watched television related to social life at appropriate times, the TE of crop farms would increase. Some factors were found to be statistically insignificant but as they are important information sources, we need to find good reasons and explanations.

Based on this research finding, some implications are suggested. First, management of annual crop production and cultivation methods for farmers needs to continue. Second, improving co-operation in cultivation, crop diversity, and optimal land use would optimize farm production. Third, the effectiveness of the Commune Cultural Post Office (CCPO), extension services, and group support should be checked and strengthened. Fourth, the quantity and quality of printed materials for farmers through the CCPO, extension service system, farm group system, or local government should be increased. Fifth, the number of programs and appropriate information for farmers through radio and television should be increased; there should be a focus on teaching and spreading information about agricultural activities, such as livestock, cultivation, and fishing. Sixth, training programs should be developed and extended for farmers in remote area to improve their experience and knowledge to access and use computers and the internet. Lastly, there should be more funds available for farmers to visit good agricultural models to help them develop agricultural information and business networks.

References

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics, 6*(1), 21–37. https://doi.org/10.1016/0304-4076(77)90052-5

Bac, H. Van, Nanseki, T., & Takeuchi, S. (2013). Technical efficiency of rice production in northern upland area of vietnam using stochastic frontier approach. *Japanese Journal of Farm Management*, *51*(3), 91–96. https://doi.org/10.11300/fmsj.51.3_91

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Journal of Empirical Economics, 20*, 325–332.

Battese, G. E., & Corra, G. S. (1977). Estimation of a production frontier model: With application to the pastoral zone of Eastern Australia. *Australian Journal of Agricultural Economics, 21*(3), 169–179. https://doi.org/10.1111/j.1467-8489.1977.tb00204.x

Binh, L. D., & Phuong, T. T. (2020). *Digital economy and digital transformation in Vietnam*, November. https://www.economica.vn/Content/files/PUBL%26REP/EVFTAandDigitalEconomyinVietnamENG.pdf

Boz, I., & Akbay, C. (2005). Factors influencing the adoption of maize in Kahramanmaras province of Turkey. *Agricultural Economics, 33*(SUPPL. 3), 431–440. https://doi.org/10.1111/j.1574-0864.2005.00305.x

Bravo-Ureta, B. E., & Pinheiro, A. E. (1997). Technical, economic, and allocative efficiency in peasant farming: Evidence from the Dominican Republic. *The Developing Economies, XXXV-1*, 48–67.

Coelli, T. (1996). *A guide to FRONTIER version 4.1: A computer program for stochastic frontier production and cost function estimation* (CEPA Working Paper 96/07). CEPA.

Coelli, T., & Battese, G. (1996). Identification of factors which influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural and Resource Economics, 40*(2), 103–128. https://doi.org/10.1111/j.1467-8489.1996.tb00558.x

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battes, G. E. (2005). *An introduction to efficiency and productivity analysis* (2nd ed.). Spriinger

FAO, CIAT, & Worldbank. (2021). *Digital agriculture profile VietNam* (p. 22). Worldbank.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society, 120*(3), 253–290.

Folz, J., Lanclos, K., Guenthner, J., Makus, L., & Sanchez, W. (1996). Reproduced with ***permission of the copyright owner. *Further Reproduction Prohibited without. Agribusiness, 12*(6), 569–581. https://doi.org/10.1016/j.jaci.2012.05.050

Ford, S. A., & Babb, E. M. (1989). Farmer sources and uses of information. *Agribusiness, 5*(5), 465–476. https://doi.org/10.1002/1520-6297(198909)5:5%3c465::AID-AGR2720050505%3e3.0.CO;2-6

Füsun Tatlidil, F., Boz, I., & Tatlidil, H. (2009). Farmers' perception of sustainable agriculture and its determinants: A case study in Kahramanmaras province of Turkey. *Environment, Development and Sustainability, 11*(6), 1091–1106. https://doi.org/10.1007/s10668-008-9168-x

Gloy, B. A., & Akridge, J. T. (2000). Computer and internet adoption on large U.S. farms. *International Food and Agribusiness Management Review*, *3*(3), 323–338. https://doi.org/10.1016/s1096-7508(01)00051-9

Gloy, B. A., Akridge, J. T., & Whipker, L. D. (2000). Sources of information for commercial farms: Usefulness of media and personal sources. *International Food and Agribusiness Management Review, 3*(2), 245–260. https://doi.org/10.1016/s1096-7508(01)00046-5

GSO. (2012). *Results of the 2011 Rural, Agricultural and Fishery Census*. General Statistic Office of Vietnam.

GSO. (2013). *Statistical Yearbook of Viet Nam 2013*. General Statistic Office of Vietnam.

GSO. (2021). *Statistical Yearbook of Viet Nam 2020*. General Statistic Office of Vietnam.

Hanley, N., & Spash, C. L. (1993). *Farm management research for small farmer development*. Food and Agriculture Organization of the United Nations.

Hasnah, F. E., & Coelli, T. (2004). Assessing the performance of a nucleus estate and smallholder scheme for oil palm production in West Sumatra: A stochastic frontier analysis. *Agricultural Systems, 79*(1), 17–30. https://doi.org/10.1016/S0308-521X(03)00043-X

Hoang, V. L. (2006). Efficiency of rice farming households in Vietnam: A DEA with bootstrap and stochastic frontier application. *Irri*, 1–18.

Hung, P. V., Macaulay, T. G., & Marsh, S. P. (2007). The economics of land fragmentation in the north of Vietnam. *Australian Journal of Agricultural and Resource Economics, 51*(2), 195–211. https://doi.org/10.1111/j.1467-8489.2007.00378.x

Kaaya, J. (1999). Role of information technology in agriculture. In *Proceedings of FOA conference* (pp. 315–328). FOA.

Khai, H. V., & Yabe, M. (2011). Technical efficiency analysis of rice production. *The International Society for Southeast Asian Agricultural Sciences, 17*(1), 135–146.

Kodde, D. A., & Palm, F. C. (1986). Wald criteria for jointly testing equality and inequality restrictions. *Journal of the Econometric Society, 54*(5), 1243–1248.

Linh, T. T., Nanseki, T., & Chomei, Y. (2014). Evaluating the economic return to participatory commune cultural post offices in Vietnam: An endogenous switching regression model approach. *European Journal of Social Sciences*, *44*, 474–487. http://www.europeanjournalofsocialsciences.com/

Linh, T. T., Nanseki, T., & Chomei, Y. (2015). Productive efficiency of crop farms in VietNam: A DEA with a smooth bootstrap application. *Journal of Agricultural Science, 7*(5), 37–46. https://doi.org/10.5539/jas.v7n5p37

Linh, V. H. (2012). Efficiency of rice farming households in Vietnam. *International Journal of Development Issues, 11*(1), 60–73.

Meeusen, W., & Ven Den Broeck, J. V. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review, 18*(2), 435–444.

Milovanovic, S. (2014). The role and potential of information technology in agricultural improvement. *Ekonomika Poljoprivrede, 61*(2), 471–485. https://doi.org/10.5937/ekopolj1402471m

National Assembly of Vietnam. (2011). *Socio-economic development plan for the 2011–2015 period.* Vietnamese Government. http://www.chinhphu.vn/portal/page/portal/English/strategies/strategiesdetails?categoryId=30&articleId=10052505

National Assembly of Vietnam. (2021). *The Resolution No.16/2021/QH15 on the 2021–2025 five-year socio-economic development plan.* National Assembly of Vietnam.

Ortmann, G. F., Patrick, G. F., Musser, W. N., & Howard Doster, D. (1993). Use of private consultants and other sources of information by large cornbelt farmers. *Agribusiness, 9*(4), 391–402. https://doi.org/10.1002/1520-6297(199307)9:4%3c391::AID-AGR2720090409%3e3.0.CO;2-K

Patrick, G. F., Ortmann, G. F., Musser, W. G., & Doster, D. H. (1993). Information sources of large-scale farmers. *Choices, 8*(3), 40–41.

Prime Minister of Vietnam. (2020). *Decision No.749/QD-TTg approving the national digital transformation programme by 2025, with orientations toward 2030.*

Rios, A. R., & Shively, G. E. (2005). Farm size and nonparametric efficiency measurements for coffee farms in Vietnam. In *The American agricultural economics association annual meeting.*

Vietnam Trade Promotion Agency. (2014). *Challenges and new opportunities for Vietnam's agriculture in the international integration process.* http://www.vietrade.gov.vn/en/index.php?option=com_content&view=article&id=2246:challenges-and-new-opportunities-f

World Bank. (2015). *Vietnam.* World Bank. http://data.worldbank.org/country/vietnam

Part II
Marketing and Organizational Innovation

Chapter 7
Impacts of Maize Production Groups on Commodity Chain in Lao PDR: An Application of Commodity Chain Analysis

Boundeth Southavilay and Teruaki Nanseki

1 Introduction

In Laos, farmer cooperation started before 1975 with organization such as the *Laos Saving and Loan Association*. In 1978, a new cooperative system in terms of "farmer organization" was established, which was called *sahakon*. The *sahakon* system was, however, gradually abolished since it was unable to maintain profitability and efficiency of production. After the unsuccessful experiences, new forms of farmer organizations have emerged again in Lao PDR in 1986, such as the Extension Group, Self-managed Farmer Groups, Water User Assosication, Association for Coffee Producer Group, Chemical-free Vegetable Growing Groups and Maize Production Groups (MPGs) in Bokeo province. These organizations Lao government considers as basic tools to transform subsistence to market based agricultural production (shift from subsistence to a market based agricultural system.

However, some of these organizations have not been successful either except of the MPGs. The MPG is already a successful organization in terms of generating income for maize farmers by enhancing farmers' access to markets. The purpose of this chapter is thus to study the MPG through the approach of farmer organization. Farmer organization is defined as a rural business, which is a producer-owned and controlled organization and which is engaged in collective marketing activities (Penrose-Buckley, 2007). The so-called farmer organization or farmer group was established in order to perform a variety of functions. The most common function was to facilitate credit delivery and credit repayment (Oxby, 1983). A study on farmer organization, collection action and market access in Meso-America showed that farmer organizations are often seen as key factors in enhancing farmers' access

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to markets. This becomese clear when it comes to accessing inputs such as credit, seeds and fertilizers (Hellin et al., 2009).

In Laos, farmer organization is gradually being developed and was introduced to support farmers who are facing a lack of market inforamtion, poor bargaining power and probkems to meet buyers' quality requirements. As a result, the MPG was established in 2006, supported by the government as the Provincial Agriculture and Forestry Office (PAFO) on the local level. This organization was accepted by maize farmers. Before 2010, there were 26 groups of MPGs in the whole Boeko province. The group members came from 207 villages and covered 50% of all villagers in the Bokeo province. 11,410 families participated in the MPGs, covering 14,401 ha in 2009 (PAFO, 2010).

Thus, this chapter aims to analyze the advantages of MPGs in facilitating farmers to obtain inputs and access to markets and therafter to investigate the profit returns from maize production among acotrs in the commodity chain.

2 Methodology, Data Collection and Study Area

2.1 Methodology

The study has been carried out in Bokeo province which is recognized as one of the largest areas of maize production in northern Laos. The tool used in the study is the Commodity Chain Analysis (CCA). This tool provides a comprehensive approach to the structure and function of maize farmer organizations in the commodity chain. The components of the analysis include:

1. *Factor Analysis*: Examine the factor of incrasing maize production in the study area.
2. *Functional Analysis*: Identify the actors in the chain and the functions they perform.
3. *Flow Analysis*: identify the trends in the commodity chain through different channels.
4. *Technical Analysis*: Reveal major constraints of different stakeholders in the chain.
5. *Economic Impact of the Chain*: Understand the situation of maize farmers in the chain in terms of production cost and margin gained among actors.

2.2 Data Collection for the Study

This chapter used both primary and secondary data from vairous sources. The primary data was collected in March 2010 through key informants, interviews, direct observation, and a questionaire survey for 30 growing maize farmers ($n = 30$) in five villages, ten maize production groups, siz companies (Lao traders), three Thai traders and one Thai Seed Company. The secondary data was collected from vairous government agencies in provincial and district leels. In this chapter, the term “production organization/group” refers to the maize production group only.

2.3 Study Area

This chapter selected Bokeo province as its target area (Fig. 1). Bokeo province is mountainous, located in northwestern Laos, bordering Myanmmar and Thailand with a total land area of 6,196 km^2. In 2008, Bokeo had about 157,500 inhabitants. Most poeple in Bokeo province live in samll rural areas and practice agriculture (cash crops). The survey data of this chapter was conducted in two districts: Huoizai and Tonpheung. In the past, maize production in Bokeo province was samll in scale, scattered and separate. Production practices were mostly depending on local market prices and for household consumption only. In the 1990s, the maize production area comprisec only 51 hectares in the whole province. In February 2010, there were 21,554 farmers growing maize in 317 villages. The maize harvested area covers 21.000 ha (PAFO, 2010). However, the farm size of sample size ($n = 30$) is small with an average size of 1 ha, and their total maize production was 234 tons in 2009.

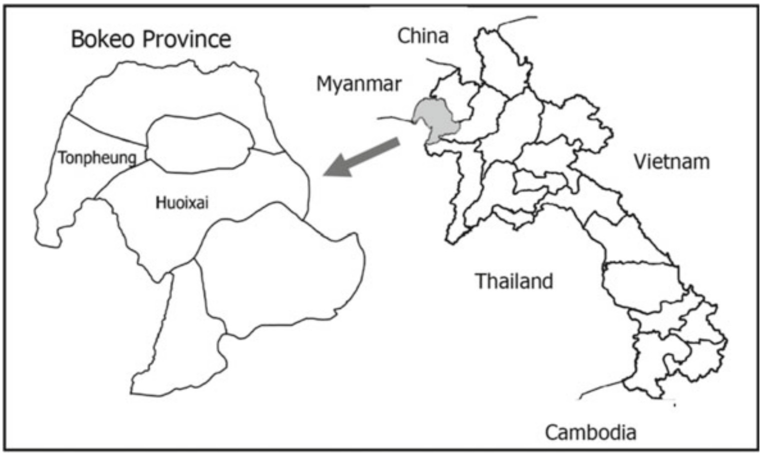

Fig. 1 Map of the study area

3 Results and Discussion

3.1 Factor Analysis

In Laos as well as in the study site, the amounts of maize products have been increased year by year caused by demand on maize products from neighboring countries as well as push and pull factors. The main factors behind this are a "policy push" aimed at reducing poverty and stabilizing farming systems and a market "pull" coming from increasing regional demand for agriculture products.

Production systems have severely changed under the influence of government policies and market opportunities from the neighboring countries (Thailand, Vietnam and China). Furthermore, maize has been increasingly demanded by the United States of America for ethanol production. For instance, the amount of maize used for producing ethanol in the US increased from 628 million bushels in 2000 to 3.6 billion in 2008. The demand for maize in the above mentioned countries has constantly increased, resulting in a greater need to improt higher quantities. This finding concurs with the work of Cuong et al. (2010) who studied the characteristics of the international grain price movements under high oil prices. An increasing maize market for Lao exports has thus evolved. Figure 2 indicates that the maize production in Bokeo province is not stable as it hs increased in 2008 and decreased from 2009 to 2010.

With the help of policy support, the maize production is in rapid developments of mechaniztion (big tractos and hand tractors). According to the field survey, farmers of 25 households have their own hand tractors, only 5 households hired tractors for their production. This is a result of policy push factors, such as tax-free import and export of agricultural products. Accordingly, the quantity of agricultural material and machineries has increased year by year. As an example, 8 big tractors and 66 hand tractors were imported into Laos in 2009. This allows a rapid expansion of the production to new areas.

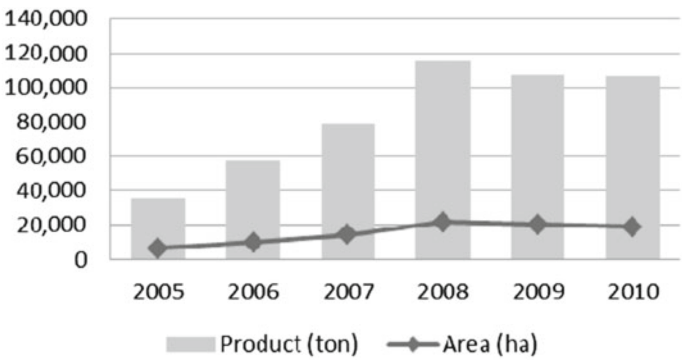

Fig. 2 Maize production in Bokeo province (Reproduced from PAFO, 2010)

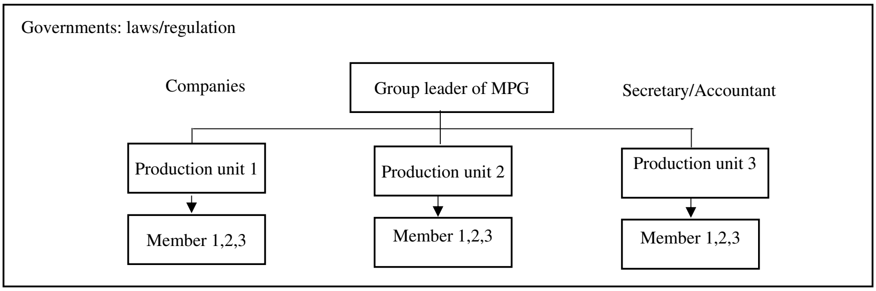

Fig. 3 Organizational Structure of the MPG

3.2 Functional Analysis

The MPG is being established and operated voluntarily by maize farmers who have the same objective of commercially producing maize. The local government as PAFO policy supports the MPGs through credit service, agricultural inputs and contracted farming.

Figure 3 shows the structure of the MPGs. The group includes three parts: Exercutive board members (group leader, deputies and secretary) are responsilbe for political and production matters. In addition, there are secretaries and other committees who are assigned for finance, credit, markets and production promotion. The group includes several production units, each unit consisting of private sectors and farm members.

In order to ensure an efficient functioning of the group, the involved government agencies encourage both parties to make a contract called "contract farming" between the group leaders, farm members and companies. This contract is finalized under the certification of the village chief and PAFO. Its aim is to protect the stability justice of benefits and the motivation of all parties. Details about the actor's functions are shown in Table 1. In the production stage, there are many acotrs such as the MPG, PAFO, internation traders (Thai) and farmers. Those actors have different functions. For instance, the MPG is in charge of providing input factors and for the purchase of products. PAFO is responsible for technical transfers and sometimes take up the role of facilitators or arbitrators. The Lao credit banks (Lao Development Bank, Commercial Bank, etc.) are the main actors, giving loans to the maize commodity production chain in the study area.

3.3 Flow Analysis

Figure 4 illustrates the relationship between different actors in the maize commodity chain. The lower part includes government agencies, MPGs and farmers. The upper part includes the export destinations of Lao maize. The highest import country for

Table 1 Summary of Different Actors and Functions in the Maize Commodity Chain

Stage of the chain	Actors	Functions	Outputs
Production	MPG committee members	• Input supply, provides credit, purchase maize, technical transfer, marketing, low price guarantee (95USD/t)	Provide inputs and purchase outputs
	Government: Agriculture and forestry office (province /districts)	• Technical follow up and awareness • Facilitator, policy supporter • Play roles in reinforcing the contract and conflicts resolution	Regulation
	Thai traders	• Provides inputs, purchase maize from MPG	Purchase outputs
	Maize farmers	• Production (land and labor)	Maize (ear/grain)
Credit	Lao banks, MPG	• Provides loan to companies, MPGs, and farmers	Low interest rates (14%/year)

Lao maize is Thailand. The MPG plays important role in the chain since it provideds the input factors and supports the farmers with bargaining power in order to access the market. The MPG is more than a mediateor between producers and buyers, being able to take loans from the banks by using the group certification which was approved by the province. The interest rate for MPGs with approximately 12–14% per year is very low compared to 20–22% for private money loans.

However, the market of the MPG is limited (trader monopoly) compared to Thai traders who have better options for export. For example, they could sell to processing factories such as aminal feed factory (Charoen Pokphan [CP]) and other traders in Thailand and China. In order to allow input flows, the buying company provides credit in form of seeds, fertilizers, pesticides, etc. Through the MPG to the farmers. The credit will be paid back after harvesting in form of products that are of equal value. If the farmer does not pay bak the credit within one year, the credit will be transferred into the following year without the need to pay interest. Farmers sometimes cannot meet buyers' demands in terms of quantity and quality of the products. This result is in accordance with the findings of Tirtha et al. (2007) who studied the maize commodity chain in Bhutan.

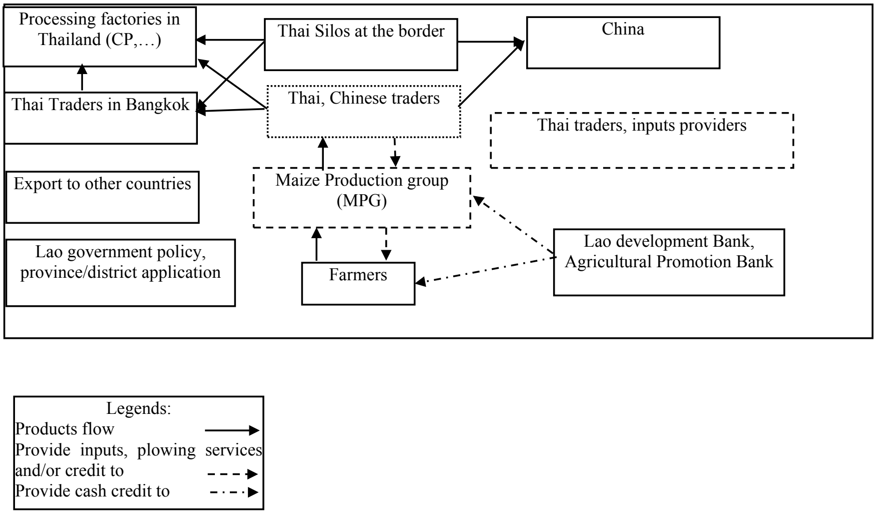

Fig. 4 The Flow of Maize Commodity Chain

3.4 Technical Analysis

The MPG does not include the productin of its own inputs used (seeds and fertilizers) and value-adding processes for the products after harvesting. For the maize production, fertilizers and seeds are the most important inputs required by the farmers. All seeds used by farmers are imported hybrid seeds. The costs of hybrid seeds range from USD 2.8 and 3.8 per kg (Supersen, LVN10, and CP888). Compared to this, the seeds produced by the Agricultural Demonstration Office in ton Pheung district (Bokeo province) at a price of UDS 1.6 per kg are much more cost-efficient. However, the office was not able to meet the farmers' demands for higher quantities of seeds. As a result, around 400 tons of maize seeds equals to approximately USD 1,260,000 are imported from Thailand each year. This does not include fertilizers and herbicides, which are also imported in large quantities (calculatiated from PAFO, 2010).

Maize products are sold without any processing (sorting and grading), so that there is no possibility to price the products differently in this area. Furthermore, farmers miz differenct qualities of maize (wet and dry) and do not have any storage facilites. This forces them to sell the green cobs at a very low price directly after harvesting (The moisture content of maize if one of the main criteria for its selling price; the required moistrue content should be between 14 and 15%). According to interviews during the field survey, Thai farmers also used to face this problem before and it was solved by their local governments and private sectors. This implies that the MPG has to work closer with both private and public sectors in order to convey appropriate post-harvest techniques to the farmers. This matches with the findings of Hellin et al. (2009), who analysed farm organization and market access in Medo-America.

Table 2 Selling price of different actors (USD/ton)

Season	Farmer (farm gate)	Lao trader	Margin (#farmer)	Thai trader	Margin (#Lao trader)
Wet	117.50	123.75	6.25	177.50	53.75
Dry	157.50	173.50	16.00	213.50	40.00

Note Source from survey data, 2010. (1) $n = 30$, (2) $n = 16$, (3) $n = 3$

3.5 Economic Analysis

In 2009, farmers' income from maize production was approximately USD 960 per household (this calculation includes 30 farmers who produced 234 tons of maize products equalt to USD 120 per ton of the ear maize at farm gate prices). This figure does not include rice and other cash crop productes and is close to the national per capita income of USD 750 in 2009.

The revenue for 1 ha of maize is estimated at LAK[1] 5.6 million (USD 700/ha). Preparing the soild takes up the larest share (27/35%) of the total production costs of maize per hectare. This is followd by tilling, weeding and harvesting. The total production costs were around LAK 3.3 million (USD 400) per hectare. This means that for maize farmers, the gross profit per hectare is about LAK 2.4 million (USD 300). This is a result of the high production costs of maize in the study area compared to the gross profit, covering about 58% of the total revenue per hectare.

Table 2 show the different prices per ton gained by different actors. In the raining season of 2008, Lao traders made profits from buying and selling maize at around USD 6.25/ton, while Thai traders were able togain USD 53.75/ton. In the dry season, the maize price is higher than in the raining season. The selling prices of the farm gate and Lao traders were USD 157.50 and 173.50/ton in the raining season and the dry season. Lao actors were thus able to gain higher profits in the dry season due to the higher quality of maize.

The different prices result from the value-adding activities such as grading, drying and shelling. Farmers, middlemen and Lao traders do not have sufficient storage facilities to store the maize products prior to selling it. This prevents them from waiting for a higher price and reduces their bargaining power. Thus, they are forced to sell their products with a high content of moisture after harvesting. This finding is in agreement with the workf of Viau et al. (2009) who analysed the impact of maize expansion on rice production in Laos. In order to solve this problem, both government agencies and private sectors should support the MPGS in order to access sustainable quantities and good quality of the products.

[1] Lao's currency (USD1 = 8,000Kip).

4 Conclusion and Policy Implications

The first objective of this chapter analyzed the advantages of MPGs in facilitating farmers to obtain inputs and access to markets. The second objective was to investigate the profits from maize production among actors along the chain.

The first results indicates that the maize production in Bokeo province is not stable and directly depend on the market of neighbor countries market and on policy implementations. The MPGs are certified and prioritized by the government to obtain low interest rates for bank loans. Farmers purchase maize seeds from the groups with low interest rates and are guaranteed a minimum price. The credits are deducted after farmers sell their products to the MPGs. If the farmers are not able to pay back the credit within the season, it will be postponded into the following season without requiring them to pay interest. On the other hand, the MPG can be considered as a facilitator among actors due to its assistance for traders to meet the products' requirements and it support for farmers to access the markets with a higher bargaining power. However, the techniques of the MPG do not include the production of seeds and post-harvest processing techniques.

Profit returns from maize production among the actors in the chain are significantly different. In particular, the price at the farm gate is very low compared to the price of the products sold by Thai traders. Thee different prices are a results of the trade margin and value-adding activities such as grading, drying and shelling. The farmers are not able to gain higher prices because they have to sell the maize quickly after harvesting. This is a results of a lack of storage facilites. It can be concluded that Thai traders obtain higher profits thatn Lao traders (about 30% of the total maize price and 45% more than the price at the farm gate (farmers)).

Based on the main findings of this chapter, it can be concluded that the main benefit of the MPG is to faciliate access to agricultural inputs in terms of credits (seeds, fertilizers and etc.…) and markets. However, the MPG does not give any technical advice regarding planting, maintenance and storage of products in order to enable good production and high profits to the members. Therefore, the MPG needs to be developed in terms of its functions. The group has to transfer harvest and post-harvest techniques, in particular the moisture control, in order to imprive the quality of the products according to the required standards. Those techniques can be improved by training, study tours or site visits in neighbor countries, and by the group members exchanging their experiences.

References

Cuong, N. H., Ito, S., & Isoda, H. (2010). Characteristics of International Grain Price Movements under the High Oil Prices: Toward Policy Implications. *Japanese Journal of Farm Management, 48*(2), 143–148.

Hellin, J., Lundy, M., & Meijer, M. (2009). Farmer organization, collective action and market access in Meso-America. *Food Policy, 34*(1), 16–22. https://doi.org/10.1016/j.foodpol.2008.10.003

Oxby, C. (1983). "Farm groups" in rural areas of the third world. *Community Development Journal, 18*(1), 50–59.

PAFO (Provincial Agriculture and Forestry Office). (2006,2009,2010). *Annual report.* Bokeo Province, Lao.

Penrose-Buckley, C. (2007). Producer organisations: A guide to developing colective rural enterprises. *Oxfam GB*. https://doi.org/10.3362/9780855988357

Tirtha, B. K., Phub, D., & Ganesh, B. (2007). *Maize commodity chain analysis.*

Viau, J., Keophosay, A., & Castella, J.-C. (2009). *Impact of maize expansion on traditional rice production systems in Northern Lao PDR: A case study in Xiengkhor district, Huaphan province.* https://doi.org/10.13140/RG.2.2.27227.92960

Chapter 8
Impacts of Farmers Group on the Technical Efficiency of Oil Palm Production in Indonesia: An Application of Stochastic Frontier Analysis

Widya Alwarritzi, Teruaki Nanseki, and Yosuke Chomei

1 Introduction

Eradicating poverty (SDG 1) and Promoting Sustainable Agriculture (SDG 2) by 2030 indicated a global commitment to improve the well-being of smallholder farmers and the environment sustainability (UN, 2021). Small-scale producers contribute substantially to agricultural production (Bizikova et al., 2020), yet they are being pushback into poverty line and highly vulnerable due to the pandemic and climate change, which are relevant with current oil palm smallholder in Indonesia.

Oil palm is the major Indonesian's plantation, which foster the economic growth indicated by largest employment share, investment, and output in agriculture sector (Raharja et al., 2020), indicated by land expansion for oil palm increased from 2.77 to 4.7% per-year in period of 2013–2017 (BPS-Statistics Indonesia, 2018). However, there are emerging challenges faced by oil palm sector where the productivity of oil palm produce by smallholders is lower than the State-Owned Estates (BPS-Statistics Indonesia, 2018). Thus, it is necessary to explore determinant factors to increase the productivity of smallholder oil palm farming.

Farmers group among the oil palm smallholder, well known as Nucleus Estates and Smallholders (NES-trans) in Indonesia, run the operation under private partnership which aims to meet Indonesia Government's target of 40M tons of crude palm oil by 2020 (Purnomo et al., 2020). Through NES-trans, farmers have wider access

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to production skill, markets, and credits. Given significant contribution to oil palm smallholders, NES-trans have become key elements of oil palm productivity, rural development, and poverty alleviation in Indonesia. In contrast, there were also independent farmers who run their farm without proper production guidance and tend to run unsustainable farming practice which have the implication on productivity gap among smallholders and environmental outcomes.

There was lack of study on investigating the role of farmers group on technical efficiency of oil palm production. One notable study was reported by Hasnah et al. (2004) which took the case of NES-Trans farmers in West Sumatera, Indonesia. Against this backdrop, we argued that the existing of non-uniform farming practice between NES-trans and independent farmers might affect the productivity performance. Further socio-economic characteristics of the farmers will be examined to provide better explanation on how to improve the oil palm farming practice in sustainable manner. Thus, this chapter aims to (1) investigate technical efficiency of oil palm production among the NES-trans and independent; (2) determine socio-economic characteristics of the farmers that have significant impact to the technical efficiency. The study was expected to provide clear evidence on the important role of farmers group, extension service and formal education to enhance oil palm productivity. Hence, the emergent implications from this paper will contribute to Indonesia on achieving Sustainable Development Goals on reducing poverty and strengthening agricultural sector, especially oil palm cultivation, in more sustainable way.

2 Data and Empirical Methods

2.1 Data

The primary data was formed from production performance of 271 oil palm smallholder farmers which gathered by structured questionnaire in 2013. The study sites were under Pelalawan Regency administration, Riau Province, western part of Sumatera, Indonesia. Hence, in the present study, two villages were under the NES-Trans program, namely “Makmur (MR)” and “Mekar Jaya (MJ)”, and other two villages were classified as non- transmigration village for independent farmers; namely “Kiyap Jaya (KJ)”and “Lubuk Ogung (LO)”. The study area holds variation of socio-economics characteristic of farmers and these 4 villages were attributed with geographical differences, particularly the characteristic of soil. Referring to the Reproduction Soil Map Kemenhut (1989), mineral soil was covering 3 selected villages (MR, MJ and KJ) and peat land was existed in the southern part of LO village. Therefore, farm location will be introduced as one of unobserved variable in the technical efficiency and incorporated to the index of individual technical efficiency of oil palm farmers.

2.2 Literature Review

Technical efficiency approach for investigating the performance level and inefficiency factors of oil palm farming has been widely applied by several studies. In West Sumatera, Hasnah et al. (2004) found that the mean of technical efficiency index of NES-Trans farmers using translog model was 0.66, which implied that farmers could increase the output of oil palm by using better extension service than using more input in production. They highlighted that the selection of progressive farmers was very important for future scheme since the progressive farmers had not been successful on disseminating farming guidance. Iwala et al. (2006) applied stochastic frontier approach to investigate efficiency among oil palm farmers in Nigeria. They implied that the index of technical efficiencies varied among oil palm farmers, ranging between 0.463 and 0.999. The results indicated that the age of palm tree, the cost of fertilizers and agrochemicals, and the cost of harvesting and processing were positively correlated to the output. On the other hand, the use of labor had negative contribution to oil palm production due to excessive labor employment in the farming practice. Farmers' education level negatively contributed to efficiency because farmers tend to have off-farm job and delegated hired labor to operate their farm.

2.3 Analysis Model

To estimate the efficient frontiers, a popular parametric method, the stochastic frontier analysis (SFA), was utilized. It has the main strength to be able to deal with the statistical noise in the data and also permits statistical testing of both the hypotheses pertaining to the production structure and the degree of inefficiency (Coelli et al., 2005). This function contains a disturbance term comprising of statistical noise and technical efficiency term (Eqs. 1 and 2). Technical efficiency consists of the ratio of the observed output, and the maximum feasible output is equal to 1. Therefore, inefficiency affects the model when technical efficiency score for each firm is less than 1.

$$Y = (\beta_0 + \sum_{n-1}^{N} \beta_0 ln X_n + \sum_{n-1}^{N} \sum_{m-1}^{N} \beta_{nm} ln X_{nm} + (V_i + U_i) \tag{1}$$

$$U = \delta_0 + \delta_1 Z_{1i} + \delta_2 Z_{2i} + \cdots + \delta_n Z_{ni} \tag{2}$$

Y = Production per hectare
$\beta_0 - \beta_{nm}$ = Regression coefficient including constant (β_0)
$X_0 - X_{nm}$ = Production input per hectare
Vi = Random error term

Ui = Non-negative random variables which assumed to account for technical inefficiency
$\delta_0 - \delta_{nm}$ = Inefficient parameters
$Z_{1i} - Z_{ni}$= Socio-economic variables.

3 Data and Empirical Methods

3.1 Descriptive Statistics

Table 1 shows the descriptive statistics of household characteristic. There are two categories of variables: the given input of production with regard to oil palm productivity, and the unobserved variables such as socio-economic and spatial heterogeneity range for explaining inefficiency effect. In the present study, geographical variation of farm represented type of soil used for plantation and it was taken into account as a potential source of efficiency variation among farmers. We conducted the analysis of the farm sample under two different geographical variations: peat soil and mineral soil. Farm location was gathered from GPS point's records that were integrated with The Reproduction Soil Map (Kemenhut, 1989). The decision to introduce farm location into unobserved variable was to explain spatial heterogeneity in technical efficiency by introducing into dummy variable (Areal et al., 2012).

As can be seen in Table 1, the yield variability was high with an average of 19.6 ton per hectare during 2012–2013. The amount of aggregated chemical fertilizer was about 1.18 ton per hectare, including urea, rock phosphate, potassium chloride, and dolomite. Farmers used herbicide 3.94 l per hectare in order to anticipate spreading of *Imperta cylindrica*, the most serious pest of oil palm. In average, 43 man-days were needed for labor input, consisted of hired and family labors to operate oil palm farm per hectare (1 days is equal to 6 hours). The total of working days was accumulated from total activities such as weeding, crop maintenance, fertilizing, and harvesting.

To emphasize the age of tree effect toward productivity, the variable of weighted oil palm tree (WPT) was introduced. WPT was calculated by dividing the average output of oil palm fruit for each age profile with the maximum output at its peak period of the yield. Based on the yield profile, oil palm tree ages were grouped into 3 categories such as w1 = 3–8 years, w2 = 9–19 years (considered as yield peak period), and w3 = over 20 years (USDA, 2012). Thus, WPT values for each age profile were determined as: w1PT1 = 70/125, w2PT2 = 125/125 and w3PT3 = 100/125. This approach had been applied by several researches to capture the effect of tree age in Cocoa in Ghana (Ofori-Bah & Asafu-Adjaye, 2011) and Vietnam's Rubber Plantation (Hasnah et al., 2004).

As for farmer group variable, 60% of NES-Trans farmer were identified. The age range of respondents was between 31 and 84 years old, with the mean age was 49 years old, implying that farmers in study area were relatively ageing. Majority of farmers gained formal education with average of 9 years, which was the level of

Table 1 Descriptive statistics of the variables of technical efficiency variables

Variable code		Definition	Unit	Mean	Std. Dev	Min	Max
Y	Yield	Oil palm fresh fruit bunch (FFB) yield	Ton/ha	19.59	6.0	4.8	46.64
Production input							
X_1	Fertilizer	Total of chemical fertilizer applied	Ton/ha	1.18	0.34	0.20	2.68
X_2	Herbicide	Total of herbicide applied	Liter/ha	3.94	1.12	1.5	7.5
X_3	Labor	Working day of hired and family labor	Man-day/ha	43.11	11.91	21	60
X_4	WPT	Weighted oil palm tree	Number/ha	0.84	0.13	0.56	1
Inefficiency variable							
Z_1	Group	1 = NES-Trans farmers; 0 = independent farmers	Dummy	0.60	–	0	1
Z_2	Education	Years of farmer education	Years	9.09	2.93	6	16
Z_3	Age	Head of households age	Years	49.15	7.44	31	84
Z_4	Drivers	1 = have farm diversification; 0 = otherwise	Dummy	0.27	–	0	1
Z_5	Credit	1 = get access to credit; 0 = otherwise	Dummy	0.75	–	0	1
Z_6	Farm location	1 = peat soil; 0 = mineral soil	Dummy	0.10	–	0	1

Note Farm location was recorded using GPS

national primary education. Around 30% of farmers have farm diversification such as crops plantation and livestock. As for credit access, 75% of oil palm farmers were facilitated by low rate interest of credit from bank. Lastly, the present study found that 10% of farmers cultivated oil palm in the large size of peat soil due to the land availability in this area, particularly in the southern part of study area.

3.2 Stochastic Frontier Analysis

The stochastic frontier approach, which deals with the stochastic frontier production, was applied with assumption that all deviations from frontier were associated with disturbance terms. Since oil palm farmers in study area were smallholding-family based operation, farmers pay less attention to farming record system, and the production record might be inaccurate. Thus, the availability of data on productivity was likely to be subject on measurement error (Coelli et al., 2005). The main point of this section was to the evidence that inefficiency effect existing among oil palm smallholder farmers. As the simultaneously estimation result, analysis of production input will be discussed.

The coefficient of fertilizer was positive and highly significant to oil palm output, which indicated that farmers need to apply the quality and quantity of each given fertilizer, in order to achieve the higher yield. Negative and significant of WPT coefficient suggested that ageing tree might reduce the output. The result was in line with the nature of oil palm tree, which its yield-peak periods were reported in between 9 and 19 years and decreased after 20 years of planting (USDA, 2012). Insignificant of labor coefficient was far from the initial expectation. It might arise from the effect of family labor that still actively involved on farming activity because oil palm was accounted as the main source of income. Furthermore, coefficient of herbicide variable, which was found negative and not significant, was consistent with the fact that the chemical herbicide should be carefully applied to the targeted pest, weed or disease. Inappropriate amount of herbicide might lead to the decreased of productivity, due to its negative effect toward tree and soil condition (RSPO, 2007). Thus, the roundtable on sustainable palm oil (RSPO) (RSPO, 2007) suggested that farmers need to consider the integrated pest management by using physical methods to minimize the application of chemicals.

The inefficiency effect in oil palm productivity could be identified by examining the value of estimated lambda (λ), as it was the main point of the present study. The value of λ is larger than 1, which implied that inefficiency term contributed significantly in the analysis of oil palm productivity. Thus, the analysis of socio-economics aspect of smallholder farmers might be more suitable to explain the existing productivity gap. The result of likelihood ratio (LR) test was 52.92, which larger than critical value in 5% of significant level with 11 degrees of freedom taken from Table 2 of Kodde and Palm (1986), and then, the null hypothesis of no inefficiency effect was rejected. Therefore, LR test confirmed that the inefficiency effect due to socio-economics background of farmers influenced strongly the technical efficiency among oil palm smallholder farmers in the study area. The explanation of socioeconomics factors which influence the technical efficiency as the result of the maximum likelihood estimation (MLE) of inefficiency effect, will be described on the later part of this report.

Table 2 The maximum likelihood estimation (ELM) for parameter of translog stochastic frontier for oil palm farmers

Variable	Parameter	Coefficients		Std. Error	z
Stochastic frontier					
Constant	β_0	0.20		0.06	3.30
ln(Fertilizer)	β_1	0.17	**	0.08	2.18
ln(Herbicide)	β_2	−0.03		0.08	−0.35
ln(Labor)	β_3	0.14		0.11	1.23
ln(WPT)	β_4	−1.66	***	0.15	−5.16
0.5([ln Fertilizer]^2	β_{11}	−0.28		0.17	−1.62
0.5([ln Herbicide]^2	β_{22}	−0.52		0.23	−2.25
0.5([ln Labor]^2	β_{33}	0.94		0.62	1.52
0.5([ln WPT]^2	β_{44}	−4.87		1.15	−4.25
[ln Fertilizer][ln Herbicide]	β_{12}	0.01		0.16	0.34
[ln Fertilizer][ln Labor]	β_{13}	0.05		0.18	0.25
[ln Fertilizer][ln WPT]	β_{14}	0.23		0.23	1.00
[ln Herbicide][ln Labor]	β_{23}	−0.07		0.18	−0.41
[ln Herbicide][ln WPT]	β_{24}	0.08		0.32	0.24
[ln Labor][ln WPT]	β_{34}	−0.05		0.38	−0.14
Variance Parameter					
Sigma-v	σ_v	0.23		0.02	
Sigma-u	σ_u	0.23		0.07	
Lamda	λ	1.01		0.09	
Lod likelihood Function		−30.33			

Note (1) *** and ** are significant at 1% and 5% levels, respectively. (2) the log-likelihood function of a stochastic frontier model is maximized by the Newton–Raphson method, and the estimated variance matrix is calculated as the inverse of the negative Hessian (second partial derivatives matrix) (STATA, 2014)

3.3 Factors Affecting Efficiency

The result of technical inefficiency effect is presented in Table 3. The present study observed that group of oil palm farmers was negative and highly significant, indicated that NES-Trans farmers were more efficient than independent farmers. The results could be justified by the fact that NES-Trans farmers have adequate guidance from their contract company about the standard practice of farming from RSPO (2007). However, the approach on how to disseminate extension program through farmers group in this chapter area seemed to generate higher efficiency, in contrast with report published by Hasnah et al. (2004). NES-Trans farmers in this chapter area, through farmers group, tended to maintain the best management of farming practice given

Table 3 The maximum likelihood estimation (MLE) of inefficiency effect for oil palm farmers

Variable	Parameter	Coefficients		Std. error	z
Constant	δ_0	−6.69		13.88	−0.48
Group	δ_1	−1.69	***	0.76	−2.23
Education	δ_2	−7.44	*	4.73	−1.57
Age	δ_3	4.66	**	2.30	2.03
Divers	δ_4	−2.00	*	1.08	−1.85
Credit	δ_5	−0.48		0.80	−0.60
Farm location	δ_6	1.55		1.04	1.49

Note ***, ** and * are significant at 1%, 5% and 10% levels, respectively

by the extension service. On the contrary, the role of farmer group and extension service on the farming practice of independent farmers was very low.

Negative sign of education and significant implied that education level of oil palm farmers might improve the technical efficiency. Educated farmers achieved less inefficiency and tended to be more responsive in technology adoption and utilization, which consistent with Coelli and Battese (1996). Dummy variable of farm diversification had negative sign and significant, which suggested that if farmers had various resources of production other than oil palm cultivation (*i.e.*, crop cultivation in different plots and livestock), these other resources were likely to generate positive impact to efficiency. Coelli and Fleming (2004) argued that farm diversification activities seemed to increase efficiency because the farmers might have opportunity to select several farming activities which complemented the given input of each other resources.

Credit access has negative value and not significant, which indicated that the access of credit might not have substantial effect to increase the efficiency. One of the specific reasons was because of inappropriate utilization of credit. Farmers in the study area tended to use credit facility for expanding oil palm farmland to increase production or buying daily expenditure rather than for improving productivity in its current farmland. The shift of the existing paradigm was needed in order to encourage the farmers to get the advantages from credit facility. In line with what was reported by Binam et al. (2004), if the farmers could appropriately manage the advantage of credit facility, it is likely to enhance the ability of the farmers in adopting farming technology and improving productivity. Therefore, the ability to manage the credit facility was a crucial factor for agricultural sector, as had been reported in Nigeria. The age of farmers had positive sign with the inefficiency and it was significant at 5%, younger farmers were observed to be more technically efficient than the older one. This fact was due to the tendency of younger farmers to be more activity in the current agricultural activity and their willingness to improve the farming knowledge, in accordance with that was reported by Coelli and Battese (1996).

Farm location had positive, but not significant correlation to efficiency, which indicated that the farmer who cultivates oil palm in peat soil area might be less efficient. According to Funakawa et al. (1996), peat soil in tropical area was generally low in nutrient supplying capacity which limiting its potential. This condition might lead to the higher effort from oil palm farmers to invest more in production input as well as in specific maintenance, in order to meet the targeted yield. However, farmers in peat soil area (LO village) might be facing difficulties to achieve the efficiency due to the fact that the farmers are lack of guidance from formal institution to maintain their farmland under peat soil condition.

3.4 Spatial Distribution of Technical Efficiency

Technical efficiency index for farmers in each village are presented in Fig. 1. The average technical efficiency of oil palm farmers in study area is 83%, which indicated that there was plenty of section which should be improved to get the maximum efficiency. The Spatial heterogeneity was considered as the variable which might affect to the differences in efficiency level among farmers (Areal et al., 2012). The results, therefore, suggested that the farmers should apply appropriate farming practice based on the characteristic of their farm locations to maintain its productivity.

By referring to the score of individual technical efficiency for each location in study area, it was concluded that the lowest average of technical efficiency score

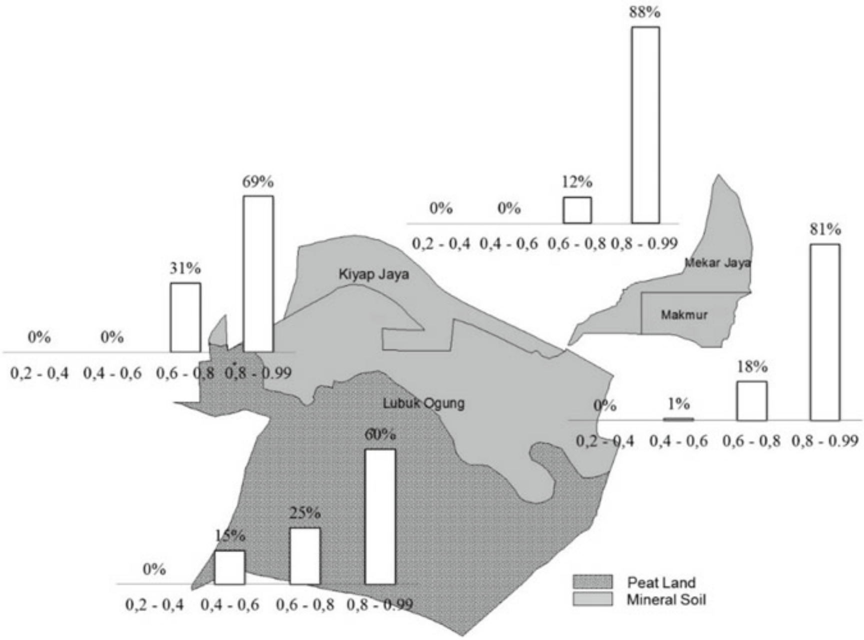

Fig. 1 Technical efficiency index of oil palm farmers in study area. (Self survey of farmers' plot investigation, Riau, Indonesia, 2013; BPS, 2012; Kemenhut, 1989)

is 74%, which was experienced by the independent farmers in peat land area. The present result implied that the farmers in the study area could not achieve optimum level of productivity due to the lack of knowledge on how to cultivate oil palm in peat land. Current farming guidance only supported the farmers who cultivate oil palm in mineral land. However, the interaction between geographical characteristic and farmer's ability to apply farming activity in particular area should be taken into account in the future projection of agricultural policy.

4 Concluding Remarks

The objective of this study is to investigate the inefficiency effect on oil palm production independent and NES-trans smallholders and to examine unobserved variable affecting efficiency. Using Stochastic Frontier Approach, we found technical efficiency index discrepancy was relatively high (41%) between two groups, suggested standardizing and uniform farming practice should be enhanced, particularly through the following socio-economic factors. (1) role farmers group in providing wider access to the guidance of sustainable farming, technology and production input. (2) as the effort to achieve sustainable agricultural practice, government should promote awareness on the impact of appropriate farming practice and technology adoption among the smallholders to increase productivity. Educated farmers were likely to be more responsive to efficient approach in farming practice. (3) Access to farming credit was also important to facilitate and increase oil palm production. (4) Average of technical efficiency index of oil palm farmers who cultivate oil palm in peat soil area was relatively low, compared to those who cultivate in mineral soil because there was lack of guidance on how to maintain farmland under peat soil condition.

This study provides ways to achieve SDG 1 and SDG 2 by improving agricultural sector, particularly oil palm productivity through farmers group, private sector partnership for sustainable farming guidance, and access to financing. Furthermore, there are some factors can be explored further to increase oil palm productivity, such as investigation of alternative agricultural activity to generate farmers' income, considering the fact that the ageing of oil palm trees had led to the decreased of productivity over time.

References

Areal, F. J., Balcombe, K., & Tiffin, R. (2012). Integrating spatial dependence into Stochastic Frontier Analysis. *Australian Journal of Agricultural and Resource Economics, 56*(4), 521–541. https://doi.org/10.1111/j.1467-8489.2012.00597.x

Binam, J. N., Tonyè, J., Wandji, N., Nyambi, G., & Akoa, M. (2004). Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. *Food Policy, 29*(5), 531–545. https://doi.org/10.1016/j.foodpol.2004.07.013

Bizikova, L., Nkonya, E., Minah, M., Hanisch, M., Turaga, R. M. R., Speranza, C. I., Karthikeyan, M., Tang, L., Ghezzi-Kopel, K., Kelly, J., Celestin, A. C., & Timmers, B. (2020). A scoping review of the contributions of farmers' organizations to smallholder agriculture. *Nature Food, 1*(10), 620–630. https://doi.org/10.1038/s43016-020-00164-x

BPS-Statistics Indonesia. (2018). *Indonesian oil palm statistics 2017*. BPS-Statistics Indonesia.

BPS. (2012). *Pelalawan in figures, Indonesia Statistic Bereau.* Indonesia Statistic Bereau.

Coelli, T., & Battese, G. (1996). Identification of factors which influence the technical inefficiency of Indian farmers. *Australian Journal of Agricultural and Resource Economics, 40*(2), 103–128. https://doi.org/10.1111/j.1467-8489.1996.tb00558.x

Coelli, T., & Fleming, E. (2004). Diversification economies and specialisation efficiencies in a mixed food and coffee smallholder farming system in Papua New Guinea. *Agricultural Economics*, *31*(2–3 SPEC. ISS.), 229–239. https://doi.org/10.1016/j.agecon.2004.09.010

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battes, G. E. (2005). An introduction to efficiency and productivity analysis (2nd ed.). Springer.

Funakawa, S., Yonebayashi, K., Shoon, J. F., & Khun, E. C. O. (1996). Nutritional environment of tropical peat soils in Sarawak, Malaysia based on soil solution composition. *Soil Science and Plant Nutrition, 42*(4), 833–843. https://doi.org/10.1080/00380768.1996.10416630

Hasnah, Fleming, E., & Coelli, T. (2004). Assessing the performance of a nucleus estate and smallholder scheme for oil palm production in West Sumatra: a stochastic frontier analysis. *Agricultural Systems*, *79*(1), 17–30. https://doi.org/10.1016/S0308-521X(03)00043-X

Iwala, O. S., Okunlola, J. O., & Imoudu, P. B. (2006). Productivity and technical efficiency of oil palm production in Nigeria. *Journal of Food, Agriculture & Environment*, *4*, 181–185. https://doi.org/10.1234/4.2006.941

Kemenhut, R. (1989). *Reproduction soil map Republic of Indonesia.* Ministry of Forestry Republic of Indonesia.

Ofori-Bah, A., & Asafu-Adjaye, J. (2011). Scope economies and technical efficiency of cocoa agroforesty systems in Ghana. *Ecological Economics, 70*(8), 1508–1518. https://doi.org/10.1016/j.ecolecon.2011.03.013

Purnomo, H., Okarda, B., Dermawan, A., Ilham, Q. P., Pacheco, P., Nurfatriani, F., & Suhendang, E. (2020). Reconciling oil palm economic development and environmental conservation in Indonesia: A value chain dynamic approach. *Forest Policy and Economics*, *111*, 102089. https://doi.org/10.1016/j.forpol.2020.102089

Kodde, D. A., & Palm, F. C. (1986). Wald criteria for jointly testing equality and inequality restrictions. *Journal of the Econometric Society, 54*(5), 1243–1248.

Raharja, S., Marimin, Machfud, Papilo, P., Safriyana, Massijaya, M. Y., Asrol, M., & Darmawan, M. A. (2020). Institutional strengthening model of oil palm independent smallholder in Riau and Jambi Provinces, Indonesia. *Heliyon*, *6*(5), e03875. https://doi.org/10.1016/j.heliyon.2020.e03875

RSPO. (2007). Principles and criteria for sustainable palm oil production. In *Roundtable on sustainability palm oil* (Vol. 22, Issue October). https://doi.org/10.1111/j.1523-1739.2008.01026.x

STATA. *Stochastic frontier model.* http://www.stata.com/manuals13/rfrontier.pdf. Accessed 20 July 2014.

UN. (2021). *Sustainable Development Goal 2: End hunger, achieve food security and improved nutrition and promote sustainable agriculture.* Sustainable Development Knowledge Platform.

USDA. (2012). Malaysia : Stagnating palm oil yields impede growth. In *Commodity intelligence report*. http://www.pecad.fas.usda.gov/highlights/2012/12/Malaysia/

Chapter 9
Traceability System of Dairy Products and Its Impacts on Consumer Behavior in China: An Application of Multinominal Logit Model

Hui Zhou and Teruaki Nanseki

1 Introduction

Food safety and food quality have increasingly come to the forefront of consumer concerns, industry strategies, and government policy initiatives. In the last several years, a number of serious food safety problems within China have negatively affected consumers' confidence in both domestic and exported food products

Dairy industry has a large potential in China. The production and consumption of milk in China has increase dramatically especially since 2000. As the income of people increased and the government encourage people to drink milk, people are changing their diet habits and costumed to have milk and milk products as daily food. Food safety problems in dairy have created lack of confidence among the public in buying dairy products.

New approach to ensure the food safety is more integrated. In order to respect the consumers' tights to be informed about the commodities they consume. Traceability system can be one of the ways to give people the information, so that consumers can have confidence in the food they consume. Basically, traceability system is a tool to monitor food producers in order to avoid food safety problems such as misuse of veterinary medicine, animal disease or others.

In China, traceability system on beef chain was developed by the Ministry of Agriculture (MOA) in 2006, the first trail fields are Beijing, Shanghai and Sichuan province. Then, this system was more focused on to ensure the food safety during the Olympic Game and after that. The State Council of China issued a policy on

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the construction of important product traceability system in 2015 and requested that management of food quality and safety must be improved and food companies are to create a system to monitor and trace every step of production and distribution. Later in 2018, MOA has built a national agricultural products quality safety traceability management information platform with all kinds of Agri-products included and it is an important part of Smart-Agriculture in China.

Traceability system is a new thing to Chinese consumers. Consumers' attitude towards traceability system has been examined. In this research, production history in traceability system is mainly studied, this is because most consumers concern on production history both in Japan and China (Nanseki et al., 2008). The main objectives are to study consumers' marginal willingness to pay (MWTP) on the information that traceability system provide and to examine which factors affect consumers' willingness to pay on traceability system.

2 Methodology

This chapter also applied in the Choice Modeling (CM) technique in examining which attributes are significant determinants of the vales people place on non-market goods i.e. traceability system. CM or stated preference (SP) that used attribute based technique was first applied by Hensher and Louviere (1983) and Louviere and Woodworth (1983) and Adamowiez et al. (1998). This technique was originated in market research and transport literatures and recently applied to the valuation of non-market goods. In this survey, attributes and levels were used to create choice sets using 3 × 6 orthogonal effects design which produced 36 choice sets and were divided into 6 versions. CM techniques requires respondent to compare and select 1 option out of 3 in all the choice sets (Table 1).

Multinominal Logit Model is used to analyze the data. The option chosen by respondents in the CM can modeled in random utility framework which can be expressed as the sum of systematic component. The utility obtained by individual *i*

Table 1 Choice and set

	Choice A	Choice B	Choice C
Farm and/or farmer	Information + Pictures	Information	I would buymore usual brand of milk
Veterinary medicine use	All medicine record	Without record	
Processing plantings	Information	Information + Pictures	
Price of 250 ml milk	No change[a]	¥ 0.20 more expensive	
I choose			

[a] No change means the basic milk price. The price of milk broad sold in China is 1.70 RMB/250 ml

from choosing alternative j in a choice set can be expressed as:

$$U_{ij} = V_{ij} + \varepsilon \tag{1}$$

where V_{ij} denoted the observable portion of the utility and ε_{ij} indicates error term. This chapter assumes that the utility for an option (i) depends on a vector of its observable attributes, (Z) and a vector of the socio-economic characteristics of respondents, (S)

$$U_{ij} = V_{ij}(Z_{ij}, S_{ij}) + \varepsilon_{ij} \tag{2}$$

Option j is chosen over alternative h of $U_{ij} > U_{th}$. The probability if individual i choosing option j is defined as follow:

$$\pi_{ij} = \Pr\{V_{ij} + \varepsilon_{ij} \geq V_{th} + \varepsilon_{th}; \forall h \in C\} \tag{3}$$

where C_i is the choice set for individual i. V_{ij} is a conditional indirect utility function and has a linear form,

$$V_{ij} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots . + \beta_n \tag{4}$$

where $\beta_1 - \beta_n$ is vector of coefficient attached to the vector of attributes X. While the socio-economic characteristics impact on attributes the function has a form:

$$V_{ij} = ASC + \sum_{k=1}^{K} \beta_k X_{ik} + \sum_{k=1}^{K} \sum_{k=1}^{K} \Upsilon_{kh} Z_{ik} S_{ih} \tag{5}$$

where β_k and Υ is parameter, Z is the attributes associated with the alternative, S are the socio-economic characteristics.

The marginal value of a change within a single attribute can be represented as ratio of coefficients as follow:

$$MWTP = \frac{B_{attribue}}{B_{price}} \tag{6}$$

Option C was coded as zero value and alternative specific constants were equal to 1 either option A and B was selected (Bateman et al., 2002). In this chapter the software package LIMDEP 9.0 NLOGIT 4.0 was used to estimated Multinominal Logit Model (Greene, 2008).

3 Survey and Data

To examine consumers' attitude toward traceability system, a face-to-face interview was conducted from September to October 2008, and 209 samples were collected in Beijing (Table 2). The survey was carried out in the 4 main supermarkets and hyper marts and their chain shops. Respondents were picked randomly in the supermarkets and hyper marts. According to the population distribution, also because of limitation of transportation, 7 districts which include 60% of the population were chosen to carry out the survey.

Table 2 Socio-economic characteristics across treatments

	Category	Percentage (%)
Sex	Male	31
	Female	69
Age	Under 18	1.44
	19–25	23.44
	26–35	29.19
	36–45	20.57
	46–55	15.31
	56–65	7.18
	Over 65	2.87
Education	Primary school	0.96
	Junior high school	5.26
	Senior high school	16.75
	College	28.23
	University	48.80
Household income	<1000	3.83
	1000–3000	19.62
	3000–6000	27.71
	6000–10,000	24.88
	10,000–15,000	11.48
	15,000–20,000	4.31
	>20,000	3.83
	No re	2.87

4 Results and Discussion

In this research, the respondents are mainly asked their attitude toward traceability system. Table 3 shows both the attribute variables and non-attribute variables used in Choice Modeling. Attribute variables are the information that traceability system can provide to consumers, and non attribute variables are mainly socio-economic information. Two models are estimated in this research. Model 1 is the estimation MWTP of information that traceability system provides, while model 2 estimated the price attributes interacted with socio-economic characteristics and estimated how these socio-economic characteristics impact on price attribute. The variables are described as AGE*PRICE, GENDER*PRICE, and so on.

Table 4 showed the result of the estimation MWTP of information that traceability system provide and the estimation of socio-economic characteristics impact on price attribute. According to Table 4, respondents preferred all the information except processing information with pictures. The reason may be that people are more familiar with these famous processing companies, they can get much information about these processing enterprises through many channels; however, most people do not have a clear mind of farms information, breeding information, feed information and animal medicine use which are very important and affect food safety, especially the feed use and the animal medicine use.

About Farm Information, consumers have a higher Willingness to Pay (WTP) on information with pictures than only information, which is 2.28RMB and 2.03RMB of 250 ml milk while the basic price of milk is 1.70RMB. For consumers, the more information is better. Besides, consumers are willing to pay about 3.69RMB for a 250 ml milk with traceability system which including antibiotics record and only 2.95RMB for all animal medicine record. This was a very high marginal willingness to pay, especially on antibiotics usage. It was more than twice higher than original price. However, the survey was carried out right after the milk powder incident happened, so that the result might have bias and higher estimate the real willingness to pay. Consumers are more concerned on animal medicine use, especially antibiotics use. Processing factories information is viewed as least preferred, while processing factory information with pictures is not significant in statistic. When asked about processing factory information, consumers have a lower WTP than other attributes and levels only 0.87 RMB while the processing information with pictures are not significant in statistic. The reason might be the consumers or the respondents already have enough information on processing factories especially these famous brand compare with other information. They can get this kind of information through many channels such as news, internet, or to see the factory by themselves. They might more interesting in some introductions of these processing factories than these pictures. And people do not prefer the attribute of price through the coefficient.

Table 4 also showed the results of socio-economic characteristics impact on price attribute (WTP). Only AGE*PRICE and EDU*PRICE are in 1% significant, INCOME*PRICE is in 10% significant. Other variables are not significant on statistics. AGE*PRICE is negative, young people are easier to accept traceability system

Table 3 Explanation of attribute and non attribute variables in Choice models

	Variables	Explanation	Code
	ASC	Alternatives Specific Constant	
Attribute variables	FARM INF	Information of Dairy Farm described by words, the information might include the address, the contact and some introduction of the farm	1 = FarmInf, 0 = No-information
	FARM INF + PIC	Information of Dairy Farm with Pictures. Besides information described by words, pictures might give consumers a direct image of the farm. And for farmers, once their pictures can be found by public, they feel they have the responsibility to provide safe food	1 = FarmInf + Pic 0 = No-Information
	ANTIBIOTIC RECORD	Antibiotic Record. The most important medicine used in cow	1 = Antibiotics, 0 = No-Record
	ALL MEDICINE RECORD	All Animal Medicine Record. Including antibiotic usage record and other medicine use record	1 = All Record 0 = No-Record
	PROCESSING INF	Processing Factory Information described by words, the information might include the address, the contact, processing method and some detail introduction of the processing factory	1 = Processing Inf 0 = No-Information
	PROCESSING INF + PIC	Processing Information with Pictures. Beside information described by words, pictures might give consumers a direct image of the processing factories	1 = ProcessingInf + Pic 0 = No-Information
Non-attribute variables	GENDER	Respondent sex	0 = Male 1 = Female

(continued)

Table 3 (continued)

	Variables	Explanation	Code
	AGE	Respondent age	1 = < = 18; 2 = 19–25, 3 = 26–35, 4 = 36–45, 5 = 46–55, 6 = 56–65, 7 > = 66
	EDU	Respondent Educational Level	1 = Primary 2 = Secondary 3 = Highschool/Colege 4 = Technical/Vocational 5 = University
	FAMILYNO	No. of member in the household	Number of membes
	KID	No. of kid in the household	Number of kids
	OLDPPL	No. of old people in the household	Number of old people
	INCOME	Total income of per household, in RMB	1 = < 1000 2 = 1000–3000 3 = 3000–6000 4 = 6000–10,000 5 = 10,000–15,000 6 = 15,000–20,000 7 = > 20,000

and willing to pay more money on traceability system. EDU*PRICE is positive, higher educated people are easier to accept traceability system and have higher WTP. INCOME*PRICE is positive, higher income people are willing to pay more money, but not very strong. This may imply that income only impact little on WTP for traceability system. No matter their income is high or low, people concern on food safety and traceability system, and they need safe food no matter they are rich or not.

5 Conclusion and Recommendation

Consumers are concerned on the information of animal medicine use record especially on antibiotic and willing to pay more for getting the information. Besides, people also care about the farm information and they thought the more information was better. So, providing this information might increase consumers' confidence on the food they consume. These younger, higher educated and higher income people are easier to accept traceability system and are willing to pay more extra money on traceability system. But income is not a strong factor to affect willingness to pay.

Table 4 Estimation of MWTP of both models

Variable	Estimation of information that traceability system provide		Estimation of socio-economic characteristics impact on price		MWTP
ASC#[a]	−0.674	***	−0.443	***	−2.07
FARM INF	0.659	***	0.654	***	2.03
FARM INF + PIC	0.741	***	0.735	***	2.28
ANTIBIOTICS RECORD	1.202	***	1.206	***	3.69
ALL MEDICNE RECORD	0.961	***	0.960	***	2.95
PROCESSINGINF	0.282	*	0.274	*	0.87
PROCESSING INF + PIC	0.127		0.121		0.39
PRICE	−0.325	***	−0.312	***	
GENDER*PRICE			−0.0023		
AGE*PRICE			−0.029	***	
EDU*PRICE			0.036	***	
FARMILYNO*PRICE			−0.247		
KID*PRICE			0.022		
OLDPP*PRICE			−0.001		
INCOME*PRICE			0.002	*	
Rho-square	0.265		0.287		
Adjusted rho-square	0.262		0.277		
Number of observations	1254		1524		

Note ***, ** and * denote statistically significant at 1%, 5% and 10%, respectively
[a] #means Alternative Specific Constants

Most dairy farmers in China were small-scale farmers before 2008, it was hard to carry out traceability system on small-scale dairy farms. Since the milk melamine incident happened in 2008, the scale of dairy farming in China has gradually expanded and the milk quality has improved. The occupation of small farms is decreasing while the occupation of large farms is increasing, Nowadays, information recording and tracing back is the trend in dairy industry and information technology and Big Data have been applied to all aspects of the dairy industry. With the advent of 5G era, smart dairy has been widely recognized by both consumers and producers.

References

Adamowicz, W., Louviere, J., & Swait, J. (1998). *Introduction to attribute-based stated choice methods introduction to attribute-based stated choice methods* (Issue January).

Bateman, I. J., Carson, R. T., Day, B., Hanemann, M. W., Hanley, N., Hett, T., Lee, M. J., Loomes, G., Mourato, S., Ozdemirogle, E., & Pearce, D. W. (2002). *Economic valuation with stated preference techniques: A manual*. Edward Elgar.

Greene, W. H. (2008). *LIMDEP version 9.0: Econometric modeling guide.*

Hensher, D. A., & Louviere, J. J. (1983). Identifying individual preferences for international air fares. An application of functional measurement theory. *Journal of Transport Economics & Policy*, *17*(3), 225–245.

Louviere, J., & Woodworth, G. (1983). Design and analysis of simulated consumer choice or allocation experiments: An approach based on aggregate data. *Journal of Marketing Research*, *20*, 350–366.

Nanseki, T., Xu, Y., & Zeng, Y. C. (2008). Preliminary survey results for comparison between Japan and China, Awareness of food risk. *Proceedings of Annual Conference of Farm Management Society of Japan*, 222–223 (in Japanese). https://jglobal.jst.go.jp/detail?JGLOBAL_ID=200902286266042291

Part III
Social Innovations by Institutional Changes and Social Welfare

Chapter 10
Impacts of Microfinance Program on Rural Households in Myanmar: An Application of Logistic Regression Model

Nem Nei Lhing and Teruaki Nanseki

1 Introduction

About three billion people, half of the world's population, are living on the income of less than two dollars a day. Poverty remains a matter of growing concern in many developing countries of the world. One study in 2006 showed that the ratio of the income between the 5% richest and 5% poorest of the population was 74 and 1, as compared to the ratio in 1960, which was 30 and 1. To enhance international development, the United Nations Organization (UNO) has introduced eight millennium development goals which aimed to eradicate poverty by half by 2015 (United Nations, 2006).

According to the report of FAO and Vulnerability Information and Mapping System (FIVIMS) program (Shwe & Hlaing, 2011) indicated that out of the national total of 324 townships, 52 townships were classified as being very highly vulnerable, 49 highly vulnerable, 62 moderately vulnerable, and the remaining 122 having a relatively low level of vulnerability. Among the 52 very highly vulnerable townships, 29 were located in Shan State. All townships in Chin State and two-third of townships in Kachin State were also reported to be highly vulnerable and mostly located in remote areas. Townships in Bago Division, Mon State and Yangon Division were reported to be the least vulnerable.

In this regards, PACT, Microfinance (MF) Program in the form of financial development that has its primary aim to alleviate the poverty and also which is significant source of finance for poor, lower income people in Myanmar. Governments, donors and NGOS, around the world responded enthusiastically with plans and

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promised to work together towards the realization of these goals. In the recognition of MF, the UNO celebrated the year 2005 as a year of micro-credit, as a result this financing instrument is perceived worldwide as a very effective mean against hunger and poverty, mainly in developing countries.

Therefore, the objectives of this chapter are: firstly to compare the demographic and socio-economic characteristics of the client and non-clients. Secondly, descriptive analysis will deal on the impact of MF program on changes in earned income, household assets, technology, education, saving, food intake, clothing, housing improvement and health aspects of the clients. Finally, Logistic Regression Analysis is used in order to examine the determinants or influencing factors on taking loans. The analysis used data on 102 clients who are participating in the program and 60 who are not participating. To do a case study, PACT Myanmar MF Program which is operating in Dry Zone Area of central Myanmar was chosen.

2 Methodology

In October 2008, a survey was conducted of 162 households in six villages of Kyaukpadaung Township which have saving groups by PACT MF program. Two strata are identified taking loans (Clients 102) and not taking loans (Non-Clients 60) prior to collecting data. Descriptive analysis is largely used to determine the comparison between two groups of socio-economic characteristics and after participating in the program what changes are occurred on clients. In this chapter, the empirical analysis of the determinants or influencing factors on taking microfinance program in the study area is carried out by using Logistic Regression Model. Logistic Regression Model is a form of regression which is used when the dependent variable is dichotomy, and the independents are of any types (categorical and continuous variables). In a Logit Model, the endogenous variable is a dummy or categorical variable with 1 representing household is taking loan and 0 if the household is not taking loan. In this model, 11 independent variables were tested to examine the determinants or influencing factors on taking loans such as family size, marital status, gender, age, education, land holding size, number of crops, income, technology adoption, participating in social activity, and establishing new business.

3 Results and Discussion

3.1 Demographic and Socioeconomic Characteristics

Table 1 provides the information about the demographic and socioeconomic characteristics for both respondents. In terms of gender distribution of the respondents, 77.45% of the clients are female while 22.55% are male. The main shares of the

Table 1 Descriptive analysis of demographic and socioeconomic characteristics of the clients and non-clients

Variables	Measuring group	Clients ($n = 102$)		Non-clients ($n = 60$)	
		Frequency	Percentage	Frequency	Percentage
Gender	Male	23	22.5	43	71.7
	Female	79	77.5	17	28.3
Age (years)	<35	23	22.5	6	10.0
	36–50	51	50.0	13	21.7
	>51	28	27.5	41	68.3
Marital status	Married	66	64.7	59	98.3
	Single	36	35.3	1	1.7
Educational	Not at all	18	17.6	13	21.7
	Primary	29	28.2	31	51.7
	Middle	43	42.4	13	21.7
	High	12	11.8	3	4.9
No. of family member	<5	58	57.0	18	30.0
	>5	44	43.0	42	70.0
Established new microenterprise	Yes	48	47.1	14	23.3
	No	54	52.9	46	76.7

respondents are women that testify to the fact that most of the beneficiaries of microfinance are female. In some microfinance institutions like the Grameen Bank which is the biggest microfinance institution in terms of outreach, 96% of their clients are women.

In terms of age, although 50% of the clients are in the age group of 36 to 50 years, non-clients are 21.6%, and above 51 years for Clients and Non-Clients are 27.7%, 68.4% respectively. Here it can be concluded that the younger the age of the respondents the more they want to participate in microfinance program. From this survey, many of the Clients (42.2%) had at least middle education, however for non-clients about 22%. According to the result of marital status, 1.7% of non-clients still single when in clients 35.3%, which indicates that respondents who unmarried are more likely to join in microfinance program. In my study, the average family size of the clients (5.5ppl) is lower than non-clients (7.2ppl). It is because as mentioned before 35.3% of clients still unmarried.

The analysis also reveals that 47.1% of clients have owned small micro-enterprise after joining the program and on the other hand for non-clients only 23.3% (last 3 years). It indicates that PACT MF program is contributing a lot to start new small-scale businesses as well as in the expansion of old businesses. Therefore, we can see that more clients have owned small micro-enterprise (SME) and also can expand their business however higher proportion of non-clients did not have owned SME. So indirectly, PACT program can support the clients to earn income from SME.

Table 2 The reasons for participating in the programs

Items	Units	Clients ($n = 102$)
Lower interest rate	%	95.5
No collateral	%	85.0
Need loan	%	77.6
Group work	%	46.5

Note Multiple responses possible

Table 3 The reasons for not participating in the program

Items	Units	Non-Clients ($n = 60$)
Procedure too complicated	%	76.7
Fear of legal action	%	63.3
Not interesting	%	60.0
No need loan	%	53.3
Lack of information	%	43.0
Unfavorable loan	%	30.0

Note Multiple responses possible

Table 2 indicated that regarding to the reasons for participating in the microfinance program, most of the clients (95.5%) are likely to participated in the microfinance program because of the lower interest rate which is the major reason and then followed by 85% of the clients are because of no collateral and 77.6%, 46.5% are the clients' need loan and they enjoyed group work in the program.

Table 3 shows the reasons for why non-clients did not participate in the program. The most finding reasons are such procedures too complicated (77%), fear of legal action when default (63%), not interesting the program (60%), because they don't need loan (53%). These findings are important to the program to provide suggestion as it will help them to remove those obstacles in order to make MF assistance program more attractive to people.

3.2 Use Loan Funds

The program emphasizes the use of loan funds in the respective enterprise. Clients may use part or all of the loan funds in their agriculture fields, small micro-enterprises, however, and set aside a portion to enable them to make their first loan repayments. The loan funds tend to be used on agriculture and enterprise. Some funds also are used for household needs, and the use of the funs varied across a range of needs such as school expenditures, and food.

3.3 *The Impact of Microfinance on Client Households' Livelihoods*

According to the Table 4, client respondents are also empowered through the program participation increasing in using the among of income on accumulation of durable household assets such as TV, VCD, furniture, etc. Acquisition of assets not only indicates a higher standard of living, but also a store of wealth that can be rented out of sold in case of an extreme financial crisis. Program participation is strongly associated with specific types of diversification of income sources such as establishing new enterprises and increasing the number of crops cultivated.

Regarding to the results of household income, the clients (53%) have reported that increase in their income is the main reason effectiveness of participating in the program. This program can help them to solve main problem like poverty, isolated from community, physical illness. Among the clients, about 63% can improve good diet with increasing rate and able to save money. In addition, they also able to send their children to school and to pay for their health care.

It is also true that household saving enables clients (39%) to deal with severe crises and to cope up with the shocks and reduce vulnerability and bought property can be sold also to deal with the crises. Saving is critical as it can be used for the expansion of economic and agricultural activities. The findings also reported that clients (53%) had increased incomes which enable them to save and to buy property.

Moreover, the other positive impacts of the program are in the education sector and health care sector. Education is a human right and an important ingredient for any progress in any society. It contributes to the accumulation of human capital. Education is one of the important components to fight poverty, disease and ignorance. And also the health care for the wellbeing of the clients is more productive in society and resources that go to health care if a client is not sick can be saved or invested in

Table 4 Overall changes on the livelihoods of the clients

Category	Units	Increased	Not changed	Decreased	Rank
Family income	%	52.9	33.4	13.7	5
Expenditure on housing	%	65.7	–	34.3	1
Expenditure on furniture	%	59.8	–	40.1	3
Household saving	%	39.2	37.3	23.5	8
Food intake expenses	%	62.8	28.4	8.8	2
Health facilities	%	57.8	42.2	–	4
Education expenses	%	46.1	25.5	28.4	6
Clothing expenses	%	21.5	52	26.5	9
Household assets	%	45.2	31	23.8	7
Technology adoption rate	%	57.8	42.2	–	4

Note Multiple responses possible; Technology includes changed cropping pattern, processed farm produce, planted improved varieties, and used chemical fertilizers income generating activities, hence progress in society and out of the poverty trap. In addition, the positive impact is viewed in improved food intake and accommodation which became better because of the microfinance program.

Therefore, microfinance program positively improved the living conditions of rural households who participated in the program as evidence by changes in their income, savings, housing improvement, education expenses, food intake, health care and clothing expenses. If the clients adopted new technology, they can improve their agricultural production. If the yields increase, their incomes also increase. Therefore, there is a positive relationship between them.

3.4 The Influencing Factors on Taking Loan by Using Logistic Regression Model

This chapter is also attempted to analyze influencing factors or determinants of taking loan on PACT microfinance program in Dry Zone Area of Myanmar by using Logistic Regression Model. Analysis of the survey data revealed that nine out of the eleven variables included in the model (Table 5) are significant (at 1 percent to 10 percent) in explaining the variation in taking loans status of household in the study area. These variables are family size, marital status, gender, age, educational level, land holding size, number of crops, technology adoption, and establishing new business and have signs in accordance with my hypotheses except family size and land holding size. The coefficients of Income and participating in social activities are insignificant variables.

The age of the respondents has a negative coefficient with significant at 1% level. This probably indicated that the older the respondents, the lower the probability that household would be taking loan. The younger respondents tend to be directly participated by increasing rate of taking loan than older respondents. In terms of the household size, it is highly significant at 1% level and having negative impact on the probability of taking loan. It suggests that higher household size has a decreasing rate on taking loan. It is because in my survey most of the clients have one or two members in their family, which indicated that respondents are either unmarried, or have no children. On the other hand, 98% of non-clients are married and almost their family members interested in working farms, which indicates that they don't want to participate in the microfinance program.

The results also show that the income variable is insignificant which means that there is no relationship and not affecting between whether the income higher or lower and taking loan. Apart from income, the other significant variables in the model are the educational level, gender of the respondents, marital status, number of crops did they grow, awareness of technology adoption, and establishing new business. This implies that the probability of taking loan is higher with educated, female, increased number of crops, higher adopted technology, and established new business. Regarding to the land holding size which is significant at 5% level, however, affect on taking loan is

Table 5 The results of logistic regression analysis

Independent variables	Coefficients (β)	Std. error	Wald statistics	Significance	Exp (β) or odds ratio
FSize	–0.77	0.23	11.17	***	0.46
MStatus	2.83	1.22	5.42	**	16.92
Gender	2.10	0.89	5.61	**	8.18
Age	–0.15	0.05	7.75	***	0.86
Edu:level	0.45	0.18	6.40	**	1.57
LHSize	–0.34	0.14	6.32	**	0.71
NCrops	1.36	0.54	6.28	**	3.90
Income	0.00	0.00	0.13	n.s	1.00
TechAdop	1.82	0.97	3.53	*	6.16
SocAct	0.76	0.85	0.80	n.s	2.14
Estbus:	2.56	0.95	7.21	**	12.93
Constant	3.21	2.31	1.12	n.s	11.54

Note $n = 162$, Nageikerke R square = 0.85, Correctly predicted = 93.2%, ***, **, and * indicate significance level at 1%, 5% and 10%, respectively

negatively. For variable of participating in social activity it is insignificant and no matter this variable increase or decrease had no affect on taking loan.

4 Conclusion

The main problems of MF program are: (1) the procedures are very complicated, it means that not to become a membership easily, (2) their rules (eg. Difficult to pay back once in two weeks), (3) for the older people, some training made bring to them, (4) need widely to distribute the information to all villages. In conclusion, the results in this research imply that the respondents who are male, older, primary educational level, lower assets and lower total income are higher percentage in non-clients than clients. In MF program those who are female, single, younger, middle educational level, small family size and small scale land holding size more willingly want to join. The increasing number of crops, established new business and higher adoption of technology are also influenced on the probability of being taken loan. More than half of the clients can improve on their livelihoods such as housing condition, food intake, furniture, and health facilities with increasing rate. Household income and education expenses are also increasing however the percentage is still lower than the other categories. Therefore, PACT MF program should introduce income generating activities and effective education program which open up more income-earning opportunities for the clients especially in the non-farm sector. Regarding to the reasons for not participating, PACT MF is suggested to collaborate with extension services to develop information program in order to disseminate the information to as many people as possible and also the program should be made easier in terms of loan procedures, legal action. More information on the advantage of taking loans should be made in order to attract peoples to join the program.

References

Shwe, T. M., & Hlaing, T. C. (2011). *Scoping study on food security and nutrition information in Myanmar*. https://themimu.info/sites/themimu.info/files/documents/Report_Food_Security_and_Nutrition_Information_Scoping_Study_EC_May11.pdf. Accessed 17 Feb 2022.

United Nations. (2006). *The millennium development goals report 2006* (p. 72). United Nations. ISBN 978-92-1-101320-7.

Chapter 11
Impacts of Dietary Diversity on Perceived Food Security in Indonesia: An Application of Ordered Logit Model

Pipi Diansari, Teruaki Nanseki, and Yosuke Chomei

1 Introduction

There is a broad consensus on the need to look at the multi-dimensionality of household food security, including the issue of combining objective and subjective methods used to determine the status of households. Discussions surrounding the need for such a combined approach are well documented and summarized (Bamberger, 2000; Baker, 2000; Coudouel et al., 2002; Hentschel, 1999). However, there is still no consensus over which method is the most successful and it is clear that both have strengths and weaknesses (Gacitúa-Marió & Wodon, 2001). Objective approaches, which mostly rely on statistics, provide good results if they involve an appropriate number of samples. However, objective data cannot fully capture causality because of their failure to provide contextual information (Hentschel, 1999). Subjective methods such as close observation or surveys with interviews can explain the economic, socio-cultural or political context of the processes under study. In the other words, subjective assessments provide a better understanding of stakeholders' perceptions and priorities (Baker, 2000).

In this chapter, both objective and subjective approaches have been utilized. For the objective approach, this chapter used the household food dietary diversity score (DDS). DDS were collected by questionnaire survey. The questionnaire itself is

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modification of the Food and Nutrition Technical Assistance Project's questionnaire (FANTA) (Swindale & Bilinsky, 2006). The subjective method is achieved via an interview of the household regarding their perceived food security status. DDS has become increasingly popular as an effective food and nutrition indicator, for three basic reasons. First, DDS defines both "food" and "nutrition security" (Ruel, 2003). Secondly, economic theories of demand as well as theories in psychology suggest that individuals will diversify into higher-value, micronutrient-rich foods only when they have satisfied their basic caloric needs. In other words, as poor people become richer, they gravitate away from relatively tasteless, staple foods towards micronutrient-rich foods that impart greater taste and therefore utility. Thirdly, it holds true that the execution of DDS-oriented research is relatively cost-effective (Headey & Ecker, 2012). DDS is an important indicator, as it more accurately reflects dietary quality than, for example, a calorie count; DDS counts the number of different food groups consumed over a given reference period, rather than the number of different foods consumed. Moreover, dietary diversity methods are promising in capturing the diverse nature of Asian diets. The assessment of micronutrients in Asian diets is further complicated by the presence of several food components that may interfere with bio-availability, in particular trace minerals (Winichagoon, 2008). The overriding aim of this chapter is to observe the relationship between the objective and subjective measurement of household food security status in North Luwu in Indonesia. The objective and subjective measurement in this chapter is by undertaken by means of DDS and a subjective food security score method (SFSS), respectively.

2 Material and Methods

The North Luwu district is located about 440 km from Makassar, the capital city of South Sulawesi province—a major province of the eastern part of Indonesia. The North Luwu district has an area of 7,502.58 km^2 and is divided into 11 sub-districts, 167 villages, and 703 neighborhoods. According to the most recent census, there were 290.365 people in 67,328 households living in this district (Central Bureau of Statistics, 2012). The household sample used in this chapter was randomly chosen from a household list supplied by the sub-district ward office of 21 villages/neighborhoods located in suburban areas with many households living below the poverty line. The number of households sampled from each village/neighborhood was determined by considering the total population of that village/neighborhood. Following the validation process, 371 households were included in the analytical process. The determination of the specifics of DDS has been carried out in Pipi et al. (2014). For Indonesia, there are nine food groups that compose DDS: GRAIN (rice, corn, sorghum), TUBER (potato, sweet potato, cassava, sago starch, taro), ANIMAL PRODUCT (fish, meat, dairy product, egg), OIL & FAT (coconut oil, palm oil), OILY SEEDS (coconut), NUTS (soybean, peanut, green bean), SWEETS (sugar, palm sugar), FRUITS AND VEGETABLES, and OTHERS (beverages, snacks). Furthermore, Pipi et al. (2014)

have explained the way that SFSS is determined. There are five categories of household food security in this measurement: INSECURE (coded: 0); SOMEWHAT INSECURE (coded: 1); SOMEWHAT SECURE (coded: 2); SECURE (coded: 3); and HIGHLY SECURE (coded: 4).

The SFSS of individual *i* is assumed to be explained either by $DDS_{composite}$ or by the food groups that compose the DDS ($DDS_{foodgroups}$). $DDS_{composite}$ is diversity score of a household (continuous variable), while the $DDS_{foodgroups}$ is the existence of each food group in a household (dummy variables).

$$SFSS_1 = f\left(DDS_{composite}\right) \tag{11.1}$$

$$\begin{aligned} SFSS_1 &= f\left(DDS_{foodgroups}\right) \\ &= f(TUBER, ANIMALPRODUCTS, OIL\&FAT,\ OILYSEED,\ NUTS, \\ &\quad SWEETS,\ FRUIT\&VEGETABLES,\ OTHERS) \end{aligned} \tag{11.2}$$

In reality, a household head's perception of their food security status is dynamic. However, for simplicity's sake and owing to the constraints of data availability, we adopted a static framework. Suppose that the perceived household food security status, $SFSS_i$, is a linear function of K factors, with values for individual i described by X_{ik}, $k = 1$, …., K. Then, the structural model is as follows:

$$SFSS_i = \sum_{k=1}^{k} \beta_k X_{ik} + \varepsilon_i \tag{11.3}$$

where β_k is the coefficient associated with the $k-th$ variable, and ε_i is an error term. The error term is assumed to have a standard logistic distribution with a mean of zero and a variance of $\pi^2/3$. $SFSS_i$ is the latent variable or unobserved dependent variable.

There is a number of different modeling approaches associated with ordinal dependent variable analysis, including cumulative, stage, and adjacent approaches (Fullerton, 2009; Menard, 1995). The data taken as well as the type of comparison that is required between the categories determines which approach is appropriate for the study. Since the SFSS status follows an ordinal scale, but represents an underlying continuous measure, Fullerton (2009) recommends using the cumulative approach. Traditionally, the cumulative approach represents the classic ordered Logit model approach. For this model:

$$SFSS_i^* = \beta_i^{'} X_{ik} + \varepsilon_i \tag{11.4}$$

where $SFSS_i^*$ is the underlying latent variable that indexes the SFSS. The latent variable exhibits itself in ordinal categories, coded as $J = 0, 1, 2, 3$, and 4. Therefore, the observed response in category J when the underlying continuous response falls in the *j*-th interval is as follows:

$$SFSS = 0\ if\ SFSS^* \le \delta_1$$

$$SFSS = 1\ if\ \delta_1 < SFSS^* \le \delta_2$$

$$SFSS = 2\ if\ \delta_2 < SFSS^* \le \delta_3$$

$$SFSS = 3\ if\ \delta_3 < SFSS^* \le \delta_4$$

$$SFSS = 4\ if\ \delta_4 \le SFSS^*$$

where $\delta_j (j = 0, 1, 2, 3, 4)$ are the unobservable cutoff point (threshold) parameters that will be estimated together with other parameter in the model. For the purpose of statistical analysis, the standard for significance is $P < 0.05$.

Table 1 summarizes the dependent and independent variables. For the Eq. (11.1), the independent variable is only the $DDS_{composite}$. For the Eq. (11.2), all variables are dummy variables that compare the effect of the existence/availability or absence of food groups in household, on the perceived household food security of the household head. Since the GRAIN food group is available in every household sample, this group is omitted from the calculation.

3 Results and Discussion

The descriptive relationship between perceived household food security and composite dietary pattern of the household is presented in Table 2. It obvious by analyzing the table that although to some extent, there is a linear correlation between $DDS_{composite}$ and SFSS, the correlation between those two methods is weak and tends to be non-linear in its pattern. A similar correlation between quantitative-objective and qualitative-subjective methods is also found in other studies. Lorenzana and Sanjur (1999) found a correlation between energy availability and self-perceived HFS scale, while Migotto et al. (2006) concluded that calorie consumption, dietary diversity and anthropometry have at best a weak correlation with subjective perceptions of food consumption. Coates et al. (2003) find a similar lack of association between anthropometric measures and subjective indicators in their Bangladesh study.

From Table 2, we can see that most of households serve 5 to 7 food groups and in all $DDS_{composite}$ levels the food SECURE category of SFSS always represents the highest percentage. It means that in general the perceived household food security status in the sample area is at a SECURE level. It also can be interpreted that most household heads regard that their household are in a food SECURE level even though they only consume two (53%) or three (79%) kinds of food groups. This finding is important because it may disguise the real state of the household food security status. It seems that there is still some misunderstanding over the concept of dietary balance,

Table 1 Summary of dependent and dependent variables

Variables	Unit	Code
Dependent:		
Subjective Food Security Status	–	SFSS
Independent:		
Dietary Diversification Score	Scores	$DDS_{composite}$
Existence of tuber food group (Dummy)		NO-TUBER
0 = Not Exist	–	TUBER
1 = Exist	–	
Existence of animal products food group (Dummy)		
0 = Not Exist	–	NO_ANIMAL_PROD
1 = Exist	–	ANIMAL_PROD
Existence of oil & fat food group (Dummy)		
0 = Not Exist	–	NO_OIL&FAT
1 = Exist	–	OIL&FAT
Existence of oily seed food group (Dummy)		
0 = Not Exist	–	NO_OILY_SEED
1 = Exist	–	OILY_SEED
Existence of nuts food group (Dummy)		
0 = Not Exist	–	NO_NUTS
1 = Exist	–	NUTS
Existence of sweets food group (Dummy)		
0 = Not Exist	–	NO_SWEETS
1 = Exist	–	SWEETS
Existence of fruits and vegetables food group (Dummy)		
0 = Not Exist	–	NO_FRUITS&VEGETABLES
1 = Exist	–	FRUITS&VEGETABLES
Existence of others food group (Dummy)		
0 = Not Exist	–	NO_OTHERS
1 = Exist	–	OTHERS

as the household head may think that having rice (GRAIN) plus one or two other food groups, which is a very common situation in this area, is enough and safe for their household. On the other hand, all households who have a DDS of 9 fall in food SECURE (41%) or HIGHY SECURE (51%) categories. It is obvious that the heads, whose household consumes 9 groups of food, are mostly very sure that their households are in the best condition, in terms of their food security status.

Figure 1 is taken from previous research (Pipi et al., 2014). It is clear that after rice in the GRAIN food group, the most available food groups that are prepared by the households with a DDS of 2 and 3 are ANIMAL PRODUCTS (90%) and

Table 2 Perceived household food security and dietary diversification score cross tabulation ($N = 371$ households)

Category	$DDS_{composite}$	SFSS					
		Insecure	Somewhat insecure	Somewhat secure	Secure	Highly secure	Total
Insecure	2	4 (31%)	1 (8%)	1 (8%)	7 (53%)	–	13 (100%)
Somewhat Insecure	3	1 (5%)	–	2 (16%)	16 (79%)	–	19 (100%)
Somewhat Secure	4	–	10 (20%)	5 (10%)	35 (70%)	–	50 (100%)
Secure	5	–	9 (10%)	26 (31%)	46 (59%)	–	81 (100%)
	6	–	17 (26%)	19 (29%)	29 (45%)	–	65 (100%)
	7	–	4 (4%)	27 (30%)	58 (66%)	–	59 (100%)
Highly Secure	8	–	–	7 (19%)	25 (68%)	5 (13%)	37 (100%)
	9	–	–	–	7 (41%)	10 (59%)	17 (100%)
Total		5 (1.3%)	41 (10.8%)	87 (23.5%)	223 (60.4%)	15 (4%)	371 (100%)

FRUITS & VEGETABLES (86%). Using the same way of thinking, it can be also said that to households with a DDS of 4, 5, 6, or 7, we might add their prepared food groups of SWEETS (82%), TUBERS (73%), OIL & FAT (65%), and OTHERS (62%) food groups, respectively. However, considering the income class of the households, those additional food groups might become a burden for some of the households. This situation may explain the perceived household food security anomaly in which the percentage of households with a DDS of 4, 5, 6, and 7 that are in a SECURE or better category is less than in households with a DDS of 2, 3, 8 and 9.

In general, when it is read independently within the food group, Fig. 2 only show the difference in household food security distribution categories based on the absence or existence of any given food group in sample households. Apart from the TUBER food group, in all food groups, when those foods are absent, the percentage of households that are in a food SECURE or better category is more than 50%. Considering that based on their dietary diversity score, the sample households were in a lower food security status (Diansari & Nanseki, 2015), that percentage probably represents the household head's own perception where they might think that the absence of those food groups will not affect their household food situation to a great extent. It is another case altogether when considering the TUBER food group. In the households where this food group is absent, those that fall under food SECURE or higher categories only contribute 42%. This percentage is almost a half lower than those where this food group is present (73%). Those numbers imply that household heads felt more food secure when they possess tuber in their household. This situation

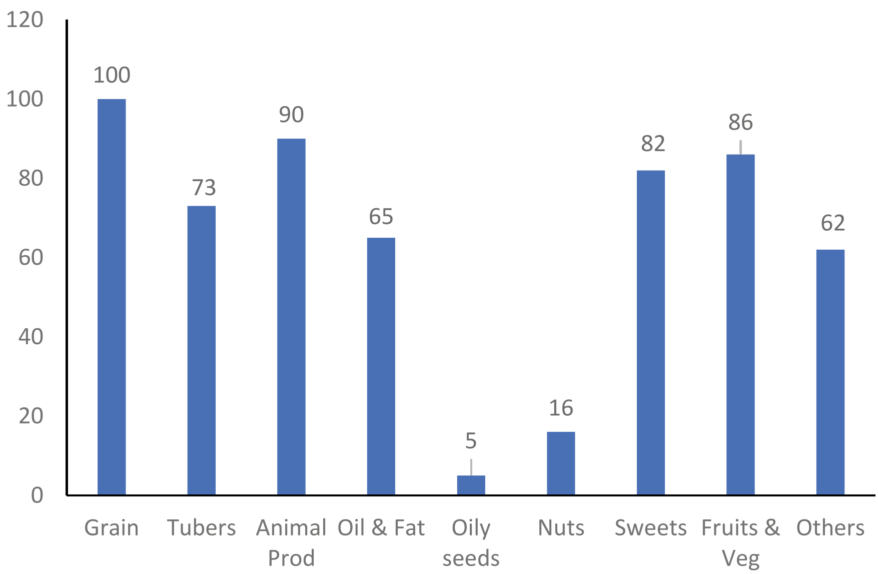

Fig. 1 Distribution of food groups consumed by the household respondents (Note $n = 371$ respondent) (Reproduced from Pipi et al., 2014)

is in line with the background of this area, as sago starch, which is a form of tuber, is the most important historical and cultural food after rice. Traditionally, people in this area consume sago starch product as their lunch, and rice for their breakfast and dinner. Therefore, in other words, in terms of the household heads' perception, being able to consume sago starch (TUBER) boosts their household food security status.

When Fig. 2 is looked at alongside Fig. 1, it can be inferred that the OILY SEED food group, which mainly consists of coconut and its derivates, is only possessed by the food SECURE or HIGHLY FOOD SECURE households. That is confirming the low percentage of this food group in Fig. 2. We believe that the same situation also applies for the NUTS food group where there are no households that fall in the 'food insecure category' that keep this food group for serving in their households. That situation is completely expected as those two food groups are relatively expensive and only be used as an additional ingredient to augment another food group (e.g. ANIMAL PRODUCT or FRUITS & VEGETABLES).

When the composite score of $DDS_{composite}$ predicts the SFSS, the odd ratio from the ordered LOGIT analysis is 1.3 (Table 3). Having the chi-square likelihood ratio of 18.5, with a P-value of <0.0001, the model tell us that for a one-unit increase in $DDS_{composite}$, the odds ratio of the HIGHLY SECURE category is 1.3 times greater than that of the other categories combined, given that the other variables in the model are held constant. The same increase (1.3 times) is found between SECURE category and the other combined categories. In a simple word, the dietary diversity in a household has the potential to influence the perceived food security status of the household in a positive direction. When the SFSS is predicted using each food group that comprises the DDS ($DDS_{food\ groups}$) then a more comprehensive result is available, as is shown in Table 4.

From the same analysis of the result in Table 3, the chi-square likelihood ratio of 120.8, with a P-value of <0.0001, tells us that the model as a whole is statistically significant. Thus, the odds ratio coefficients imply that the existence of TUBER, OILY SEED, NUTS, as well as FRUIT AND VEGETABLES food groups in the household are likely to increase the probability of a household's SFSS being in a better food security category. On the other hand, the SWEETS food group is likely to increase the probability of a household's SFSS being in a worse category. Specifically, when the TUBER food group is available in household, the odds ratio of the HIGHLY SECURE category is 3.8 times greater than that of the other categories combined, given that the other variables in the model are held constant. When highlighting SECURE category, it will be subject to the same increase, 3.8 times, is found between SECURE category and the combined other categories. Likewise, the odds ratio of the HIGHLY SECURE category is 4.7, 2.8, and 2.5 times greater than the other categories combined if OILY SEED, NUTS, as well as FRUIT AND VEGETABLES are prepared in the household, respectively. Furthermore, when the SWEETS food group is prepared in households, the odds ratio of the SECURE category versus the other categories combined is 0.4 times less, given that the other variables in the model are held constant.

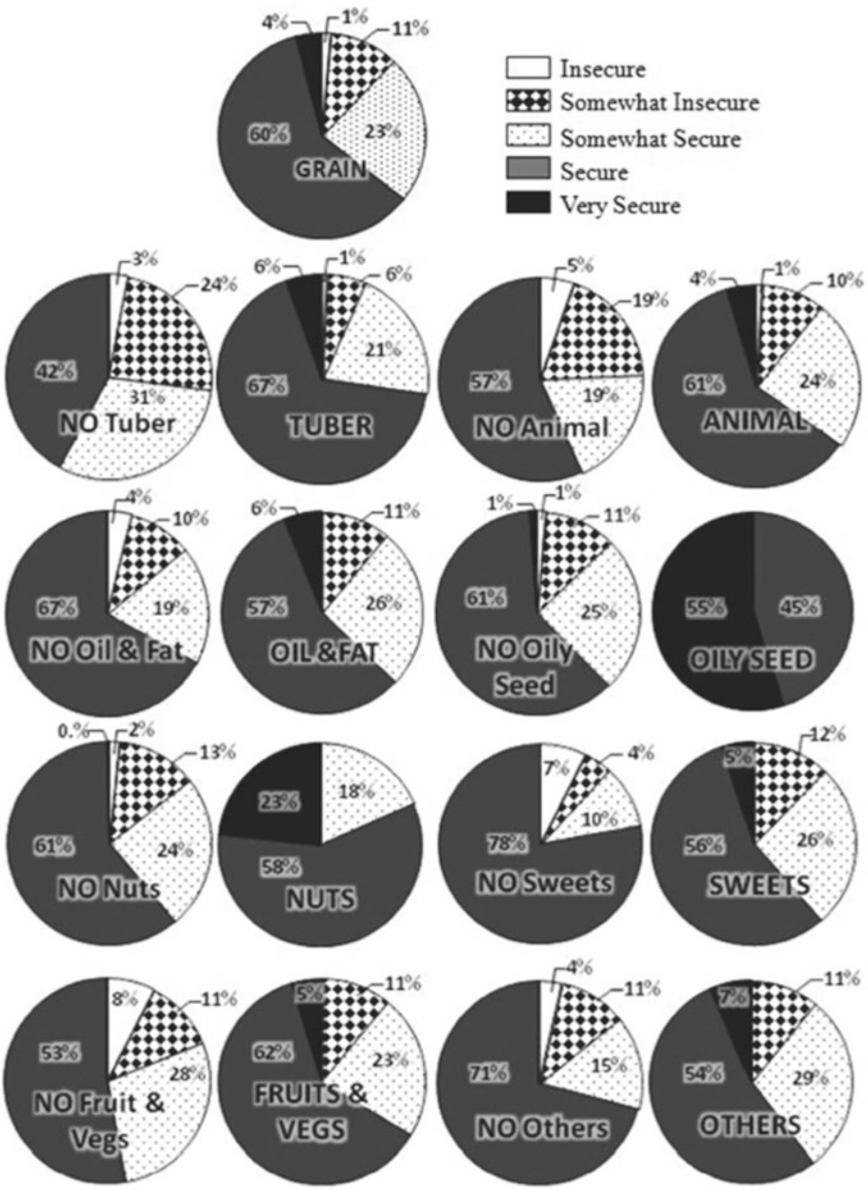

Fig. 2 Perceived household food security distribution among the food groups

Table 3 Ordered logistic regression analysis results between SFSS and $DDS_{composite}$

	Odds ratio	Std. err	$P > \|z\|$
$DDS_{composite}$	1.342***	0.812	0.000

Note *** significant at $P < 1\%$

Table 4 Ordered logistic regression analysis results between SFSS and DDS_{food_group}

	Odds ratio	Std. err	$P > \|z\|$
TUBER	3.875***	0.910	0.000
ANIMAL_PROD	1.926	0.714	0.077
OIL&FAT	0.673	0.181	0.142
OILY_SEED	4.693***	3.849	0.000
NUTS	2.827**	1.141	0.010
SWEETS	0.437**	0.160	0.024
FRUIT&VEGETABLE	2.467***	0.800	0.005
OTHERS	0.763	0.215	0.336

Note *** and ** significant at $P < 1\%$ and $P < 5\%$, respectively

4 Conclusion

In this chapter, we have observed the relationship between the objective and subjective measurement of household food security status in North Luwu. The objective measurement was achieved by means both of the composite Dietary Diversity Score ($DDS_{composite}$) and food groups in the Dietary Diversity Score ($DDS_{food\ groups}$), while the subjective measurement was carried out using the Subjective Food Security Score (SFSS). Specifically, this chapter estimated the probability of households being more or less food secure as a result of their dietary diversity status and their available food groups.

The descriptive analysis showed that in general, the correlation between $DDS_{composite}$ and SFSS was weak and tended to be non-linear in pattern. In all $DDS_{composite}$ levels the perceived food SECURE category always had the highest percentage. However, what is a more important finding from this chapter was that household heads largely regarded their households to be in a food secure level even though they only consumed food from only two or three of the food groups. This finding is important because it implies that there is still a misunderstanding about the concept of the kind of dietary balance needed to support the food security of a household. Another finding from the descriptive analysis is that keeping the TUBER food group, in this case sago starch, available in a household will make household heads feel more food secure, a perceived impact which is similar with a household that keep a OILY_SEED food group for daily use.

From the regression estimation, the $DDS_{composite}$ as a composite score of the availability of food groups in a household was found to significantly improve the perceived food security status of the household. Furthermore, among the food groups composing the $DDS_{food\ groups}$, the existence of TUBER, OILY SEED, NUTS, as well as FRUIT & VEGETABLES food groups are likely to increase the probability of a household's SFSS being in a better food security category, whereas the SWEETS food group gave a reverse effect.

There are at least three major implication of this research. Firstly, enlightenment as to the important of dietary balance has to be rectified and efforts in this direction need intensifying. Reflecting on the results of the previous study, the concept of dietary balance should be taught both in formal as well as in non-formal educational institutions. Secondly, considering the dietary history of the area, local stakeholders must encourage households to utilize sago starch more than before and in a more varied form so as well as enhancing the household's food security status, it also can lead to the substitution of rice as a staple food in general. Lastly, a reduction in the consumption of food from the SWEETS group must be started not only in order to achieve a better household food security status but also to yield healthier household members.

References

Baker, J. L. (2000). Evaluating the impact of development projects on poverty. In *Evaluating the impact of development projects on poverty*. https://doi.org/10.1596/0-8213-4697-0

Bamberger, M. (2000). *Integrating quantitative and qualitative research in development projects.* The World Bank.

Central Bureau of Statistics. (2012). *South Sulawesi in figures 2011.* BPS Press.

Coates, J., Webb, P., & Houser, R. (2003). *Measuring food insecurity: Going beyond indicators of income and anthropometry.* Food and Nutrition Technical Assistance Project (FANTA), FHI 360; Issue November.

Coudouel, A., Hentschel, J. S., & Wodon, Q. T. (2002). Poverty measurement and analysis. In J. Klugman (Ed.), *A sourcebook for poverty reduction strategies: Core techniques and cross-cutting issues*. The World Bank.

Diansari, P., & Nanseki, T. (2015). Perceived food security status—A case study of households in North Luwu, Indonesia. *Nutrition and Food Science, 45*(1), 83–96. https://doi.org/10.1108/NFS-01-2014-0007

Fullerton, A. S. (2009). A conceptual framework for ordered logistic regression models. *Sociological Methods & Research, 38*(2), 306–347.

Gacitúa-Marió, E., & Wodon, Q. (2001). Measurement and meaning: Combining quantitative and qualitative methods for the analysis of poverty and social exclusion in Latin America. In *World Bank technical paper* (No. WTP518). https://openknowledge.worldbank.org/bitstream/handle/10986/14035/multi0page.pdf?sequence=1&isAllowed=y

Headey, D., & Ecker, O. (2012). *Improving the measurement of food security* (IFPRI Discussion Paper 01225, Issue November).

Hentschel, J. (1999). Contextuality and data collection methods: A framework and application to health service utilisation. *Journal of Development Studies, 35*(4), 64–94. https://doi.org/10.1080/00220389908422581

Lorenzana, P. A., & Sanjur, D. (1999). Abbreviated measures of food sufficiency validly estimate the food security level of poor households: Measuring household food security. *Journal of Nutrition, 129*(3), 687–692. https://doi.org/10.1093/jn/129.3.687

Menard, S. (1995). *Applied logistic regression analysis* (2nd ed.). Sage.

Migotto, M., Davis, B., Carletto, C., & Beegle, K. (2006). *Measuring food security using respondents' perception of food consumption adequacy* (Research Paper No. 2006/88).

Pipi, D., Nanseki, T., & Takeuchi, S. (2014). The determinants of food security in Indonesia—A case of households in the North Luwu of South Sulawesi Province. *Journal of Rural Economics, 16*(1), 41–48.

Ruel, M. T. (2003). Operationalizing dietary diversity: A review of measurement issues and research priorities. *Journal of Nutrition, 133*, 3911S-3926S. https://doi.org/10.1093/jn/133.11.3911S

Swindale, A., & Bilinsky, P. (2006). *Household dietary diversity score (HDDS) for measurement of household food access: Indicator guide* (FHI 360/FANTA).

Winichagoon, P. (2008). Limitations and resolutions for dietary assessment of micronutrient intakes. *Asia Pacific Journal of Clinical Nutrition, 17*(S1), 296–298. https://doi.org/10.6133/apjcn.2008.17.s1.72

Part IV
Smart Farming and Innovation

Chapter 12
Practice, Promotion and Perspective of Smart Agriculture in China

Dongpo Li and Teruaki Nanseki

1 Introduction

Compared with the United States (US), Australia, and most European Union (EU) countries, China has a larger number of farmers, but lower scale of agricultural management. The average size of a farmland in the US is over 200 hm^2, with an average area of over 113 hm^2 per farmer. In the EU, 82% of farms are over 20 hm^2, 52% of them over 100 hm^2 in area. In contrast, 95% of Chinese farms are less than 3.4 hm^2 in area, and these account for over 80% of the total national cultivated land (Zhao, 2021). In recent years, with the acceleration in urbanization, China's rural population is showing a trend of reduction, an aging labor force, and an increase in per capita cultivated land area. The small scale and limited capacity of farmers constrain their production efficiency and profitability. Smart agriculture is an important measure to solve these problems by confronting the diminishing advantage of population-driven economic growth and the resources and environment constraints (Klerkx et al., 2019). Smart agriculture is gaining popularity with its significant economic impacts reflected in increasing crop output, reducing labor intensity, and expanding farm size (Charania & Li, 2020). For instance, large-scale smart production management in Beijing could reduce the labor, water, fertilizer, and medicine use by 55%, 25%, 31%, and 70%, respectively (Zhao et al., 2021). It can also help promote smart technologies and maintain sustainability in agriculture (Hassina et al., 2019). Policies promoting smart agriculture have been proposed by the Communist Party of China's (CPC) central committee and the State Council in their annual

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Central No. 1 Document since 2012. Smart agriculture has become a component of China's modern agriculture following the 14th *Five-Year Plan (2021–2025) for National Socioeconomic Development and the Outline of Long-Term Objectives by 2035* adopted by the National People's Congress on March 11, 2021. A variety of other official documents have been issued to promote smart agriculture in China.

Many studies have focused on smart agriculture in China from the technical perspective, including climate-smart (Liang et al., 2021; Tong et al., 2019; Wang et al., 2018), internet (Zheng et al., 2022), and cloud (Yang et al., 2022) services. The other topics considered vary from general status and practice to path selection and policy suggestion, economic effect, and international comparison. Using macro statistical data and a national survey, Song (2020) and Cao et al. (2021) summarize the features, problems, and promotion strategies of smart agriculture in China. In the context of rural revitalization, Zhao et al. (2021) summarize the macro demand for high-quality science and technologies and the strategies and route of China to reach its smart agriculture development goal by 2035. Liu et al. (2021) examine the impact of smart agricultural production investment (SAPI) announcements on shareholder value using sampled data of 118 listed companies in China from 2010 to 2019. Ma et al. (2020) explore the smart agriculture path of China in a comparative analysis with Japan.

In summary, few studies have comprehensively reviewed the policy framework of smart agriculture in China integrating the present status, perspective, and policy suggestions. This chapter tries to fill the research gap in this regard as follows. Section 2 summarizes the definition and components of smart agriculture from the perspective of Chinese academics, discusses the extension rate and domestic industry chain, and presents a case study of smart agriculture in Zhejiang Province. Section 3 reviews the national and local policies for the promotion of smart agriculture in China. Section 4 examines the opportunities and problems of smart agriculture and the countermeasures suggested. Section 5 concludes the study, presenting the major findings and promotion features of smart agriculture in China.

2 Smart Agriculture

2.1 Definition and Components of Smart Agriculture

2.1.1 Concept and Features of Smart Agriculture

Smart agriculture originated from the agricultural informatization of developed countries after their industrialization and agricultural mechanization. This can be traced back to the soybean disease diagnosis system of plant/DS invented by the University of Illinois in 1978 (Michalski et al., 1982). According to a research report of smart agriculture development in China released by CAICT and CARD (2021), smart agriculture is defined as a new agricultural production mode and comprehensive solution deeply integrating the new generation information technology with decision-making, production, circulation, and trading.

Chinese scholars summarized smart agriculture into the following five features (Cao et al., 2021; Kang et al., 2019; Song, 2020): (1) Digitization of information perception: Using certain underlying information acquisition technologies such as Internet of Things (IoT) and 5S,[1] smart agriculture applies big data in decision making for agricultural production and management. Thus, man, machine, and things are connected in different processes to automatically perceive and accurately identify various agricultural elements, information, and environments. (2) Scientific management of decision-making: This is carried out with a highly integrated model using big data, machine learning, and artificial intelligence (AI), among other technologies. This model promotes personalized services such as quantitative analysis and investment in agricultural management. (3) Intelligent control: An intelligent network integrates AI and IoT to promote the automatic, intelligent, and unmanned operation of equipment. (4) Precision investment: A quantitative decision-making model helps to accurately optimize the resource allocation in each agricultural process and improve investment efficiency through reduced costs and consumption. (5) Personalized information service: A big data platform supplies diversified information for the benefit of agricultural business entities. Smart agriculture is a new business model and industry that will reshape the production, supply, and industrial chain. Thus, smart agriculture has great potential in the field of high-quality, efficient, green, and safe development (CAICT & CARD, 2021).

2.1.2 Components of Smart Agriculture

The fields suitable for smart agriculture in China and other countries include precision production, economic benefit accounting, food safety, and electronic commerce. Smart agriculture forms a closed loop that starts with complete and accurate data acquisition. Thereafter, a network provides a pipeline for the flow of data, taking scientific and accurate analysis as the core, and accords efficient execution by the end of the closed loop (CAICT & CARD, 2021).

Smart agriculture mainly uses the next generation information and communication technologies (ICTs), represented by the following elements (Fig. 1). (1) Big data: A database on temperature, air humidity, wind speed, wind direction, sunshine, precipitation, crop growth, irrigation and fertilization, field management, disasters, soil characteristics, and facilities useful for mining and analyzing the relationship between variables and optimizing agricultural production (Huang et al., 2018). (2) IOT: An information aggregation platform based on the interconnection of various sensors, radio frequency identification (RFID), and other electronic terminals. Its core component and foundation are still the internet, but it highlights the automatic interconnection between terminals and business applications (Yang, 2019).

[1] "5S" refers to remote sensing technology (RS), geographic information system (GIS), global positioning system (GPS), digital photogrammetry system (DPS), and expert system (ES).

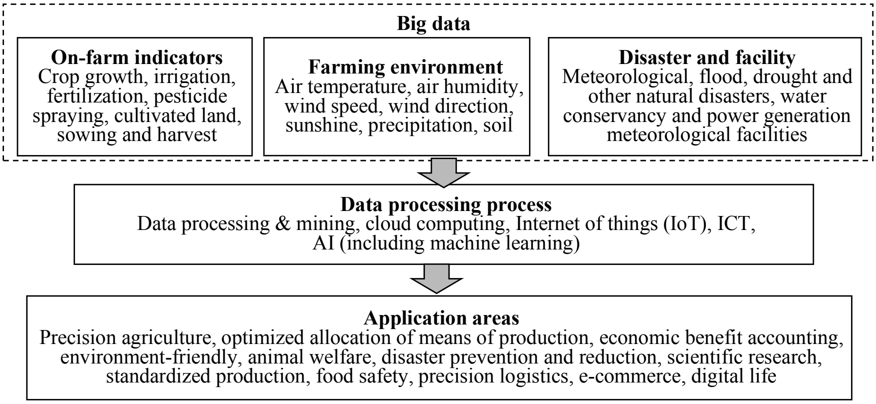

Fig. 1 Components and application fields of smart agriculture (Summarized and drawn by the authors)

(3) ICT: The general name for all communication equipment such as computers, network hardware, satellite system, and various services and application software for video conference, distance education, and so on. It provides great potential for better management of big data and efficiency improvement of agricultural production and business (Zhang et al., 2016). (4) Data mining: A process to determine the general and essential relationship between variables using statistical theories and methods through empirical analysis of large volumes of data (Xiang, 2019). (5) Cloud computing: A network formed by the interconnection of multiple computer terminals. Huge data computing tasks are decomposed into several small programs, processed and analyzed by different servers, and then fed back to users through the network (Yang et al., 2022).

2.2 Smart Agriculture Practices in China

2.2.1 Extension Rate Among Regions and Sectors

China's smart agriculture started in the 1980s. Although China's smart agriculture is backward compared with that of some leading countries, it is developing rapidly in recent years. Several new generation technologies such as IoT, sensor and remote monitoring, wireless transmission, big data and AI have been applied to agriculture. Through automation, digitalization, networking and intellectualization, smart agriculture has improved the agricultural management and production efficiency of China. According to the estimation of Qianzhan Industry Research Institute (QIRI),[2] the potential market size of China's smart agriculture has increased from US$13.7

[2] "Qianzhan" means "foresight" in Chinese. This listed institute was founded in 1998 at Tsinghua Campus, Beijing. It is committed to providing enterprises, governments, and research institutes

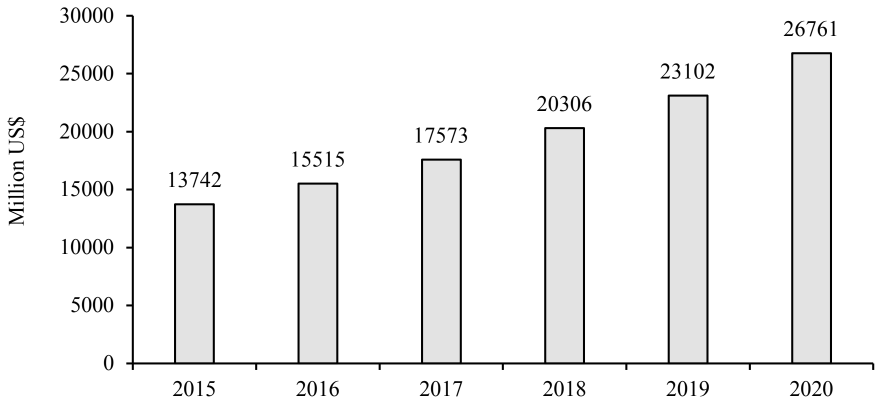

Fig. 2 Market size of smart agriculture in China from 2015 to 2020 (Reproduced from https://www.qianzhan.com/analyst/detail/220/190513-8c89e13f.html)

billion in 2015 to US$26.8 billion in 2020, representing an annual growth rate of 14.3% (Fig. 2). China's smart agriculture includes four typical application scenarios. From the market share released by the QIRI (2019), they are data platform services (40%), unmanned aerial vehicle (UAV) plant protection (35%), automatic agricultural machinery (10%) and fine breeding (15%). The 2015 and 2020 agricultural GDP of China were US$977.3 billion and US$1127.3 billion, respectively. Thus, in 5 years, the share of smart agriculture in China increased by one percent, from 1.4% to 2.4%. This indicates that China has a large potential for smart agriculture.

2.2.2 Smart Agriculture Industry Chain

China's smart agriculture has formed a relatively perfect industrial chain. The upstream chain consists of integrated circuits, satellite navigation systems, and sensors, whose components are manufactured mainly using nonferrous metals, monocrystalline silicon, and electronic ceramics. The midstream chain includes data platform, UAV plant protection, automatic machinery, and smart breeding, while the downstream chain involves the processing of plant and animal products (Fig. 3).

From Table 1, China's domestic enterprises provide the necessary products and technical support for the spread of smart agriculture in China in all sectors. Many of these enterprises are listed companies, such as CHC, Hi-Target, Hwali Create, SMIC, HIK Vision, and New Hope Group. While several of these enterprises were established around 2000, some such as COFCO Corporation, a time-honored state-owned enterprise group, were established in the 1940s, and others such as UML-Tech were new companies registered in the middle of the 2010s. The favorable policies of

with forward-looking advisory and solution reports in the fields of industrial application, planning, layout, upgrading and transformation, segmentation, and big data.

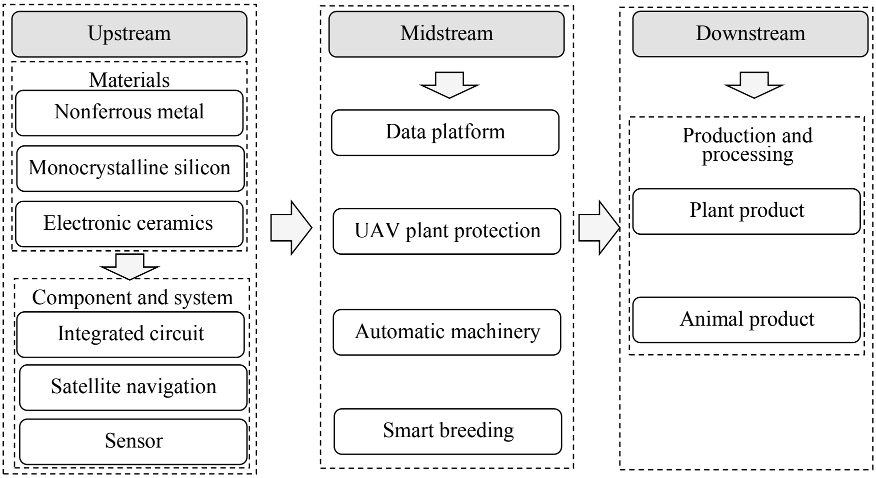

Fig. 3 Schematic diagram of China's smart agriculture industry chain (Reproduced from https://bg.qianzhan.com/trends/detail/506/211009-d9290910.html)

China prompted several traditional planting and breeding enterprises such as COFCO and Wens to adopt smart agriculture. In addition, many modern internet enterprises with smart technology have actively entered this field. For example, the internet giant NetEase started smart pig raising in 2009. It used modern technology to remotely monitor the physical condition, food intake, and excretion of pigs to provide them with a high-quality and comfortable living environment and produce delicious and safe pork (QIRI, 2021).

2.3 Case Study of the Smart Agriculture Model in Ruian County, Zhejiang Province

Located on the southeast coast, Zhejiang is one of the most economically developed provinces in China, with rural reform in a leading position. In January 2006, Zhejiang started a triune reform by integrating the farmers' cooperatives of agricultural production, supply and marketing, and credit access. In March 2006, China's first triune cooperative was established in Ruian County, southeastern Zhejiang. With hills and mountains accounting for 60.8% of the total area, Ruian is subject to frequent climatic disasters, complicated topography and soil types, and scattered individual small-scale family farms. Since 2020, Ruian has adopted the Modern Agriculture Platform (MAP) of the Syngenta Group,[3] to actively integrate smart technologies into the triune system (CPC committee & government of Ruian, 2021).

[3] Syngenta Group is a multinational state-owned enterprise established by China Sinochem Holdings Co., Ltd. on January 5, 2020. It is a global agricultural technology giant headquartered in Basel,

Table 1 Representative products suppliers of smart agriculture in China (Summarized by the authors, https://bg.qianzhan.com/trends/detail/506/211009-d9290910.html)

	Sector	Representative supplier (Year of establishment, headquarter location)
I	Satellite navigation	BdStar (2000, Beijing), CHC (2003, Shanghai), Hi-Target (1999, Guangzhou), Hwali Create (2001, Beijing)
	Integrated circuits	SMIC (2000, Shanghai), TSMC (1987, Taiwan), SK hynix (1987, Korea)
	Sensors	HIK Vision (2001, Hangzhou), Dali technology (2001, Hangzhou), Goertek (2001, Weifang)
	Nonferrous metal	Xinjiang Joinworld (1958, Urumqi), Wanfang aluminum (1996, Jiaozuo)
	Monocrystalline silicon	TJSemi (1988, Tianjin), Longi (2001, Xi'an), Jinglong (1996, Xingtai)
	Electronic ceramics	Kyocera (1959, Japan), CCTC (1970, Chaozhou)
II	Data platform	Haixinhuaxia (2008, Beijing), Aoko (2009, Beijing)
	UAV plant protection	DJI (2006, Shenzhen), XAG (2007, Guangzhou)
	Automatic machinery	UML-Tech (2014, Beijing), ComNav (2014, Shanghai)
	Smart breeding	NetEase (1997, Guangzhou), Tequ (1997, Chengdu), Wens (1983, Yunfu)
III	Plant product	COFCO Corporation (1949, Beijing)
	Animal product	Deep Agriculture AI (2015, Nanjing), New Hope Group (1982, Beijing & Chengdu)

Thus, Ruian has been able to overcome the constraints of natural conditions and achieve remarkable economic and social benefits. Using a cloud platform, MAP builds digital applications (APPs) for mobile terminals and personal computer (PC) to integrate agricultural production, management and governmental affairs. Thus, it establishes a comprehensive online service system covering subsidies and credit access, agricultural production, supply, and marketing, and the processes before, during, and after production. Using digital technologies such as remote sensing, big data, cloud computing, IoT, blockchain and the AI, this system could mainly built the four worry-free agricultural service scenarios of subsidy, loan, planting, and selling in Ruian (Fig. 4). MAP is designed to digitally promote the comprehensive upgrading of cooperative services and benefit the farmers through reduced costs and risk, and improved efficiency and profitability.

Within two years, the smart agriculture mode incorporated 1,094 cooperatives, 1,734 agricultural business entities, and 1,425 online farmer platforms. Using the whitelist system of credit authentication, it certified the credit identity of 1,425 farmers and granted 80.3 million yuan of loans. To support production, among 28

Switzerland, with operations in more than 100 countries around the world. Its main businesses include plant protection, seeds, crop nutrition, and smart agricultural technology.

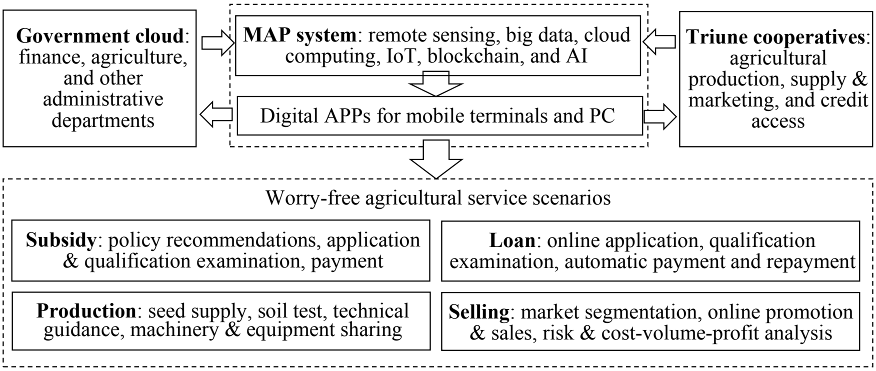

Fig. 4 Constitution of the smart agriculture system in Ruian, Zhejiang Province (Summarized and drawn by the authors)

agriculture-related services, it developed a smart early-warning system to realize real-time decision-making and action. It also established extensive cooperation in agricultural product supply, direct selling, and corresponding mechanisms for unsalable products with at least 15 e-commerce platforms, 45 farmers markets, and 196 public institution canteens (CAICT & CARD, 2021). For instance, using unified trademarks and packaging, the Meiyu vegetable cooperative created brand vegetables to enter the local high-end supermarkets and Hong Kong market, increasing their profits by four to five times. Furthermore, the introduction of robots reduced the production cost by US$1,200 per hectare (Li & Liu, 2021). In short, this case study showed that smart agriculture can play a significant role in the development of regional agriculture and the rural economy.

3 Promotion of Smart Agriculture

3.1 National Policies in China

In China, the CPC Central Committee and the State Council jointly issue their annual *Central No. 1 Document* specifying the key issues to be solved with priority every year. In 2012, the document proposed the promotion of precision agriculture technology. The following years saw the document specifying more relevant terms and preferential policies favoring the rapid extension of precision agriculture technology. In 2015, the document adopted "intelligent agriculture" with necessary technological breakthrough. In 2016, it proposed the vigorous promotion of information technologies such as internet plus, IoT, cloud computing, big data, and remote sensing. Since

2017, the document has been using the term of "smart agriculture",[4] regarding rural revitalization, rural e-commerce, and other post-2018 promotion measures[5] (Table 2).

In January 2019, the Ministry of Agriculture and Rural Affairs and the Office of the Central Network Security and Information Technology Commission jointly released the *Digital Agriculture and Rural Development Plan 2019–2025*. This plan defined the specific objectives and key tasks, and scheduled the smart transformation of agriculture and rural areas from the perspectives of resources, production and management, public service, and governance. In May 2019, the Central Committee of the CPC and the State Council issued the *Outline of Digital Village Development Strategy* proposing to complete rural digitalization by the middle of the century, specifying their phased goals and plans.

The central government's specific policies on the spread of smart agriculture must be implemented through the relevant ministries and commissions. The Ministry of Agriculture and Rural Affairs has a key role in promoting smart agriculture from the following aspects: (1) Implementing key projects: By September 2021, their targets include 9 provinces and 426 projects demonstrating IoT, 100 digital pilot projects, 210 digital demonstration bases, and 120,000 informatized machinery. (2) Special subsidies: The Guidance on Agricultural Machinery Purchase Subsidy 2021–2023 was issued jointly with the Ministry of Finance in March 2021. This increased the subsidy rate for some products to 35% and stipulated that the machinery excluded can be subsidized through special pilot or appraisals. A special project was set up to promote R&D, demonstrate and promote smart machinery, and form an innovative consortium of leading machinery enterprises. (3) Construction of informatization standards: A technical committee for agricultural informatization standardization established in 2016 included four working groups for big data, IoT, network information security, and e-commerce. A *standard system for agricultural informatization* (provisional) was formulated, and two standards, *the basic metadata of agricultural information and technical specification for agricultural data sharing*, were officially released. (4) Data sharing: Since 2016, big data and data sharing have been promoted in 21 province-level regions, with big data centers constructed for eight agricultural products such as rice, soybean, oil, and cotton. An online market information platform for staple agricultural products was established in 2017. This provided large amounts of authoritative, timely, and machine-readable data. (5) Talent training: Since 2015, 100 million farmers have been trained nationwide in smart phone application skills. Fourteen e-commerce courses have been held after 2018 covering a total of 1500 trainees (MARA, 2021a).

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[4] Here, "intelligent agriculture" and "smart agricultural" are used to differentiate the two Chinese terms of "智能农业" and "智慧农业". The main difference is that "intelligent agriculture" emphasized the industrialization of agricultural production under relatively controllable environment and conditions (Yang, 2019, p. 11).

[5] The background is that the 19th CPC National Congress held in October 2017 put forward the goal of rural revitalization.

Table 2 Topic and contents relating to smart agriculture in the *Central No. 1 Document* jointly issued annually by the Central Committee of CPC and the State Council of China in January to February (Summarized by the authors)

Year	Topic of the No. 1 Document and contents relating to smart agriculture
2012	*Accelerating the innovation of agricultural science and technology to continuously enhance the supply capacity of agricultural products*: to accelerate research on cutting-edge technologies to achieve major independent innovation achievements in information communication and precision agriculture
2013	*Accelerating the development of modern agriculture and further enhancing the vitality of rural development*: to develop agricultural information services with emphasis on information collection, accurate operation, remote digitalization and visualization, meteorological prediction and forecasting, and disaster warning
2014	*Comprehensively deepening rural reforms and accelerating agricultural modernization*: to build an information and mechanization technology system focusing on the IoT and precision equipment, promote the R&D of new industrial especially facility agriculture and intensive processing
2015	*Strengthening reform and innovation to speed up the construction of agricultural modernization*: to make major breakthroughs in intelligent agriculture, agricultural machinery and equipment
2016	*Implementing the new development concept, speeding up agricultural modernization, and the building of all-round well-off society*: to implement key projects of intelligent agriculture; to promote smart meteorology and remote sensing; Internet plus; updating agriculture through Internet^{+}, IoT, cloud computing, big data and remote sensing
2017	*Deepening the agricultural supply-side structural reforms and accelerating the cultivation of new driving forces for agricultural and rural development*: to implement smart agricultural projects and promote the demonstration of the IoT and smart equipment; to promote smart meteorology and disaster monitoring
2018	*Implementing the rural revitalization strategy*: vigorously promote digital agriculture, implement smart agriculture, and promote IoT pilot demonstration and remote sensing technology applications
2019	*Giving priority to improving the work on agriculture, rural areas and farmers*: to foster a number of technological innovation forces, and promote independent innovation in smart agriculture
2020	*Promoting the key work in agriculture, rural areas and farmers to ensure the realization of all-round well-off society on schedule*: to build agricultural and rural big data center, promoting the application of IoT, big data, blockchain, AI, the 5G mobile communication network, and smart weather forecasting
2021	*Comprehensively promoting rural revitalization, accelerating agricultural and rural modernization*: to promote smart agriculture, establish agricultural and rural big data system, and deepen the integration with new generation IT
2022	*Key work of comprehensively promoting rural revitalization in 2022*: to support the construction of smart grain depots, R&D and application of high-end smart machinery, and develop smart environmental controlling

3.2 Local Polies Promoting Smart Agricultural Technology

Under unity arrangement of the national authority, local governments have a role to play in strategic guidance, rule formulation, policy support, standard construction and improvement in public services. Many province-level regions have issued plans, guidelines, opinions and schemes to set goals for smart agriculture promotion with different paths based on their respective endowment features (Table 3). These policies aimed to promote smart agriculture by activating the key issues of infrastructure, e-commerce and information services. Local governments are encouraging and guiding the inflow of funds, talents, technology and other elements from multiple market entities such as internet enterprises, farms, groups or individuals engaging in agricultural production and management. Thus, China is forming a mechanism incorporating government guidance and market entity coordination to accelerate the digitization, networking and intellectualization of agriculture. This is a mechanism guiding resources from cities and towns to rural areas, and from other industries to agriculture.

4 Perspective of Smart Agriculture in China

4.1 Development with High Speed and Quality

4.1.1 Promoting Continuously Enriched and Improved Policies

In China, the government provides strategic guidance, rule-making, and policy support considering the specific advantages and actual conditions of various regions. The central government issues increasing plans, guidelines, opinions, and schemes to the local governments and updates them to promote smart agriculture in terms of infrastructure, e-commerce, and information services. Through standard construction and public service improvement, the government guides and encourages multiple market entities to participate in and improve the evolving system of smart agriculture, which is closely integrating with rural vitalization and digitalization of the national economy. Furthermore, China has declared to achieve its carbon emission peak and neutralization goals by 2030 and 2060, respectively. On October 24, 2021, the State Council issued the country's action plan for carbon peak by 2030, which included a plan for agriculture in 10 key sectors to promote green and low-carbon growth. Smart agriculture provides a feasible path to change the traditional mode through digital transformation and dynamically obtain resource information, support intelligent, and accurate management. Thus, it supports the precise utilization of resources, improves production efficiency, and reduces carbon emission.

Table 3 Policies related to smart agriculture in some Chinese province-level regions (Summarized by the authors)

Region	Document and main contents concerning smart agriculture
Shandong	*Digital development plan (2018–2022)* (Issued in Feb. 2019): Build a provincial smart agriculture cloud platform, a number of smart agriculture parks and demonstration bases, information centers, new ecological agriculture models integrating smart planting, breeding and processing
Heilongjiang	*Digital development plan (2019–2022)* (Issued in July 2019): Construct sky-land integrated information remote sensing and monitoring network. Accelerate the digital transformation standardization for characteristic industries of grain, oil, fruits, vegetables, dairy, forest frogs, and black pigs. Build a number of smart agriculture demonstration areas and promote the application of big data
Chongqing	*Action plan of smart agriculture development (Trial)* (Issued in Nov. 2019): Develop smart agricultural application standards and specifications, low-cost technologies and equipment, standardized data collection and AI data models, and 200 demonstration bases by 2022
Yunnan	*Implementation Opinions on accelerating the construction of digital countryside* (Issued in April 2020): Promote the dynamic monitoring of permanent basic farmland using remote sensing, the application of cloud computing, big data, IoT and AI in agriculture. Establish an intelligent supply chain for agricultural products
Jiangxi	*Three-year action plan for digital economy development (2020–2022)* (Issued in April 2020): Promote digital projects in field planting, horticultural crops, livestock and poultry breeding and aquaculture. build a smart agricultural service system and 200 Agricultural IoT demonstration bases by 2022
Henan	*Opinions on accelerating agricultural informatization and digital village construction* (Issued in April 2020): Build IoT demonstration bases for field crops such as wheat, corn, rice and peanut, build smart modes of facility agriculture, forestry and fruiter, improve information service system of animal husbandry, promote smart fishery and seeding, and improve the level of intelligence, automation and refinement of agricultural processing
Fujian	*Implementation plan of "Internet plus" agricultural products coming out of villages* (Issued in June 2020): 2020–2022, build more than 700 smart agricultural parks and IoT application bases. Improve the coverage of rural broadband, optical fiber, mobile network, satellite network to meet the needs of agricultural network
Liaoning	*Development planning of digital village* (Issued in Aug. 2020): Promote the dynamic monitoring of permanent basic farmland using remote sensing, high-resolution earth observation system in agriculture, smart agriculture center, agricultural and rural big data system

(continued)

Table 3 (continued)

Region	Document and main contents concerning smart agriculture
Hebei	*Special action plan for smart agriculture demonstration construction (2020–2025)* (Issued in Oct. 2020): By 2020, 100 bases and improve the ratio of agricultural IoT over 18%; large-scale smart facility planting, livestock, poultry, and aquaculture over 60%. By 2025, 100 large-scale smart agriculture demonstration bases and the intelligent rate of national and provincial modern agricultural parks reach 100%
Jiangsu	*Opinions on promoting the construction of digital countryside with high quality* (Issued in Jan. 2021): Build the provincial agricultural IoT service platform, 100 provincial digital agricultural in 3–5 years. Strengthen the R&D and application of key digital agricultural technology and equipment
Shanghai	*Action plan for promoting high-quality agricultural development (2021–2025)* (Issued in Jan. 2021): Build smart agricultural production bases, 10 ha unmanned farms, smart vegetable (fruit) gardens. Construct the digital agricultural information platform, improve the innovation ability of modern seed industry
Beijing	*Plan on promoting rural revitalization and accelerating agricultural-rural modernization* (Issued in Mar. 2021): Build smart agricultural innovation workshops, 5 national and 15 municipal modern agricultural parks, and 100 agricultural science and technology demonstration bases to improve agricultural digitization
Jilin	*The 14th five-year plan for the development of digital agriculture (2021–2025)* (Issued in May 2021): By 2025, build digital agriculture big data centers and cloud platforms at provincial, prefecture and county levels, to cover 80% of corn, rice, pigs and beef cattle farmers; build variety-specific big data service platform in 4 characteristic industrial fields: sika deer, ginseng, edible fungi and blueberry, covering over 90% farmers
Tianjin	*The 14th five-year plan for promoting agricultural and rural modernization* (Issued in June, 2021): Promote the construction of Tianjin Smart Agriculture Institute, the R&D in agricultural remote sensing, UAV, new sensors, big data, blockchain and robot, accelerate the industrialization of achievements in key fields such as field crops, protected horticulture, livestock and poultry breeding and aquaculture

4.1.2 Rapidly Developing Rural Telecommunication to Consolidates the Foundation

With the fast and steady deployment of infrastructure, China has roughly realized full internet coverage of its rural areas. Since 2015, the Ministry of Industry and Information Technology and Ministry of Finance have jointly implemented six universal telecommunication service pilot projects supporting the construction of more than 50,000 4G base stations with optical fiber in 130,000 villages, with about 1/3 of the facilities deployed in rural areas. By May 2021, more than 99% of the villages had access to optical fiber or 4G network, thus giving China the world's largest optical fiber and 4G network. During this period, the construction speed and scale of China's 5G network ranked first in the world, with an accelerating spread to rural areas. By the end of 2020, China had at least 718,000 5G base stations and over 200 million 5G terminals (CAICT & CARD, 2021). The rapid spread of new generation high-speed networks to rural areas could thus lay the foundation for smart agriculture in terms of hardware facilities, public interest, and skills.

4.1.3 Rapidly Increasing Capacity of New Generation Information Technology

With agricultural modernization and informatization becoming a key topic in the *Central No. 1 Document* after 2015, an increasing number of enterprises and scientific institutions have been investing in smart agriculture, significantly accelerating the transformation of achievements. According to the China National Intellectual Property Administration (https://pss-system.cnipa.gov.cn), 134 patents related to smart agriculture, internet agriculture, and agricultural informatization have been registered by August 2021. The World Intellectual Property Organization (WIPO) reported that 2064 patent applications related to smart agriculture were registered in China by August 2021; this was ranked first in the world. The number of patents in the major sectors were as follows: management and control (661), growth and breeding (580), monitoring and detection (304), information collection (276), picking and processing (64), e-commerce logistics (45), agricultural decision-making (35), and social services (26).

4.2 Constraints and Bottlenecks of Smart Agriculture

4.2.1 Need to Improve Sustainability and Independence of Most Smart Agricultural Projects

The R&D of smart agriculture takes a long period because it must cross several disciplines such as digital technology, agronomy, meteorology, and geography. Moreover, smart agriculture projects require continuous investment and face relatively greater technical and investment risks, making them less attractive to social funds. According to Cao et al. (2021), almost 50% of smart agriculture enterprises found the start-up construction costs too high, while 33% found the maintenance costs even higher, making it difficult for them to even recover their original investment. Furthermore, although the number of patent applications related to smart agriculture in China was the highest in the world, China faces a low rate of converting smart agriculture research achievements into field application. Some studies pursue the academic novelty and cutting-edge nature of the study or are guided by the criteria of article publication and project assessment, and do not fully consider the practical needs and acceptability. Moreover, China lacks independent innovation in key technologies such as crop growth modeling and production control software. Smart planting platforms, both in the field and facility of agriculture, are still in the early stages of commercialization. Several models and software were imported from institutions in the Netherlands, the US, Israel, and other countries (CAICT & CARD, 2021). Most smart agriculture pilot projects focus on the transmission and display of information, and do not deeply integrate with agriculture or have the means to solve the practical problems (Song, 2020).

4.2.2 Insufficient and Unbalanced Fiscal Investment

By having greater social than economic benefits for a long period, smart agriculture in China has made it obligatory for the government to invest and promote it. However, because of limited budgets and awareness, the government at all levels have relatively insufficient funds for investment in smart agriculture. According to the information center of the Ministry of Agriculture and Rural Affairs, the county-level[6] financial investment in agricultural and rural informatization in 2020 accounted for only 1.4% of the national financial expenditure on agriculture, forestry, and water affairs. Of the 2703 county-level administrative regions sampled for monitoring and evaluation, 535 regions, accounting for 20.2% of the sample, did not have financial investment for agricultural and rural informatization; 22% of the regions still have neither administrative department nor public institution, such as an information center to undertake information work. This indicates the urgent need to improve the institutional and personnel capacity of smart agriculture (MARA, 2021b). In addition, the funds earmarked by the government for smart agriculture tend to support platform construction, especially those with large visual screens. According to the Chinese government's procurement website, of the 709 local government procurements relating to smart agriculture during the period 2014–2020, 268 were used for platform construction. These platforms have highly similar functions and poorly meet the needs of smart agriculture (CAICT & CARD, 2021).

4.2.3 Farmers Lack the Foundation to Extend Smart Agriculture

At present, owing to the low profitability of agriculture, most young and middle-aged people seek employment in other industries. Thus, the elderly and women constitute the main labor force of agriculture and the demand for new agricultural technologies is insufficient. The multiple cropping index of cultivated land has decreased and many farmlands have been abandoned. Rural land transfer lacks orderly guidance, and this affects the scale enlargement of agricultural management. More than 98% of agricultural business entities are household farms; these account for 90% of the

[6] China has five administrative divisions, central, provincial, municipal, county, and township, of which the county and township are generally classified as rural areas.

agricultural labor and 70% of the cultivated land (CAICT & CARD, 2021). The small scale of household farms makes them less profitable and incapable to adopt new information technologies. Since 2016, the average net profit per unit area of the three major grain crops, wheat, rice, and corn, has remained negative when labor cost is included. In 2019, the average output per labor was equivalent to only 4% in Israel, 5% in the US, 15% in the EU, and 17% in Japan (Zhao et al., 2021). The high costs are generally not affordable for most farmers, and this, along with the technical thresholds, constrains the promotion of smart agriculture. Therefore, smart agriculture is generally applied to some high-value cash crops, with only a few economically strong enterprises exploring its small-scale application.

4.2.4 Smart Agricultural Talent-Training System yet to be Established

The *Outline of digital rural development strategy* and the *Digital agriculture rural development plan (2019–2025)* have a series of arrangements to train digital agricultural talent. Since 2018, the Ministry of Education has approved the proposal of more than 10 agricultural universities to set up undergraduate majors in areas such as AI, data science, and big data technology and the establishment of 15 majors in smart agriculture, 6 majors in agricultural intelligent equipment engineering, and 2 majors in smart animal husbandry science and engineering. However, this is insufficient to meet the social demand for professional talent, and most studies are still in the stage of exploration and theoretical research. In a survey by Cao et al. (2021), nearly 60% of the business entities estimated that the largest obstacle to agricultural informatization as shortage of talent. More than 80% of the enterprises have a demand gap for smart agricultural talent, of which the demand for technical talent is the largest, accounting for 59.3%. Among them, 62.9% found it difficult to recruit excellent talent, while 14.8% found this very difficult. In addition, the information technology skills training for farmers and new agricultural business entities is insufficient, with 40% of business entities saying that they lacked professional skills guidance. Thus, China's interdisciplinary smart agricultural talent training base and academic platform are yet to be fully established, implying a great demand for smart agricultural application and management talent.

4.3 Suggestions to Accelerate the Promotion of Smart Agriculture in China

4.3.1 Improve the Quality of General Development Plans

At present, the governments at all levels continue to issue plans for smart agriculture promotion, but there are problems of unclear objectives and measures, and convergence of policies in different regions (Zhao, 2020). (1) National plans should focus on financial support and R&D in key technologies, clarify the objectives of smart agriculture at each stage, such as every five years, and decompose the responsibilities to different departments and regions (Cao et al., 2021). (2) Local plans should formulate schemes in combination with the national arrangements and regional resource endowment. (3) The plans should gradually guide, considering the basic position of the market in resource allocation and the leading role of enterprises in technical R&D and promotion (Song, 2020). (4) The plans should be formulated in combination with the goals of carbon emission peaking and neutralization, with focus on smart technologies promoting energy conservation and green development in agriculture and rural areas. (5) Specific paths should be planned for different entities with focus on promoting the effective connection between small farms and modern agriculture, optimizing the scales to improve the managerial capacity of family farms, supporting cooperatives, and leading enterprises along with other large-scale entities to build modern agricultural parks (Zhao et al., 2021).

4.3.2 Increase the Amount and Efficiency of Fiscal Support

(1) Provide policy subsidies to enterprises that produce, manufacture, promote, and apply key smart agriculture technologies and products under the subsidy policy for purchase of agricultural machinery. (2) Strengthen the guiding role of finance, taxation, and insurance to attract private capital to smart agriculture infrastructure construction through loan interest discounts, finance guarantees, and other policies (Zhao, 2020). (3) Increase the support for projects set up jointly by production, teaching, and research institutions to ensure that financial funds are used more efficiently for scientific research and agricultural production through direct connection between the market, enterprises, and farmers.

4.3.3 Identify the Key Technologies and Promote Independent Research

Key technologies have the following aspects. (1) Smart service: new generation agricultural visual human-computer interaction and adaptive agricultural cloud service. (2) Smart decision-making: Agricultural big data and computational intelligence, support decision-making system, and knowledge model and algorithm. (3) Smart control: High-end plant protection UAV, smart equipment for harmless treatment of dead livestock and poultry, agricultural robot, postpartum treatment, and circulation equipment control of agricultural products. (4) Information perception: Agricultural product quality information perception, environmental information perception, agricultural machinery sensor, and life information perception (Zhao et al., 2021).

The promotion measures could be as follow: (1) Update the laws, regulations and policies related to investment, credit access, taxation and intellectual property rights protection. (2) Rely on the national key R&D program of China,[7] and the innovation fund for technology-based firms[8] to guide enterprises to participate in the R&D of smart agriculture. (3) Integrate the market mechanism and specific projects in R&D, demonstrate and apply key smart technologies and products, encourage service-oriented enterprises to engage in agricultural businesses in market report and digital finance forms, and guide the smart transformation of agricultural enterprises (CAICT & CARD, 2021).

4.3.4 Improve the Education, Training and Technology Promotion System

(1) Strengthen the information technology training for farmers: Use highly popularized information means such as smart phone Apps, social network sites (SNS), and webcasts to improve farmers' cognition and interest in smart technology, and supplement this through offline training activities to remove the constraints of conventional production (Wang, 2020). (2) Create a multiple-subject cultivation system: Following the government or industry association initiatives, collaborate with the education, research, and technology institutes in promoting smart skills in rural areas by providing platforms, personnel, and resources. (3) Cultivate skills in school education: Innovate the curriculum, teaching material, and methods of courses to ensure that students obtain digital skills. Furthermore, promote the vocational education system by increasing the enrollment of students and create smart technology-related courses to meet the needs of agricultural production and management (CAICT & CARD, 2021). (4) Create conditions for all types of talents to participate in smart agriculture: Establish cooperatives, information platforms, and other institutions and supplement them through preferential measures, such as low-interest loans and tax reliefs to facilitate entrepreneurship and social services, and popularize smart technologies in agriculture and rural areas (Song, 2020).

[7] This was established in 2015 and managed by the Ministry of Science and Technology to fund major studies of social welfare as well as the development of key technologies and products relating to the core industrial competitiveness, the overall independent innovation ability and national security.

[8] This was established with the approval of the State Council in 1999 and managed by the Ministry of Science and Technology under the supervision of the Ministry of Finance. It gives full play to the guiding role of financial funds and channel social funds and other innovative resources to support the development of science and technology-based small and medium-sized enterprises, through free subsidies, loan discount, and capital investment (http://innofund.chinatorch.gov.cn/english2/index.shtml).

5 Conclusion

The government of China has issued a series of policies at the national and regional levels for the promotion of high-quality agricultural development, rural revitalization, and green and low-carbon development and to accelerate the spread of smart agriculture, which has attracted the attention of many scholars. In recent years, China is witnessing a rapid increase in its smart agriculture market scale, technology, R&D, and promotion, and the industrial chain has begun to take shape. With the support of consistently improving policies, popularization of the rural telecommunications industry, and the continuous enhancement of information technology and R&D capacity, the overall perspective of smart agriculture in China appears optimistic. A case study of the practices in Ruian County of Zhejiang Province has confirmed this. However, smart agriculture confronts constraints from poor project independence and sustainability, unbalanced and inefficient financial support, weak economic and knowledge base of farmers, and a lagged talent training system. From academic findings, smart agriculture in China can be further promoted through better overall planning, increased efficiency of financial investment and R&D of independent technology, and an improved training and technology promotion system.

China's mode to promote smart agriculture depends on the overwhelming ratio of small-scale farms, relying on government policies and investment to increase the participation of large enterprises. It also focuses on the digital village, carbon peak and neutralization to gradually improve the farmers' professional quality, managerial scale and the utilization efficiency of agricultural resources and rural ecological environment. The huge agricultural and rural economy of China and its ever-changing production and R&D practices provide a broad space for further qualitative and quantitative studies, summarizing the modes and effect, popularizing the experience, and deepening the follow-up analyses of smart agriculture.

References

CAICT (China Academy of Information and Communications Technology), & CARD (Center for Agricultural and Rural Digital Development) of Renmin University. (2021). *Research report on the development of China's smart agriculture: new generation information technology improves rural revitalization* (in Chinese). http://www.caict.ac.cn/kxyj/qwfb/ztbg/202201/P020220104495485440718.pdf. Accessed 10 February 2022.

Cao, B. X., Li, J., Feng, X., & He, F. (2021). Development status, path, and countermeasures of smart agriculture in China (in Chinese). *Research of Agricultural Modernization, 42*(5), 785–794. https://doi.org/10.13872/j.1000-0275.2021.0091

Charania, I., & Li, X. (2020). Smart farming: Agriculture's shift from a labor intensive to technology native industry. *Internet of Things (Netherlands), 9*, 100142. https://doi.org/10.1016/j.iot.2019.100142

CPC committee and government of Ruian. (2021). Theoretical guidance and reform innovation: The deepening comprehensive triune cooperation reform in Ruian (in Chinese). *China Farmers' Coop, 8*, 40–42.

Hassina A. I., A. Rachida & J. P. Joel. (2019). A comprehensive review of data mining techniques in smart agriculture. *Engineering in Agriculture, Environment and Food, 12*(4), 511–525.

Huang, Y., Chen, Z. X., Yu, T., Huang, X. Z., & Gu, X. F. (2018). Agricultural remote sensing big data: Management and applications. *Journal of Integrative Agriculture, 17*(9), 1915–1931. https://doi.org/10.1016/S2095-3119(17)61859-8

Kang, M., Wang, X., Hua, J., Wang, H., & Wang, F. (2019). Parallel agriculture: Intelligent technology toward smart agriculture (in Chinese). *Chinese Journal of Intelligent Science and Technology, 1*(2), 107–117. https://doi.org/10.11959/j.issn.2096-6652.201904

Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS—Wageningen Journal of Life Sciences, 90–91*(October), 100315. https://doi.org/10.1016/j.njas.2019.100315

Li, X., & Liu, X. (2021). Implementing the triune reform to improve the cooperative development: On Ruian Meiyu vegetable professional cooperative (in Chinese). *China Farmers' Coop., 8*, 43–44.

Liang, Z., Zhang, L., Li, W., Zhang, J., & Frewer, L. J. (2021). Adoption of combinations of adaptive and mitigatory climate-smart agricultural practices and its impacts on rice yield and income: Empirical evidence from Hubei China. *Climate Risk Management, 32*, 100314. https://doi.org/10.1016/j.crm.2021.100314

Liu, W., Long, S., Wang, S., Tang, O., Hou, J., & Zhang, J. (2021). Effects of smart agricultural production investment announcements on shareholder value: Evidence from China. *Journal of Management Science and Engineering*. https://doi.org/10.1016/j.jmse.2021.12.007

Ma, H., Mao, S., & Chen, X. (2020). Exploring the development path of smart agriculture in China: Based on the comparative analysis between China and Japan (in Chinese). *Issues in Agricultural Economy, 12*, 87–98.

MARA (Ministry of Agriculture and Rural Affairs). (2021a). *Reply to recommendation No. 9961 of the fourth session of the 13th National People's Congress* (in Chinese).

MARA (Ministry of Agriculture and Rural Affairs). (2021b). *National County agricultural and rural information development level evaluation report* (in Chinese). http://www.agri.cn/V20/ztzl_1/sznync/ltbg/202112/P020211220311961420836.pdf. Accessed 10 February 2022.

Michalski, R., Davis, J., Bisht, V., & Sinclair, J. (1982). Plant/ds: An expert consulting system fo the diagnosis of soybean diseases. *Ecai-82 1982 European Conference on Artificial Intelligence*. http://mars.gmu.edu/handle/1920/1565. Accessed 10 February 2022.

QIRI (Qianzhan Industry Research Institute). (2019). *Status and market prospect of smart agriculture in China* (in Chinese).

QIRI. (2021). *Status, competition pattern and development prospect of China's smart agriculture industry chain* (in Chinese). https://bg.qianzhan.com/trends/detail/506/211009-d9290910.html

Song, H. (2020). The status and problems of smart agriculture development and responses (in Chinese). *People's Tribune Academic Frontier, 24*, 62–69.

Tong, Q., Swallow, B., Zhang, L., & Zhang, J. (2019). The roles of risk aversion and climate-smart agriculture in climate risk management: Evidence from rice production in the Jianghan Plain China. *Climate Risk Management, 26*(May), 100199. https://doi.org/10.1016/j.crm.2019.100199

Wang, J. (2020). Research on development situation of big data application in the era of smart agriculture (in Chinese). *Journal of Technical Economics and Management, 2*, 124–128.

Wang, Y., Guan, D., Wang, Q., Li, C., Liu, H., Xin, L., & Hu, Z. (2018). The practical exploration of climate-smart agriculture in China (in Chinese). *Chinese Journal of Agricultural Resources and Regional Planning, 39*(10), 43–50. https://doi.org/10.7621/cjarrp.1005-9121.20181007

Xiang, M. (2019). Design of agricultural data platform based on internet + data mining (in Chinese). *Journal of Southwest China Normal University (Natural Science Edition), 44*(9), 76–81.

Yang, D. (2019). Smart agriculture practice, Beijing (in Chinese) (pp. 3–15). People's Posts and Telecommunications Press.

Yang, G. F., Yang, Y., He, Z. K., Zhang, X. Y., & He, Y. (2022). A rapid, low-cost deep learning system to classify strawberry disease based on cloud service. *Journal of Integrative Agriculture, 21*(2), 460–473. https://doi.org/10.1016/S2095-3119(21)63604-3

Zhang, Y., Wang, L., & Duan, Y. (2016). Agricultural information dissemination using ICTs: A review and analysis of information dissemination models in China. *Information Processing in Agriculture, 3*(1), 17–29. https://doi.org/10.1016/j.inpa.2015.11.002

Zhao, C. (2021). Current situations and prospects of smart agriculture (in Chinese). *Journal of South China Agricultural University, 42*(6), 1–7.

Zhao, C., Li, J., & Feng, X. (2021). Development strategy of smart agriculture for 2035 in China (in Chinese). *Strategic Studies of CAE, 23*(4), 1–9. https://doi.org/10.15302/J-SSCAE-2021.04.001

Zhao, M. (2020). Economic explanation and breakthrough path of smart agriculture. *People's Tribune Academic Frontier, 24*, 70–79.

Zheng, Y. Y., Zhu, T. H., & Jia, W. (2022). Does Internet use promote the adoption of agricultural technology? Evidence from 1449 farm households in 14 Chinese provinces. *Journal of Integrative Agriculture, 21*(1), 282–292. https://doi.org/10.1016/S2095-3119(21)63750-4

Chapter 13
Impacts and Policy Implication of Smart Farming Technologies on Rice Production in Japan

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1 Introduction

Rice is the most important staple crop in Japan as well as many Asian countries. It accounted for the largest proportion in the gross agriculture output in long period as a single crop. However, the gross production of rice has been decreasing in recent decades, although it slightly increased since 2015. In this context, Japanese government decided to promote efficient and competitive rice production. According to the *Japan Revitalization Strategy* released in 2013, the costs of rice production need to be reduced by 40% in the following 10 years. To this end, the adoption of advanced technologies and optimized farm management are essential for further agricultural development.

Since the 1990s, smart farming technologies have been widely applied in developed western countries to monitor and analyze the farming condition and yields, and optimize management accordingly (Nanseki, 2019a; Nanseki et al., 2016). Within the latest decades, agricultural legal persons/entities including corporations have become important in farm management in the agricultural sector. Some are "*corporation qualified to own cropland*" (formerly, *agricultural production legal person*), who can possess and transact farmland like a farmer. They have grown significantly in

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number from 2,740 in 1970 to 19,550 by 2020 (MAFF, 2021), covering all agricultural sectors. Compared with the small-scale farms mostly operated by family labor, farming corporations are operated by hired labor. Many larger farms are agricultural legal persons that have larger farm size and better market channels as well as capable human resources (Nanseki, 2021). Thus, it is feasible for farming corporations to adopt smart farming technologies for their further development.

This chapter aims to discuss impacts and policy implications of smart farming technologies on rice production in Japan. Based on several research projects, which are organized by the first author of this chapter, research framework and major findings of impacts of smart farming on rice production are outlined in this chapter. Then policy implications, in terms of impacts of smart agriculture on rice farming, are discussed based on these findings.

2 Research Framework and Methodology

In the project, we aimed to build big data on rice farming in light of the findings on yields and quality analysis, soil analysis, plant growth, environmental observation of air temperature, water temperature, water depth, and records of cultivation and management. Furthermore, via the analysis of this large database, we developed and demonstrated the new generation large-scale rice farming technology system, integrating with the agricultural machinery, field sensors, farming visualization and skill-transferring system. The system can be useful to increase yield and reduce production cost of rice. This chapter is based on Nanseki et al. (2016, 2021), Nanseki (2019a, 2019b), and Li and Nanseki (2021).

The research framework and smart farming technologies in the project are illustrated in Fig. 1. They are summarized in three stages: (1) The field-specific data of farming, meteorology, soil and cropping, collected and visualized using the farming visualization system (FVS). (2) Big data visualization and analysis in the cloud system. (3) Optimized production and operational management against the risks of meteorological and market changes. The application of these technologies mainly led to stabilized and improved yield and quality, through visualized soil properties, meteorology, high-precision cultivation responding to meteorological changes, and efficient, time and costs saving operation by visualized know-how, IT agriculture machinery, labor, and inputs saving cultivation.

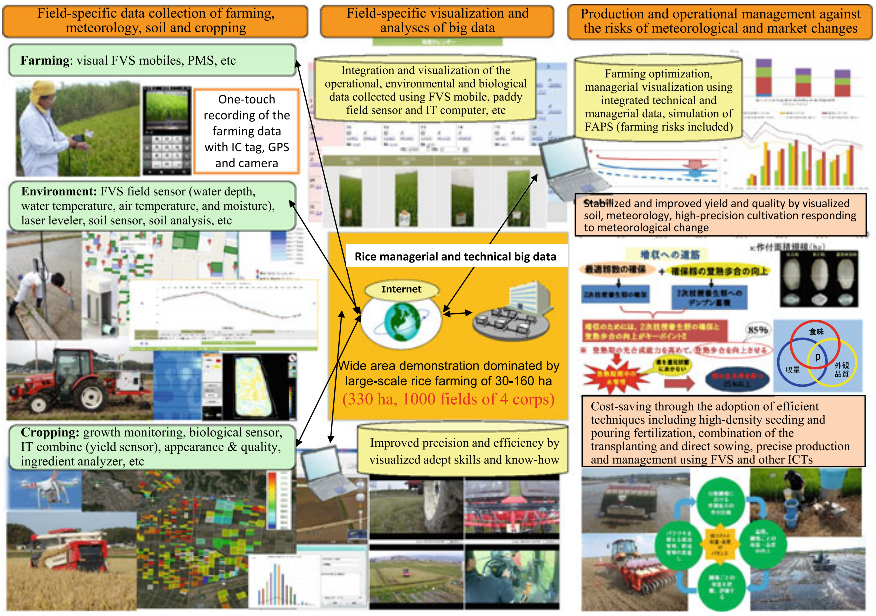

Fig. 1 Research flamework and smart farming technologies in the project (Reproduced from Nanseki, 2019a, p. 163)

2.1 Rice Production Cost

To propose the actions to decrease unit production cost (e.g. JPN/kg) of rice, it is important to increase yield (e.g. ton/ha) of rice as well as to decrease total cost of the farm. Therefore, it is crucial to measure cost of rice production based on farm records including both economic and physical inputs as well as both outputs. Yield is important physical output. This makes it possible to estimate unit production cost of rice shown in this chapter.

2.2 Rice Yield and Its Determinants

To increase yield at farm level, it is important to measure yield of each parcel of all paddy fields of the farm. To date, this was only possible in research paddy fields of research institutes and universities and was not feasible in actual farm operation on real farms. However, smart farming technologies make this possible in real farms recently.

There are several types of yield measuring both the quantity and quality of rice (Fig. 2). First, the data of raw paddy yield (Y1) and moisture is collected using the IT combines, where a small matchbox sized sensor is set at the input slot of

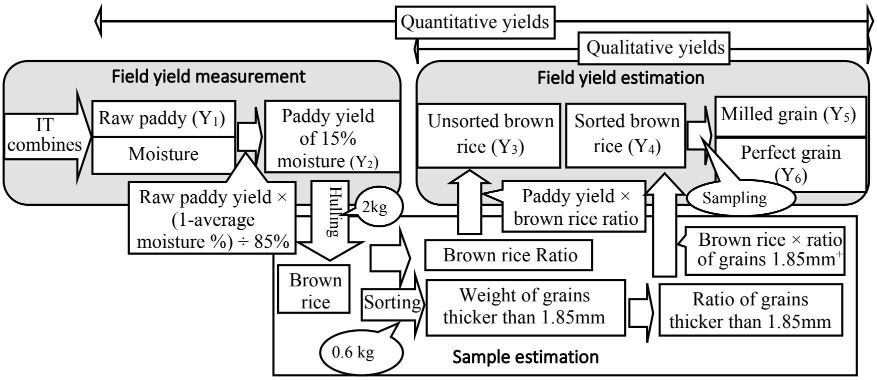

Fig. 2 Process of estimating the rice yields from raw paddy to milled and perfectly shaped grains (Reproduced from Nanseki, 2019a, p. 166)

the grain tank. Thereafter, the field-specific data with the global navigation satellite system (GNSS) is conveyed to the cloud server shared by the company, institutes, and farms. Furthermore, the yield of the paddy with 15% moisture (Y2) is calculated. Brown rice yield (Y3) is then sampled and estimated after hulling, and the sorted yield (Y4) retains only grains thicker than 1.85 mm. Finally, rice yield is estimated in terms of the sampled weight of milled rice (Y5), and perfectly shaped rice (Y6). Since the unsorted brown rice, ratios of a certain yield to another, prior to this estimating process, indicate the grain quality of each paddy field. In addition, due to their closer link to the market value in Japan, average weights of the milled and perfect grain can also indicate rice quality.

To identify the determinants of rice yield, we conducted series empirical studies, using data of the 1000 paddy fields totaling 330 ha, from four farming corporations in different regions of Japan. The yields of Y1 through Y6 defined above are used as the output variables. The inputs included (1) field properties of the area, soil property and farming condition, (2) production management of the transplanting or sowing date and fertilized nitrogen amount, (3) stage-specific growth indices of panicles per hill, culm length, and so on, (4) average temperature and solar radiation of 20 days since heading, (5) water temperature and depth in four growth stages, and (6) rice variety, cultivation regime, and soil type. The major empirical models included multivariate regression, analysis of variance (ANOVA), and correlation analysis. Path analysis was adopted to include the interacting effects of the yield determinants. Data envelopment analysis and Tobit regression were applied to analyze production efficiency and significant determinants of individual paddy fields (Fig. 3).

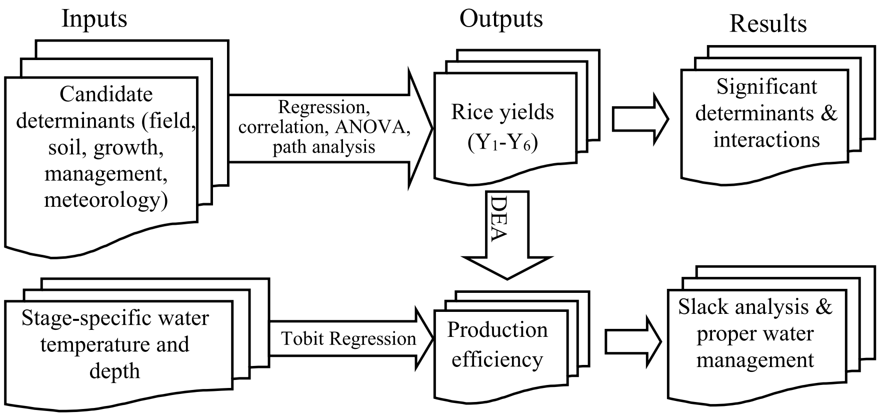

Fig. 3 General scenario of estimating the results in empirical analyses summarized in this research (Reproduced from Nanseki, 2019a, p. 167)

2.3 Cost–benefit Analysis of Automatic Paddy Water Supply Systems

Based on results of the big data, it was considered that improving water management is one of feasible way to increase efficiency and yield in rice production. Thus, we developed several types of automatic water supply systems and conducted field tests of these. One type is the Internet of Things (IoT) type and the other type is basic type. The IoT–type system has an Internet connection and digital camera. The system can be controlled by smart phone to supply and stop water as well as setting upper and lower limits manually. It can send images of paddy captured by equipped digital camera. This enables farmers to monitor both water and rice plants via the Internet. Basic type has no Internet connection or digital camera. The system can be controlled to supply and stop water by setting upper and lower limits manually. We then estimated the benefits and costs of both automatic paddy water supply systems for a 50 ha rice farm.

3 Results and Discussion

3.1 Rice Production Cost and the Reduction

Empirical findings of the project (Nanseki, 2019a; Nanseki et al., 2016) find factors contribute to increase rice yields in real farming. This leads to a reduction in the production cost of rice. The cost is mainly comprised of the property and labor costs. The percentage of labor cost to total cost is 67.41% for over 15 ha farm average of Japan nationwide statistics. In the project, the percentage is 67.64% for farms of

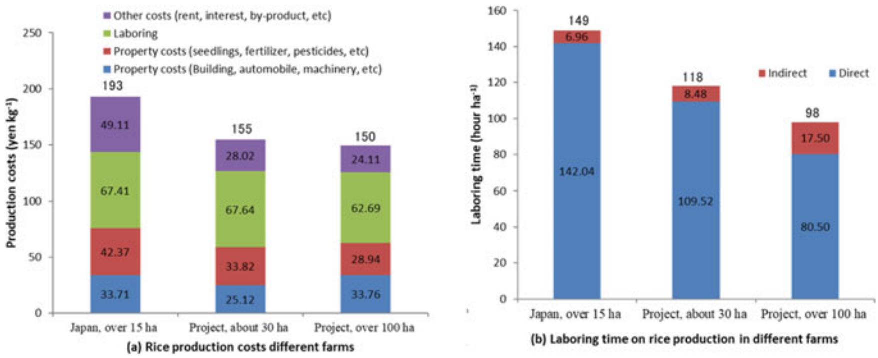

Fig. 4 Production cost and labor time of the farms in the project (Reproduced from Nanseki et al., 2016, pp. 9–10)

30 ha and 62.69% for those over 100 ha. Thus, as shown in Fig. 4, labor costs account for the highest percentage of costs in all farms involved in the project.

In farms scaled over 15 ha of the nationwide statistics, the average production cost of sorted rice was 193 JPY per kilogram (Fig. 4(a)). On the other hand, the average cost per kg of farms involved in the projects decreased to 155 JPY for 30 ha farms and 150 JPY for those over 100 ha. According to national statistics, the average labor time for farms over 15 ha is 149 h per ha. On the other hand, that for farms involved in the projects decreased to 118 h and 98 h per ha for farms over 30 ha and over 100 ha, respectively (Fig. 4(b)).

Cost curves of existing farms, present frontiers of advanced farms, and future frontiers of advanced farms are illustrated in Fig. 5. The cost curve of existing farms is drawn based on government statistics. That of present frontiers of advanced farms is drawn based on actual data of farms involved in the projects. For future frontiers of advanced farms, it is drawn based on the perspective based on the analysis in the project. The cost typically decreases when farming scale increases, by adopting new management and technologies. Nevertheless, it is difficult to further reduce production cost by merely increasing scale without any innovation. Hence, it is essential to adopt smart technologies to increase yield for efficient and competitive rice production. Through further technological innovation, the cost curve of future frontiers of advanced farms can be shifted to approximately 100 JPY per kg. To achieve this, it is necessary to increase yield by 20% as well as a 20% decrease in both fixed and variable costs (Nanseki, 2020).

For improving the average yield of an entire farm by 20%, we need to reduce the yield gap between fields by developing and introducing new high-yield varieties that meet demand and smart agriculture technologies represented by advanced production management utilizing information and communication technology (ICT). For reducing fixed costs by 20%, those such as depreciation expenses need to be reduced by increasing the scale of complexes (e.g., more than 200 ha) and expanding each parcel of paddy (e.g., 1 ha), as well as improving operation skills of machines and

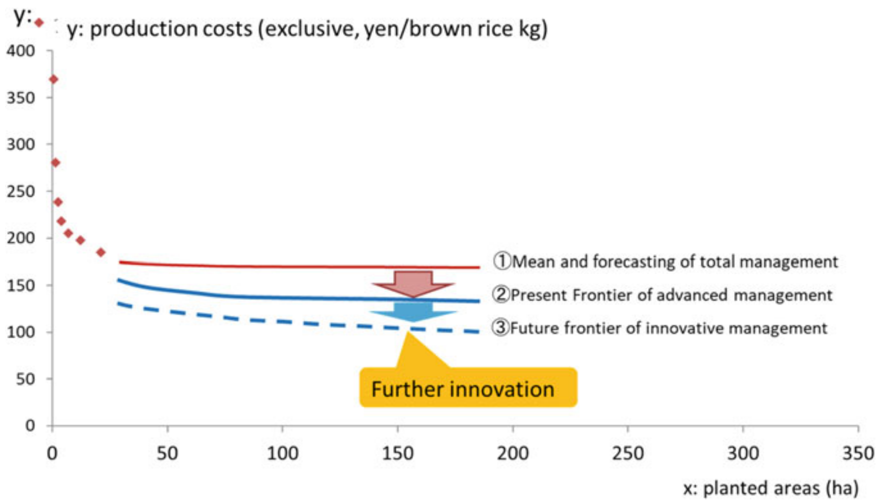

Fig. 5 Rice production cost and planted area in Japan (Reproduced from Nanseki et al., 2016, p. 5)

facilities. For reducing variable cost by 20%, we need to reduce variable expenses by optimizing the prices and input volumes of input materials, such as fertilizers and pesticides and machinery facilities, as well as land rent levels.

3.2 Rice Yield of Each Paddy Field and Its Determinants

The results of big data analysis (Li & Nanseki, 2021) indicate that the significant determinants of rice yield include suitable variety adoption, earlier transplanting or sowing and hence longer period for vegetative accumulation, sufficient nitrogen application, temperature and solar radiation, appropriate field areas as well as both temperature and depth of paddy water. Water temperature affects the technical efficiency more than water depth, and the 25 days from heading to grain filling is important to improve technical efficiency. Therefore, better water management based on real time sensing of paddy environment and plant is important under the situation of climate changes.

A summary of the results regarding the impact of water temperature and depth on yields is reported in Table 1 (Li & Nanseki, 2021, pp. 131–166). In the second stage DEA of two farms of the project (Farm B and Y), 10 paddy fields with the highest and lowest technical efficiency were selected for comparison. From the average values of the two groups, Farm B (0.026) was smaller than that of Farm Y (0.054), which indicates that the disparity of technical efficiency between paddy fields was smaller in Farm B. The growth stage was divided into four stages. S1 included the 40 days from transplanting to fully tillering, S2 covered the duration from fully tillering to heading, S3 referred to the 25 days from heading to grain filling, that

Table 1 Average water depth and water temperature of High-10 and Low-10 paddy fields in terms of efficiency (Li & Nanseki, 2021, pp.131–166)

Farm	Mean of paddy fields	Peer count	Technical efficiency	Water depth (mean of 18:30, mm)				Water temperature (mean of 18:30, °C)			
				S_1	S_2	S_3	S_4	S_1	S_2	S_3	S_4
B	High-10	24.9	1.000	36.72	22.18	16.43	5.58	23.26	26.23	26.16	23.00
	Low-10	0.0	0.974	51.68	29.90	12.75	9.55	24.42	26.36	27.39	24.24
	Differ (high-low)	24.9	0.026	-14.96^{**}	–7.71	3.68	–3.97	-1.16^{**}	–0.13	-1.23^{**}	-1.24^{***}
Y	High-10	18.4	1.000	45.62	19.90	35.82	11.21	24.63	27.54	26.67	22.93
	Low-10	0.0	0.946	43.45	18.65	39.50	8.19	24.31	26.46	27.94	22.82
	Differ (high-low)	18.4	0.054	2.17	1.25	–3.68	3.02	0.32	1.08^{***}	-1.27^{**}	0.11

Note Peer is a model reference for evaluating the efficiency of other paddy fields. *** and **: significant at 1% and 5%, respectively is, the early-middle maturity stage, and S4 consisted of the remaining days until complete maturity. The water depth and temperature were measured by sensors at 10-min intervals. According to the previous research results and expert opinions (Nanseki, 2019a, 2019b), the daily data of specific time (18:30), with the greatest impact of water depth on water temperature, was selected for analysis. According to the average values of 10 paddy fields with the highest and lowest technical efficiency, there are significant differences between S1 water depth and water temperature of all the stages except S2 in Farm B, while significant differences were observed in water temperature between S2 and S3 in Farm Y (Table 1). Therefore, the results indicate that water depth and water temperature had a stronger impact on rice y ield.

Furthermore, the results reveal that the water temperature had a stronger impact on rice yield than water depth; specifically, the lower the average water temperature of S3, the higher the technical efficiency of production. According to Tsujimoto et al. (2009), rice is most sensitive to water temperature in the early booting stage. When the measured temperature is higher than 26 °C, it is beneficial to maintain the activity of root and stem and promote the growth of rice grain.

Direct control of the water temperature of paddy fields is not practically possible in real farms because of the cost. However, control of the water depth is possible and much easier than that of water temperature. The results also empirically confirm that the water temperature is affected by the water depth based on the data of real farm as expected. This implies that better control of the water depth makes it possible to increase yields of rice.

3.3 Cost and Benefit Analysis of Automatic Paddy Water Supply Systems

Figure 6 shows the Internet of Things (IoT) type and the basic type of automatic paddy water supply systems. Table 2 shows the results of both types of costs-benefit analysis of automatic paddy water supply systems for a 50 ha rice farm. In the case of the IoT-type system, which can be controlled through Internet, the benefit of labor-saving effect and revenue (yield) increase effect are 2.80 and 3.38 million JPY, respectively. The total benefit is thus 6.18 million JPY. On the other hand, the cost is 5.60 million JPY. Consequently, the net balance for the IoT-type is plus 0.58 million JPY. This result implies that if both the effects of labor-saving and revenue (yield) increase can be realized, the IoT-type system should be introduced. Furthermore, this result implies that any single effect is not sufficient. This is also true in the case of the basic type; the advantage of the basic type exceeds that of the IoT-type. This implies that the basic type is more useful than IoT-type from an economic viewpoint.

Additionally, the impacts of advanced smart farming technologies are introduced and discussed here based on our research. One of the most well-known smart farming technologies in Japan is the robot tractor, which can run and tillage automatically without a human operator. We estimated the impact of future robot tractor, baby rice

Fig. 6 Automatic paddy water supply systems (IoT type: photo by the author. Basic type: reproduced from https://www.facebook.com/watch/?v=260776628541439)

plant planting robot, harvester robot and water supply robot via stochastic optimal farm planning analysis (Nanseki, 2019a, 2019b, 2022). The results reveal that physical farm size expansion effect is less than 8% at maximum for all kinds of farming robots. This implies that the impacts of these smart agriculture technologies on the expansion of both physical and economic farm size are limited. Furthermore, the cost of introducing these robots overcomes the benefit. As a result, production costs of a farm that introduces these robots is higher than the cost of a farm without these. The reason is that they are for only specific farming operations such as baby rice plant planting, water depth control, and harvesting, as well as tillage and plowing. Additionally, they can be used in only specific season of the year. This is unlike dairy farms, which utilize many kinds of farming robots every day. Our latest results (Nanseki, 2022, pp. 183–208) demonstrate that these advanced smart agriculture technologies have much larger impacts on labor saving.

4 Conclusion and Implications

The challenge of our research project on rice production Japan is demonstrating that a technology package (Nanseki 2019a, 2020) can achieve a production cost of 100 yen for brown rice at the actual production scale. The technology package should optimally combine the elemental technologies of agricultural technology (e.g., transplanting, dense seedling, direct sowing cultivation, etc.) and ICT (e.g., robotic agricultural machines, IoT sensors, management optimization systems, artificial intelligence, etc.) according to the management strategy. Further research and development on these topics are expected.

These results of the project reveal that smart farming technologies have positive impacts on rice production. However, the results also indicate that more practical smart farming technologies, such as the basic type of water supply system, may have

Table 2 Cost–benefit analysis of automatic paddy water supply systems (Revised version of Nanseki, 2019b)

Type	Benefits/ costs	In million JPY	Assumption (based on local demonstration results)
IoT type	1. Labor-saving effect by introducing IoT type	2.80	80% reduction in water management (labor cost: 5600 JPY/10a)
	2. Revenue increase effect by introduction of IoT type	3.38	Yield increased by 5% from 450 kg/10a, unit price 300 JPY/kg
	3. Cost increase due to introduction of IoT type	5.60	One automatic water supply system is installed at 25a (Practical target price of 80,000 JPY, service life of 5 years). System operation cost for agricultural platform etc. is 12,000 JPY/year Total annual cost increased by 28,000 JPY/25a
	4. IoT type balance (=1 + 2–3)	0.58	
Basic type	5. Labor saving effect by introduction of basic type	1.75	50% reduction in water management (labor costs 3,500 JPY/10a)
	6. Increased sales due to introduction of basic type	1.69	Yield increased by 2.5% from 450 kg/10a, unit price 300 JPY/kg
	7. Cost increase due to introduction of basic type	2.00	One automatic water supply system is installed at 25a (Practical target price of 50,000 JPY, useful life of 5 years). Annual cost increase of 10,000 JPY/25a
	8. Basic type balance (=5 + 6–7)	1.44	

Note 50 ha rice farm is assumed for estimation of cost and benefit

larger impacts on real rice production than more advanced technologies, such as the IoT-type of water supply system at this moment. This implies that only appropriate technologies for real farms can contribute to agricultural innovation.

Research and development (R&D) and extension of advanced smart farming technologies are now strongly promoted by the policy of the government. As shown in this chapter, the results of our research projects imply that R&D of practical technologies that have more impacts on real farms should be also promoted in policy. Advanced technologies are not always useful for real farms in developing countries but also in developed countries.

The cost reductions can be made through management efforts, such as increasing yield by improving cultivation management technology and skills, optimizing the amount of input materials, using machinery and facilities efficiently by improving operation technology and skills, and expanding the management scale, accumulating farmland, and performing large compartmentalization. However, none of the following cost reductions can be achieved solely through the efforts of farmers, and policy support is also essential: the development of high-yield new varieties and smart agricultural technology, improvements in the service life of machinery facilities, the optimization of agricultural materials, machinery prices, and land rent levels, and the expansion of the management scale, the accumulation of farmland, and large compartmentalization, all at regional level.

A remain topic for further research is to estimate impacts of smart farming technologies on the environment. It has been reported that paddy fields are a source of methane, which accelerate climatic change. Better water depth control can decrease methane emissions from paddy field (NARO, 2012). From these aspects, estimates of the impact of automatic paddy water supply system on methane emissions will be an important and practical research topic. As shown in Nanseki (2022), smart farming is expected to contribute to environmentally friendly agriculture in EU. These issues will become to be more important in Asia.

On smart farming in general, an important topic which we do not discuss in this chapter is risk of smart farming. Any technology has benefits, limitations and risks. This is true for smart farming technology. Evaluation of risk of smart farming is needed for better understanding the technology. The other topic is differences in impacts of smart farming among crops. Nanseki (2022) gives details explanations and discussions on these points.

References

Li, D., & Nanseki, T. (2021). In D. Li & T. Nanseki (Eds.), *Empirical analyses on rice yield determinants of smart farming in Japan*. Springer.

MAFF (Ministry of Agriculture Forestry and Fisheries). (2021). *Corporation qualified to own cropland* (in Japanese). https://www.maff.go.jp/j/keiei/koukai/sannyu/attach/pdf/kigyou_sannyu-28.pdf

Nanseki, T. (2019a). In T. Nanseki (Ed.), *Smart agriculture practice in rice-farming and perspective of farm in next-generation* (in Japanese). Yokendo.

Nanseki, T. (2019b). Impacts of smart agriculture technologies on farm management. *APFITA 2019b International conference, Taichung, Taiwan* (vol. 4).

Nanseki, T. (2020). Comparison of rice production costs in Japan, Italy, and the US and measures to improve the international competitiveness of Japanese rice. In S. Ito & Y. Matsue (Eds.), *Japonica rice in the world : Marketing, palatability and prospects* (in Japanese) (pp. 18–45). Yokendo.

Nanseki, T. (2021). *Agricultural corporations as seen from fact data: Profile, business operation, strategy and innovation* (in Japanese). Agriculture and Forestry Statistics Publishing Inc.

Nanseki, T. (2022). In T. Nanseki (Ed.), *Agricultural innovation in the era of digital & genome revolution* (in Japanese) (p. 322). Agriculture and Forestry Statistics Publishing Inc.

Nanseki, T., Chomei, Y., & Matsue, Y. (2016). In T. Nanseki, Y. Chomei, & Y. Matsue (Eds.), *Rice farm management innovation and smart agriculture in TPP era: Farming technology package and ICT applications* (in Japanese). Yokendo.

Nanseki, T., Li, D., & Chomei, Y. (2021). Impacts and policy implication of smart farming technologies on rice production in Japan. *The 10th Asian society agricultural economist international conference, Beijing, China.*

NARO (National Agriculture and Food Research Organization). (2012). *New water management technical manual for controlling paddy methane generation* (in Japanese). https://www.naro.affrc.go.jp/archive/niaes/techdoc/methane_manual.pdf

Tsujimoto, Y., Horie, T., Randriamihary, H., Shiraiwa, T., & Homma, K. (2009). Soil management: The key factors for higher productivity in the fields utilizing the system of rice intensification (SRI) in the central highland of Madagascar. *Agricultural Systems, 100*(1–3), 61–71. https://doi.org/10.1016/j.agsy.2009.01.001

Chapter 14
Smart Farming Technology Adoption and Its Determinants in Japan

Jie Mi, Teruaki Nanseki, Yosuke Chomei, Yoshihiro Uenishi, and Thi Ly Nguyen

1 Introduction

Many scholars discuss that acute labor shortage due to shrinking and aging of farmers has become one of the critical constraints of agricultural development in Japan. According to census by the Ministry of Agriculture, Forestry and Fisheries (MAFF), the labor force primarily engaged in agriculture has decreased from 1.76 million in 2015 to 1.36 million in 2020. Alarmingly, more than 70% of farmers were above the age of 65 years in 2020, compared with 65% in 2015 (MAFF, 2020). Under these circumstances, the Japanese government has encouraged the vigorous development of smart agriculture to overcome the disadvantages of agricultural labor shortage, improve agricultural production efficiency, and revitalize the progress of agriculture and rural areas (MAFF, 2022). Moreover, the widespread application of information and communication technology (ICT) in agriculture has proven crucial for optimizing the market activities, promoting the succession of agricultural skills, and boosting the development of agricultural informatization in Japan.

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Meanwhile, a structural change toward consolidation is ongoing in Japanese agriculture, with the decline of agricultural households but the rise of large-scale farming and agricultural corporations in recent decades (EU-JAPAN CENTRE FOR INDUSTRIAL COOPERATION ECOS GmbH, 2021; Nanseki, 2021). The emergence of agricultural corporations has become the backbone of realizing large-scale production, heightening the strategic management of agribusiness and accelerating industrial clusters. Intensive adoption of ICT and smart farming (SF) by corporations is anticipated to allow for the technological optimization of agricultural production systems and food value chains, ultimately contributing positively to agricultural development. Ogata et al. (2019) analyzed the cost-effectiveness of ICTs for agricultural corporations using factor analysis and observed that the factors for production and accounting visualization are related to human resource development. Their factor scores comparisons by farm characteristics revealed three points: (1) ICT cost-effectiveness is greater for livestock farms than for farms producing other goods in terms of enhancing the profitability factor; (2) farms with higher sales place a greater value on production and accounting visualization factors than those with lower sales; and (3) farms with more employees place a higher value on production visualization factors than those with fewer employees. Nanseki (2019) and Nanseki et al. (2016) reported on interdisciplinary aspects based on ICT and smart farming technology by focusing on rice farming. Bucci et al. (2019) discussed factors affecting ICT adoption in Italian agriculture and reported Internet access, web pages, production standards, age, and educational background as the factors affecting successful adoption of management information systems on farms. However, the determinants of ICT and smart farming (ICT&SF) technology adoption by agricultural corporations in Japan remain unclear.

To this end, the objective of this chapter was to identify the determining factors of ICT&SF technologies adoption by Japanese agricultural corporations. Section 2 outlines empirical models, followed by a description of data sources and variables used in econometric analysis. Section 3 discusses the empirical results, and Sect. 4 presents the key conclusions.

2 Methodology and Data

2.1 Methodology

Previous studies have analyzed the adoption of a particular or several agricultural technologies by applying ordered probit models, multinomial logit regressions, and double-hurdle models (Knowler & Bradshaw, 2007; Zhang et al., 2020). In this chapter, we investigated the intensity of ICT&SF technologies adopted by agricultural corporations. Accordingly, the dependent variable is a count variable taking a non-negative integer value from 0 to 21. Thus, count data models were deemed appropriate to estimate the effect of potential influencing factors on the number of technologies adopted (Cameron & Trivedi, 1986; Isgin et al., 2008; Rahelizatovo & Gillespie, 2004). Count integer values were assumed to follow a compound Poisson regression, in which the number of technologies adopted and the probability density function of Y can be given as follows:

$$f(y_i|x_i) = P(Y_i = y_i) = \frac{e^{\lambda_o}\lambda_i^{y_i}}{y_i},\ y_i = 0,\ 1,\ 2,\ 3\ldots \tag{1}$$

where y_i is the total number of ICT&SF technologies adopted by the agricultural corporation i and x_i is the expected determinant of ICT&SF technology adoption. The expected mean parameter (λ) of this function is defined as $\lambda_i = \exp\left(x_i'\beta\right)$, the β can be estimated using the maximum likelihood.

The Poisson model assumes the mean and variance of dependent variable are equal; that is, λ_i=mean $(y_i|x_i)$= variance $(y_i|x_i)$. However, when the conditional variance is greater than the conditional mean, overdispersion is the most likely situation (Ehiakpor et al., 2021). Thus, a negative binomial (of which Poisson is a special case) may be an appropriate count data handling procedure to accommodate the overdispersion issue by modeling variance as a function of mean. The variance in negative binomial model is given as follows:

$$Var(Y_i|x_i) = \lambda_i + \alpha\lambda_i^2 \tag{2}$$

where α is the dispersion parameter to be estimated. If α is zero, the negative binomial model is the same as the Poisson regression model, and the corresponding log-likelihood is log L $= \sum_i log[\Pr(y_i)]$. In this chapter, the test indicated the presence of overdispersion, which led to the selection of a negative binomial model.[1]

2.2 Data

2.2.1 Data Collection

The data used in this chapter were obtained from the "Business Development and Innovation in Agricultural Corporation Management" survey conducted by the Laboratory of Farm and Management at Kyushu University in 2019 (Nanseki, 2021). Information was gathered through mail questionnaires sent to agricultural corporations across Japan. The names of agricultural corporations were collected from the relevant publications, reports, and website of the Japan Agricultural Corporations Association (https://hojin.or.jp/).

In the survey, respondents were asked questions covering six parts: (1) basic information and operating policy of the corporation, such as corporate form, location,

[1] The variance of the dependent variable is approximately 15.907, which is nearly two-times greater than mean (6.623), implying that the count data present overdispersion.

establishment year, development stage, annual sales/profit margin, operating targets in the next 5 years, and so on; (2) innovative realization of corporations within the past 3 years; (3) current status of ICT&SF technologies adoption; (4) detailed business content, management strategy, and self-evaluation; (5) social contribution and perception of the Free Trade Agreement (FTA); and (6) profile of corporate representatives, such as age and education.

The questionnaires were sent to 2885 corporations, and 505 corporations provided valid answers, resulting in the effective response rate of 18% (Nanseki, 2021). The outline and basic survey results is shown in Nanseki (2021). In this study, we eliminated the observations without sufficient supporting information on questions of technology adoption and deleted the missing data of corporate and representative attributes. After screening for the missing data of all variables, most respondents made a single selection for the indicators of corporate attributes, and only one respondent made multiple selections for corporation's establishment background. Finally, 183 valid observations were used for further analyses.[2]

2.2.2 Variable Description

The dependent variable used in this chapter was the number of technologies adopted by an agricultural corporation. It is a count variable that can be used to estimate the intensity of technology adoption. Specifically, we counted the number of combined technology categories involved in both ICT and SF technologies. According to the Food and Agriculture Organization of the United Nations (FAO), ICT is defined as "a broader term for Information Technology (IT), which refers to all communication technologies, including the internet, wireless networks, cell phones, computers, software, middleware, video-conferencing, social networking, and other media applications and services enabling users to access, retrieve, store, transmit, and manipulate information in a digital form.[3]" According to MAFF (2022), "smart agriculture" or "smart farming" refers to the utilization of cutting-edge technologies, such as robots, artificial intelligence (AI), and the Internet of Things (IoT), in agricultural or farm management. Recent studies have distinguished SF technologies into the following types: (1) recording and mapping technologies, which collect precise data for subsequent site-specific application; (2) tractor GPS and connected tools, which use real-time kinetics to appropriately apply variable rates of inputs and accurately guide tractors; (3) apps and farm management and information systems, which integrate and connect mobile devices for easier monitoring and management; and (4) autonomously operating machines, such as weeding and harvesting robots (Fountas et al., 2015; Knierim et al., 2019). In this study, the ICT&SF technologies adopted by Japanese agricultural corporations are tentatively identified as two types. One

[2] The results of analysis including 195 observations (12 missing data were replaced by 0 in independent variables; See Appendix for details) were previously presented orally at the 10th Asian Society of Agricultural Economists International Conference (Mi et al., 2021).

[3] http://aims.fao.org/information-and-communication-technologies-ict.

refers to the smart farming technologies (SFTs) contained ICT and (2) common ICTs applied in SF.

The definitions and adoption rates of each technology categories are shown in Table 1. Three aspects including data monitoring and collection, operation automatization, and robotization, and business management, were involved, and 21 ICT&SF technology categories were described. The most frequently adopted technology category was financial management systems, such as bookkeeping and accounting, with an adoption rate of 84.2%. Advertisement for companies and products was a relatively frequently used technology category with an adoption rate of 65.0%. The third most frequently adopted technology category was sales information management, with an adoption rate of 61.7%. In contrast, technologies with relatively low adoption rates included "automation of crop cultivation machines/robots", "automatic measurement of product harvest", and "measurement of crop growth using drones and artificial satellites", with adoption rates of 8.2, 7.7, and 5.5%, respectively. These trends are consistent with the statistics reported by Nanseki (2021).

The independent variables in our count data modelling covered wide range of corporation attributes and representatives characteristics, classified into the following 17 groups: (1) corporate form; (2) eligibility to own farmland; (3) location of corporations; (4) age of corporations; (5) establishment background; (6) human capital; (7) annual sales; (8) profit margin, (9) development stage of the corporations; (10) sales target for the next 5 years; (11) profit target for the next 5 years; (12) major product; (13) self-evaluation of ICT utilization and information management; (14) perception of FTA participation of Japan; (15) age of representatives; (16) educational background of representatives; (17) non-agricultural experience of representatives. The definition, along with the unit and expected signs, are listed in Table 2.

3 Results and Discussion

3.1 Descriptive Results

Distribution of ICT&SF Technology Adoption. Figure 1 presents the distribution of the ICT&SF technology adoption rates by Japanese agricultural corporations. Of the 183, 175 corporations had adopted at least one ICT&SF technology category until 2019, indicating an overall adoption rate of 95.6%. In contrast, 4.4% corporations implemented none of these technologies. Majority (82.0%) of the corporations adopted 10 or fewer technologies, and only 18.0% adopted 11 or more technologies. Moreover, the observed Japanese agricultural corporations adopted nearly 6.6 technologies on average.

Summary of the Descriptive Statistics. Table 3 depicts the summary of descriptive statistics for all variables. Majority (84.7%) of the corporations are limited and stock companies. Approximately 86.9% corporations are judicially qualified to own farmland. Nearly 24.6% corporations are located in Tohoku, 23.5% are located in

Table 1 Definition and adoption rates of ICT&SF technologies

Technology categories	Type[a]	Frequency	Adoption rate (%)
Data monitoring and collection technologies			
1. Measurement of environmental information of crops and livestock (temperature, water temperature, soil moisture, solar radiation, and so on)	ICTs applied in SF	56	30.601
2. Measurement of biological information of crops and livestock (growth status, livestock estrus, body temperature, and so on)	SFTs contained ICTs	52	28.415
3. Collection of work information from each field (recorded using a personal computer, smartphone, camera, GPS, and so on)	ICTs applied in SF	76	41.530
4. Automatic measurement of product harvest (combined with sensor and so on)	SFTs contained ICTs	14	7.650
5. Automatic measurement of product quality (livestock milk/meat quality, crop sugar content/acidity, and so on)	SFTs contained ICTs	16	8.743
6. Browsing of farming information on smartphones (weather information, crop growth status, farm work amount, and so on)	ICTs applied in SF	80	43.716
7. Measurement of crop growth using drones and artificial satellites (leaf color, pests, and so on)	ICTs applied in SF	10	5.464
Robotization technologies and autonomously operating machines			
8. Automatic detection/notification of abnormal information (temperature, humidity, soil moisture, livestock estrus, body temperature, and so on)	SFTs contained ICTs	25	13.661
9. Automation of agricultural land irrigation and water supply (paddy pipelines, open waterways, upland fields, and so on)	SFTs contained ICTs	32	17.486
10. Agricultural machinery with operation assist function (straight-ahead assist function and so on)	SFTs contained ICTs	17	9.290
11. Automatic environmental controls of greenhouses and barns (temperature, humidity, soil moisture, CO_2 concentration, and so on)	SFTs contained ICTs	40	21.858
12. Livestock feeding, manure cleaning, and milking automation and robotization	SFTs contained ICTs	19	10.383

(continued)

Table 1 (continued)

Technology categories	Type[a]	Frequency	Adoption rate (%)
13. Automation of crop cultivation machines/robots [plowing, fertilization, control (including drone), harvest, and so on]	SFTs contained ICTs	15	8.197
14. Automatic sorting of harvested products (weight/shape sorting, color sorting, sugar content sorting, and so on)	SFTs contained ICTs	41	22.404
Business management technologies			
15. Management of production record information (including data analysis such as tabulation and graphing)	ICTs applied in SF	100	54.645
16. Provision of production information to business partners and consumers (product quality, production history, and so on)	ICTs applied in SF	78	42.623
17. Sales information management (including customer management and internet sales)	ICTs applied in SF	113	61.749
18. Inventory management of materials, such as pesticides and fertilizers (recorded using a personal computer, smartphone, and so on)	ICTs applied in SF	83	45.355
19. Financial management systems, such as bookkeeping and accounting (settlement, management diagnosis, payroll, and so on)	ICTs applied in SF	154	84.153
20. Planning of business strategy and creation of business plan (simulation on a personal computer and so on)	ICTs applied in SF	72	39.344
21. Advertisement for companies and products (information on homepage and so on)	ICTs applied in SF	119	65.027

[a]Types of technology categories are tentative. ICTs and SFTs are broad concepts, they intersect with each other. With the development of each technology category, the types may be updated

Kyushu and Okinawa, and only 1.6% are located in Hokkaido. The average age of the sampled corporations is approximately 19.0 years. Regarding establishment background, approximately 47.5% are solely owned corporation, established by a farmer and 26.8% are joint corporations founded by several farmers. Regarding human capital, the number of board members is approximately 3.6 on average, and the number of regular employees is approximately 11 on average. Nearly half of the corporations have a profit margin between 1 and 10%, while 20.8% are running in financial deficit. Regarding development stage, approximately 40.4% corporations are at the "growing stage," compared with 16.4 and 6.0% corporations at the

Table 2 Definition of the variables in estimation (Nanseki, 2021)

Variables name	Definition	Unit
TECH (dependent)	Number of ICT&SF technologies adopted (Values ranging from 0 to 21)	Number
1. Corporate form (±)		
CFORM_1	1 if the corporation is limited company; 0 otherwise	Dummy
CFORM_2	1 if the corporation is stock company; 0 otherwise	
CFORM_3	1 if the corporation is agricultural cooperative corporation; 0 otherwise	
CFORM_4	1 if the corporation form is others; 0 otherwise	
2. Eligibility to own farmland (+)		
FARML	1 if the corporation is judicially qualified to own farmland; 0 otherwise	Dummy
3. Location of corporations (±)		
R_HKD	1 if the corporation located in Hokkaido; 0 otherwise	Dummy
R_TH	1 if the corporation located in Tohoku; 0 otherwise	
R_KT	1 if the corporation located in Kanto; 0 otherwise	
R_HR	1 if the corporation located in Hokuriku; 0 otherwise	
R_KKTK	1 if the corporation located in Kinki Tokai; 0 otherwise	
R_CHSK	1 if the corporation located in Chugoku and Shikoku; 0 otherwise	
R_KSON	1 if the corporation located in Kyushu and Okinawa; 0 otherwise	
4. Age of corporations (±)		
AGE_C	2019—establishment year	Year
5. Establishment background (±)		
ESTAB_1	1 if a farmer established a solely owned corporation; 0 otherwise	Dummy
ESTAB_2	1 if a farmer established a joint corporation with other members; 0 otherwise	
ESTAB_3	1 if a Farmer has established corporations in collaboration with non-farmers and companies from other industries; 0 otherwise	
ESTAB_4	1 if a non-farmer entered agriculture as individuals and established a corporation; 0 otherwise	
ESTAB_5	1 if the company's main business is non-agriculture, but they have entered agriculture as a new business; 0 otherwise	
ESTAB_6	1 if a corporation parent/main company or group company has established a new corporation and entered agriculture; 0 otherwise	
ESTAB_7	1 if the establishment background of a corporation is others; 0 otherwise	

(continued)

Table 2 (continued)

Variables name	Definition	Unit
6. Human capital (+)		
BM	Total number of board members	Persons
RE	Total number of regular employees	
7. Annual sales (+)		
SALE	Categorical variable of corporations' annual sales: 1 = <30 million yen; 2 = 30–50 million yen; 3 = 50–100 million yen; 4 = 100–300 million yen; 5 = 300–500 million yen; 6 = 500–1000 million yen; 7 = 1000–1500 million yen; 8 = 1500–2000 million yen; 9 = >2000 million yen	Category
8. Profit margin (+)		
PROF_1	1 if profit margin of a corporation is 0% (break-even); 0 otherwise	Dummy
PROF_2	1 if profit margin of a corporation is 1–5%; 0 otherwise	
PROF_3	1 if profit margin of a corporation is 5–10%; 0 otherwise	
PROF_4	1 if profit margin of a corporation is 10–15%; 0 otherwise	
PROF_5	1 if profit margin of a corporation is 15–20%; 0 otherwise	
PROF_6	1 if profit margin of a corporation is >20%; 0 otherwise	
PROF_7	1 if the deficit; 0 otherwise	
9. Development stage of the corporations (±)		
STAGE_1	1 if the development stage is "starting"; 0 otherwise	Dummy
STAGE_2	1 if the development stage is "growing"; 0 otherwise	
STAGE_3	1 if the development stage is "mature"; 0 otherwise	
STAGE_4	1 if the development stage is "recession"; 0 otherwise	
STAGE_5	1 if the development stage is the second period of "starting"; 0 otherwise	
STAGE_6	1 if the development stage is the second period of "growing"; 0 otherwise	
STAGE_7	1 if the development stage is the second period of "mature"; 0 otherwise	
STAGE_8	1 if the development stage is the second period "recession"; 0 otherwise	
STAGE_9	1 if others	
10. Sales target for the next 5 years (+)		
TSALE_1	1 if the sales target for the next 5 years is "maintain"; 0 otherwise	Dummy
TSALE_2	1 if the sales target for the next 5 years is "1.2 times"; 0 otherwise	
TSALE_3	1 if the sales target for the next 5 years is "1.5 times"; 0 otherwise	

(continued)

Table 2 (continued)

Variables name	Definition	Unit
TSALE_4	1 if the sales target for the next 5 years is "1.8 times"; 0 otherwise	
TSALE_5	1 if the sales target for the next 5 years is "2.0 times"; 0 otherwise	
TSALE_6	1 if the sales target for the next 5 years is "2.0–3.0 times"; 0 otherwise	
TSALE_7	1 if the sales target for the next 5 years is "over 3 times"; 0 otherwise	
TSALE_8	1 if the sales target for the next 5 years is "decrease"; 0 otherwise	
TSALE_9	1 if no target; 0 otherwise	
11. Profit target for the next 5 years (+)		
TPROF_1	1 if the profit target for the next 5 years is "0%"; 0 otherwise	Dummy
TPROF_2	1 if the profit target for the next 5 years is "1%–5%"; 0 otherwise	
TPROF_3	1 if the profit target for the next 5 years is "5%–10%"; 0 otherwise	
TPROF_4	1 if the profit target for the next 5 years is "10%–15%"; 0 otherwise	
TPROF_5	1 if the profit target for the next 5 years is "15%–20%"; 0 otherwise	
TPROF_6	1 if the profit target for the next 5 years is "over20%"; 0 otherwise	
TPROF_7	1 if no margin; 0 otherwise	
12. Major product[a] (±)		
PROD_1	1 if the major product is "paddy rice"; 0 otherwise	Dummy
PROD_2	1 if the major product is "wheat"; 0 otherwise	
PROD_3	1 if the major product is "beans and coarse cereals"; 0 otherwise	
PROD_4	1 if the major product is "open-ground vegetables"; 0 otherwise	
PROD_5	1 if the major product is "house vegetables"; 0 otherwise	
PROD_6	1 if the major product is "flowers and foliage plants"; 0 otherwise	
PROD_7	1 if the major product p is "fruit"; 0 otherwise	
PROD_8	1 if the major product is "mushrooms"; 0 otherwise	
PROD_9	1 if the major product is "dairy"; 0 otherwise	
PROD_10	1 if the major product is "beef cattle"; 0 otherwise	
PROD_11	1 if the major product is "swine"; 0 otherwise	

(continued)

Table 2 (continued)

Variables name	Definition	Unit
PROD_12	1 if the major product is "poultry (meat/eggs)"; 0 otherwise	
PROD_13	1 if the major product is "others"; 0 otherwise	
PROD_14	1 if the major product is "multiple crops"; 0 otherwise	
13. Self-evaluation of ICT utilization and information management (+)		
SELF_U	1 = weaker than others; 2 = slightly weaker than others; 3 = neither weaker nor stronger than others; 4 = slightly stronger than others; 5 = stronger than others	Likert scale
14. Perception of the FTA participation of Japan (+)		
FTA	Respondents' perception of the FTA participation of Japan: 1 = major crisis; 2 = crisis; 3 = neutral; 4 = opportunity; 5 = great opportunity	Likert scale
15. Age of representatives (±)		
AGE_R	Value ranging from 1 to 7: 1 = 10–20 years old; 2 = 20–30 years old; 3 = 30–40 years old; 4 = 40–50 years old; 5 = 50–60 years old; 6 = 60–70 years old; 7 = over than 70 years old	Category
16. Education background of representatives (+)		
EDU_1	1 if the representative graduated from a high school; 0 otherwise	Dummy
EDU_2	1 if the representative graduated from a specialized school; 0 otherwise	
EDU_3	1 if the representative graduated from a vocational college; 0 otherwise	
EDU_4	1 if the representative graduated from a junior college; 0 otherwise	
EDU_5	1 if the representative graduated from a university; 0 otherwise	
EDU_6	1 if the representative graduated from a graduate school; 0 otherwise	
EDU_7	1 if others	
17. Non-agricultural experience of representatives (±)		
NAGRI	Values ranging from 1 to 6: 1 = none; 2 = 1–5 years; 3 = 5–10 years; 4 = 10–15 years; 5 = 15–20 years; 6 = >20 years	Category

Note Symbols in parentheses denote the expected signs of each category of independent variables
[a]Major product of an agricultural corporation is classified as a product that accounts for over 60% of that corporation's annual sales

"mature" and "recession" stages, respectively. Regarding the operating target, the largest proportion of companies (approximately 29.5%) have set the target of 1.5 times sales growth in the next 5 years. Moreover, 83.6% corporations have set the target of 1–20% profit growth, compared with 10.4% corporations with a target of over 20% profit growth in the next 5 years. Regarding the major product, the corporations with major products as 'paddy rice' account for the largest proportion (18.0%),

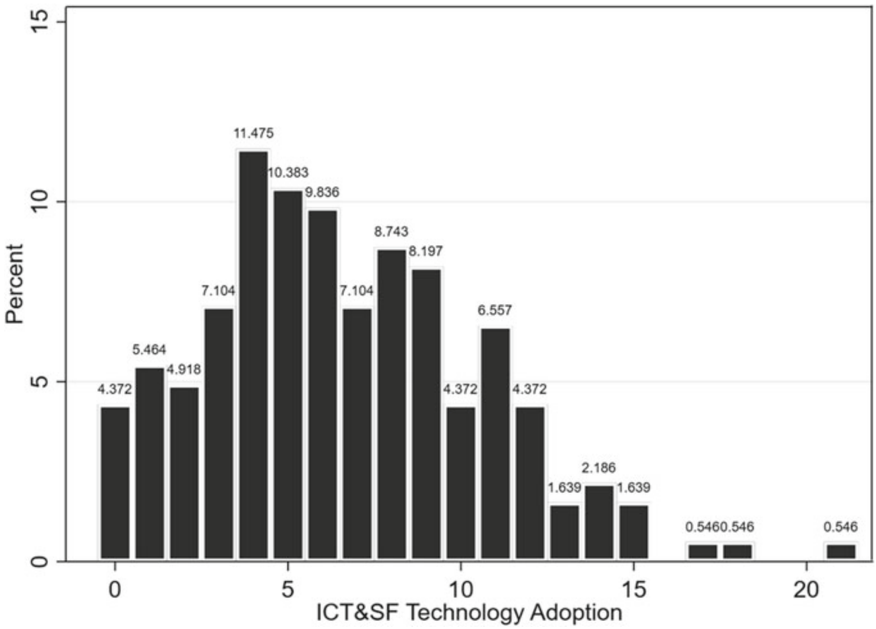

Fig 1 Distribution of technology adoption frequency of agricultural corporations ($N = 183$) (The Questionnaire Survey on Business Development and Innovation in Agricultural Corporation Management in 2019)

whereas the 'beans and coarse cereals' accounted the least, only for 1.1%. Moreover, approximately 8.7% corporations follow multiple crop farming. Regarding the profile of corporate representatives, over half of the representatives (54.6%) graduated from high schools and 36.6% from universities. Of the corporate representatives, 2.7% held a postgraduate degree.

3.2 Empirical Results

We applied a negative binomial model to identify the potential determinants of ICT&SF technologies adoption by Japanese agricultural corporations. We tested two non-nested forms of the negative binomial model denoted NB1 (which is a negative binomial model with constant dispersion) and NB2 (which is a negative binomial model with no constant dispersion) and compared their estimates according to Akaike's information criterion (AIC) and Bayesian information criterion (BIC). The results are presented in Table 4.

The result of NB1 revealed corporate form, eligibility to own farmland, sales targets, profit target, major product, self-evaluation of ICT utilization and information

Table 3 Result of descriptive statistics

Variables	Mean	SD	Min	Max	Obs.	Variables	Mean	SD	Min	Max	Obs.
TECH (dependent)	6.623	3.988	0	21	–	10. Sales target for the next 5 years					
1. Corporate form						*TSALE_1*	0.126	0.332	0	1	23
CFORM_1	0.410	0.493	0	1	75	*TSALE_2*	0.284	0.452	0	1	52
CFORM_2	0.437	0.497	0	1	80	*TSALE_3*	0.295	0.457	0	1	54
CFORM_3	0.137	0.344	0	1	25	*TSALE_4*	0.038	0.192	0	1	7
CFORM_4	0.016	0.127	0	1	3	*TSALE_5*	0.137	0.344	0	1	25
2. Eligibility to own farmland						*TSALE_6*	0.060	0.238	0	1	11
FARML	0.869	0.338	0	1	–	*TSALE_7*	0.055	0.228	0	1	10
3. Location of corporation						*TSALE_8*	0.005	0.074	0	1	1
R_HKD	0.016	0.127	0	1	3	*TSALE_9*	0.000	0.000	0	0	0
R_TH	0.246	0.432	0	1	45	11. Profit target for the next 5 years					
R_KT	0.137	0.344	0	1	25	*TPROF_1*	0.038	0.192	0	1	7
R_HR	0.087	0.283	0	1	16	*TPROF_2*	0.213	0.411	0	1	39
R_KKTK	0.137	0.344	0	1	25	*TPROF_3*	0.350	0.478	0	1	64
R_CHSK	0.142	0.350	0	1	26	*TPROF_4*	0.158	0.366	0	1	29
R_KSON	0.235	0.425	0	1	43	*TPROF_5*	0.115	0.320	0	1	21
4. Age of corporation						*TPROF_6*	0.104	0.306	0	1	19
AGE_C	19.071	12.516	2	76	–	*TPROF_7*	0.022	0.147	0	1	4
5. Establishment background						12. Major product					
ESTAB_1	0.475	0.501	0	1	87	*PROD_1*	0.180	0.386	0	1	33
ESTAB_2	0.268	0.444	0	1	49	*PROD_2*	0.000	0.000	0	0	0
ESTAB_3	0.044	0.205	0	1	8	*PROD_3*	0.011	0.104	0	1	2
ESTAB_4	0.055	0.228	0	1	10	*PROD_4*	0.077	0.267	0	1	14
ESTAB_5	0.044	0.205	0	1	8	*PROD_5*	0.115	0.320	0	1	21
ESTAB_6	0.060	0.238	0	1	11	*PROD_6*	0.038	0.192	0	1	7
ESTAB_7	0.060	0.238	0	1	11	*PROD_7*	0.137	0.344	0	1	25
6. Human capital						*PROD_8*	0.033	0.179	0	1	6
BM	3.552	2.394	1	20	–	*PROD_9*	0.022	0.147	0	1	4
RE	11.055	21.956	0	238	–	*PROD_10*	0.049	0.217	0	1	9
7. Annual sales						*PROD_11*	0.044	0.205	0	1	8
SALE	3.760	1.741	1	9	–	*PROD_12*	0.049	0.217	0	1	9
8. Profit margin						*PROD_13*	0.158	0.366	0	1	29
PROF_1	0.087	0.283	0	1	16	*PROD_14*	0.087	0.283	0	1	16
PROF_2	0.322	0.469	0	1	59	13. Self-evaluation of ICT utilization and information management					
PROF_3	0.191	0.394	0	1	35	*SELF_U*	2.628	0.985	1	5	–

(continued)

Table 3 (continued)

Variables	Mean	SD	Min	Max	Obs.	Variables	Mean	SD	Min	Max	Obs.
PROF_4	0.098	0.299	0	1	18	14. Perception of the FTA participation of Japan					
PROF_5	0.071	0.258	0	1	13	*FTA*	2.891	1.010	1	5	–
PROF_6	0.022	0.147	0	1	4	15. Age of representatives					
PROF_7	0.208	0.407	0	1	38	*AGE_R*	5.098	1.158	2	7	–
9. Development stage of the corporation						16. Educational background of representatives					
STAGE_1	0.066	0.248	0	1	12	*EDU_1*	0.546	0.499	0	1	100
STAGE_2	0.404	0.492	0	1	74	*EDU_2*	0.077	0.267	0	1	14
STAGE_3	0.164	0.371	0	1	30	*EDU_3*	0.142	0.350	0	1	26
STAGE_4	0.060	0.238	0	1	11	*EDU_4*	0.055	0.228	0	1	10
STAGE_5	0.169	0.376	0	1	31	*EDU_5*	0.366	0.483	0	1	67
STAGE_6	0.104	0.306	0	1	19	*EDU_6*	0.027	0.163	0	1	5
STAGE_7	0.027	0.163	0	1	5	*EDU_7*	0.027	0.163	0	1	5
STAGE_8	0.000	0.000	0	0	0	17. Non-agricultural experience of representatives					
STAGE_9	0.005	0.074	0	1	1	*NAGRI*	3.186	1.980	1	6	–

$N = 183$

management, and educational background of representatives as the potential determinants of ICT&SF technologies adoption by Japanese agricultural corporations. Here we mainly discuss these indicators with parameters at 1 and 5% significance levels. First, the marginal effect of *CFORM_3* on ICT&SF technology adoption was −2.431 at 5% significance level, indicating that cooperative agricultural corporations tend to adopt fewer technologies than limited companies. Second, the coefficient of *FARML* was positive and statistically significant at 5% level, indicating that corporations eligible to own farmland were likely to adopt two more technologies. Third, the self-evaluation of ICT utilization and information management significantly and positively affected technology adoption ($p < 0.01$). It demonstrated that corporations with a higher self-evaluation of ICT utilization and information management tended to use more ICT&SF technologies. Finally, the marginal effects of *EDU_2* and *EDU_3* are both positive statistically significant at 5% level, indicating the representatives who graduated from specialized schools and vocational colleges were more likely to adopt ICT&SF technologies. These results differ from the finding of Carrer et al. (2017), who demonstrated that university-level education positively affected the likelihood of technology adoption in farm management. This discrepancy may be explained by the fact that representatives who graduate from specialized schools and vocational colleges have more opportunities to receive specific agricultural knowledge and training lessons on farming skills and are, therefore, more willing to adopt technologies.

Table 4 Result of negative binomial regression model

	NB2		NB1	
	Parameter	Marginal effect	Parameter	Marginal effect
1. Corporate form (benchmark: *CFORM_1*, limited company)				
CFORM_2	−0.046	−0.306	−0.049	−0.323
CFORM_3	−0.361**	−2.391**	−0.367**	−2.431**
CFORM_4	−0.273	−1.805	−0.290	−1.923
2. Eligibility to own farmland				
FARML	0.246**	1.627**	0.257**	1.700**
3. Location of corporation (benchmark: *R_HKD*, Hokkaido)				
R_TH	−0.032	−0.209	−0.021	−0.141
R_KT	−0.040	−0.265	−0.031	−0.204
R_HR	0.030	0.201	0.036	0.240
R_KKTK	0.380	2.516	0.395	2.616
R_CHSK	−0.083	−0.547	−0.078	−0.516
R_KSON	−0.088	−0.581	−0.080	−0.532
4. Age of corporation				
AGE_C	0.001	0.009	0.001	0.008
5. Establishment background (benchmark: *ESTAB_1*, a farmer established a solely owned corporation)				
ESTAB_2	0.014	0.091	0.020	0.131
ESTAB_3	0.218	1.442	0.219	1.453
ESTAB_4	0.029	0.193	0.046	0.305
ESTAB_5	0.115	0.764	0.127	0.842
ESTAB_6	0.107	0.707	0.115	0.764
ESTAB_7	−0.179	−1.184	−0.166	−1.097
6. Human capital				
BM	0.038*	0.249*	0.038	0.252
RE	0.000	−0.002	0.000	−0.002
7. Annual sales				
SALE	−0.016	−0.107	−0.017	−0.110
8. Profit margin (benchmark: *PROF_1*, 0%)				
PROF_2	0.012	0.078	0.011	0.075
PROF_3	−0.136	−0.900	−0.138	−0.916
PROF_4	0.041	0.271	0.053	0.354
PROF_5	−0.139	−0.921	−0.129	−0.855
PROF_6	−0.267	−1.770	−0.251	−1.665
PROF_7	0.073	0.486	0.075	0.495

(continued)

Table 4 (continued)

	NB2		NB1	
	Parameter	Marginal effect	Parameter	Marginal effect
9. Development stage of the corporation (benchmark: *STAGE_1*, starting)				
STAGE_2	0.079	0.522	0.096	0.634
STAGE_3	0.186	1.233	0.205	1.358
STAGE_4	−0.029	−0.193	−0.004	−0.025
STAGE_5	0.186	1.234	0.212	1.403
STAGE_6	0.313	2.075	0.331	2.195
STAGE_7	0.165	1.095	0.160	1.059
STAGE_8	(omitted)	0.000	(omitted)	0.000
STAGE_9	−0.245	−1.620	−0.203	−1.342
10. Sales target for the next 5 years (benchmark: *TSALE_1*, maintain)				
TSALE_2	0.241*	1.595*	0.247*	1.637*
TSALE_3	0.110	0.728	0.114	0.753
TSALE_4	0.318	2.105	0.340	2.249
TSALE_5	−0.020	−0.135	−0.011	−0.076
TSALE_6	0.107	0.711	0.124	0.818
TSALE_7	0.114	0.754	0.125	0.826
TSALE_8	0.042	0.280	0.090	0.595
TSALE_9	(omitted)	0.000	(omitted)	0.000
11. Profit target for the next 5 years (benchmark: *TPROF_1*, 0%)				
TPROF_2	0.262	1.736	0.268	1.776
TPROF_3	0.419*	2.778*	0.414	2.739
TPROF_4	0.319	2.111	0.314	2.079
TPROF_5	0.528**	3.494**	0.520*	3.443*
TPROF_6	0.475*	3.149*	0.469	3.104
TPROF_7	−0.724	−4.795	−0.731	−4.844
12. Major product (benchmark: *PROD_1*, paddy rice)				
PROD_2	(omitted)	0.000	(omitted)	0.000
PROD_3	−0.031	−0.206	−0.048	−0.317
PROD_4	0.030	0.201	0.038	0.255
PROD_5	0.042	0.275	0.036	0.241
PROD_6	−0.452**	−2.996**	−0.475*	−3.144*
PROD_7	−0.072	−0.474	−0.064	−0.425
PROD_8	−0.253	−1.675	−0.240	−1.587
PROD_9	−0.026	−0.169	−0.022	−0.145

(continued)

Table 4 (continued)

	NB2		NB1	
	Parameter	Marginal effect	Parameter	Marginal effect
PROD_10	−0.139	−0.922	−0.133	−0.882
PROD_11	0.343	2.269	0.365	2.415
PROD_12	0.364*	2.413*	0.376*	2.493*
PROD_13	−0.045	−0.296	−0.051	−0.341
PROD_14	0.003	0.017	0.014	0.092
13. Self-evaluation of ICT utilization and information management				
SELF_U	0.344***	2.279***	0.345***	2.287***
14. Perception of the FTA participation of Japan				
FTA	0.058	0.386	0.059	0.394
15. Age of representatives				
AGE_R	−0.035	−0.232	−0.036	−0.237
16. Educational background of representatives				
EDU_2	0.287**	1.901**	0.293**	1.939**
EDU_3	0.287**	1.900**	0.289**	1.913**
EDU_4	−0.179	−1.188	−0.198	−1.309
EDU_5	−0.027	−0.177	−0.033	−0.217
EDU_6	−0.153	−1.012	−0.156	−1.031
EDU_7	−0.010	−0.068	−0.002	−0.017
17. Non-agricultural experience of representatives				
NAGRI	0.020	0.135	0.021	0.142
_cons	−0.045		−0.092	
N	183		183	
Pseudo-R^2	0.145		0.146	
Log likelihood	−433.160		−432.347	
Lnalpha	−1.5603			
Lndelta			−1.882**	
AIC	1006.319		1004.694	
BIC	1230.983		1229.358	

Note ***, **, * denote statistically significance level of 1%, 5%, 10% respectively; The parameter here can be interpreted as semi-elasticity, and marginal effect is calculated at the mean of the dependent variable (Paxton et al., 2011)

With regard to the empirical results at 10% significance level, first, the marginal effect of *TSALE_2* was 1.637, indicating that corporations targeting 1.2 times sales growth in the next 5 years were likely to use two more technologies than corporations aiming to maintain the current sales. Second, the marginal effect of *TPROF_5* was 3.443, indicating that corporations targeting 15–20% profit growth in the next 5 years were likely to use three more technologies than corporations that aimed to maintain the profit. Finally, the marginal effects of *PROD_6* and *PROD_12* were −3.144 and 2.493, respectively. Compared with the benchmark major product “paddy rice”, corporations operating “flowers and foliage plants” were likely to use three less technologies, whereas corporations operating “poultry” were likely to use two more technologies.

In particular, indicators with estimated parameters at 10% significance level were slightly different from the previous results, which based on 193 samples (see Table 5 in Appendix). Some variables with 10% significance level in the previous version, such as the number of board members and representatives’ age, were altered. As shown in Table 14.4, the number of board members promoted ICT&SF technologies adoption even the marginal effect is not significant. Similarly, the coefficient of *AGE_R* was insignificant as well, but still, it revealed a negative sign. This is also consistent with a previously reported finding from the adoption literature, which demonstrated a negative association between the age of decision-makers and technology adoption (Simmons et al., 2005).

4 Conclusion

Through a national questionnaire survey of “Business Development and Innovation in Agricultural Corporation Management”, this study identified the determinants of ICT&SF technology adoption by Japanese agricultural corporations. Negative binomial models were employed to examine the relevant corporate attributes and representative characteristics potentially affecting the technology adoption by agricultural corporations.

The results revealed that, of the 183 sampled corporations, 175 had adopted at least one ICT&SF technology until 2019, indicating an overall adoption rate of 95.6%. Among the 21 ICT&SF technologies, the most frequently adopted component was financial management systems, such as bookkeeping and accounting, with an adoption rate of 84.2%, whereas the least frequently adopted technology was the measurement of crop growth using drones and artificial satellites, with an adoption rate of 5.5%. Regarding the attributes of sampled corporations, majority (84.7%) of the corporations were limited and stock companies and 86.9% were qualified to own farmlands. In addition, 18.0% corporations operated paddy rice as major product and only 1.1% mainly operated beans and coarse cereals. Regarding the profile of corporate representatives, over half of the representatives (54.6%) graduated from high schools and 36.6% from universities.

The results of empirical models revealed corporate form, eligibility to own farmland, sales target, profit target, major product, self-evaluation of ICT utilization and information management, and educational background of representatives as the potential determinants of technologies adoption by Japanese agricultural corporations. Specifically, regarding corporate form, cooperative agricultural corporations tended to adopt fewer technologies than limited companies. Moreover, corporations eligible to own farmland were likely to adopt two more technologies. Regarding sales and profit targets, corporations aiming to increase their sales by 1.2 times the current value or raise their profits by 15–20% of the current margin in the next 5 years were likely to adopt more technologies than those aiming to maintain the current status. Compared with corporations operating paddy rice as the major product, those mainly operating flowers and foliage plants were likely to use less technologies, whereas those targeting poultry were likely to adopt more technologies. Moreover, the self-valuation of ICT utilization and information management positively affected technology implementation. Finally, in terms of corporate representatives' characteristics, those who graduated from specialized schools and vocational colleges were more likely to adopt the technologies.

Appendix

See Table 5.

Table 5 Comparison of NB1 results with different sample sizes

	$N = 195$		$N = 183$	
	Parameter	Marginal effect	Parameter	Marginal effect
1. Corporate form (benchmark: *CFORM_1*, limited company)				
CFORM_2	−0.001	−0.004	−0.049	−0.323
CFORM_3 (agricultural cooperative corporations)	−0.334**	−2.184 **	−0.367**	−2.431**
CFORM_4	−0.249	−1.627	−0.290	−1.923
2. Eligibility to own farmland				
FARML	0.195	1.274	0.257**	1.700**
3. Location of corporation (benchmark: *R_HKD*, Hokkaido)				
R_TH	−0.292	−1.908	−0.021	−0.141
R_KT	−0.263	−1.721	−0.031	−0.204
R_HR	−0.203	−1.328	0.036	0.240
R_KKTK	0.108	0.704	0.395	2.616
R_CHSK	−0.276	−1.808	−0.078	−0.516
R_KSON	−0.276	−1.808	−0.080	−0.532
4. Age of corporation				
AGE_C	0.003	0.017	0.001	0.008
5. Establishment background (benchmark: *ESTAB_1*, a farmer established a solely owned corporation)				
ESTAB_2	0.025	0.161	0.020	0.131
ESTAB_3	0.182	1.193	0.219	1.453

(continued)

Table 5 (continued)

	$N = 195$		$N = 183$	
	Parameter	Marginal effect	Parameter	Marginal effect
ESTAB_4	0.2	1.309	0.046	0.305
ESTAB_5	0.162	1.063	0.127	0.842
ESTAB_6	0.146	0.953	0.115	0.764
ESTAB_7	−0.189	−1.239	−0.166	−1.097
6. Human capital				
BM (number of board members)	0.041*	0.270*	0.038	0.252
RE	0.000	−0.003	0.000	−0.002
7. Annual sales				
SALE	−0.024	−0.157	−0.017	−0.110
8. Profit margin (benchmark: *PROF_1*, 0%)				
PROF_2	0.084	0.547	0.011	0.075
PROF_3	−0.010	−0.065	−0.138	−0.916
PROF_4	0.129	0.842	0.053	0.354
PROF_5	−0.011	−0.075	−0.129	−0.855
PROF_6	−0.168	−1.098	−0.251	−1.665
PROF_7	0.130	0.849	0.075	0.495
9. Development stage of the corporation (benchmark: *STAGE_1*, starting)				
STAGE_2	0.202	1.321	0.096	0.634
STAGE_3	0.261	1.710	0.205	1.358
STAGE_4	0.042	0.274	−0.004	−0.025
STAGE_5	0.252	1.648	0.212	1.403
STAGE_6	0.331	2.166	0.331	2.195
STAGE_7	0.215	1.407	0.160	1.059
STAGE_8	−14.031	−91.810	(omitted)	0.000
STAGE_9	−0.065	−0.427	−0.203	−1.342
10. Sales target for the next 5 years (benchmark: *TSALE_1*, maintain)				
TSALE_2 (1.2 times)	0.149	0.978	0.247*	1.637*
TSALE_3	0.046	0.298	0.114	0.753
TSALE_4	0.313	2.045	0.340	2.249
TSALE_5	−0.043	−0.281	−0.011	−0.076
TSALE_6	0.042	0.275	0.124	0.818
TSALE_7	0.126	0.823	0.125	0.826
TSALE_8	−0.101	−0.659	0.090	0.595
TSALE_9	(omitted)	0.000	(omitted)	0.000

(continued)

Table 5 (continued)

	N = 195		N = 183	
	Parameter	Marginal effect	Parameter	Marginal effect
11. Profit target for the next 5 years (benchmark: *TPROF_1*, 0%)				
TPROF_2	0.095	0.622	0.268	1.776
TPROF_3	0.203	1.328	0.414	2.739
TPROF_4	0.092	0.603	0.314	2.079
TPROF_5 (10–15%)	0.279	1.828	0.520*	3.443*
TPROF_6	0.192	1.257	0.469	3.104
TPROF_7 (no target)	−0.926*	−6.060*	−0.731	−4.844
12. Major product (benchmark: *PROD_1*, paddy rice)				
PROD_2	(omitted)	0.000	(omitted)	0.000
PROD_3	−0.034	−0.220	−0.048	−0.317
PROD_4	−0.012	−0.080	0.038	0.255
PROD_5	−0.065	−0.428	0.036	0.241
PROD_6 (flowers and foliage plants)	−0.499**	−3.265**	−0.475*	−3.144*
PROD_7	−0.155	−1.011	−0.064	−0.425
PROD_8	−0.279	−1.825	−0.240	−1.587
PROD_9	−0.140	−0.916	−0.022	−0.145
PROD_10	−0.240	−1.572	−0.133	−0.882
PROD_11	0.257	1.681	0.365	2.415
PROD_12 (poultry)	0.218	1.425	0.376*	2.493*
PROD_13	−0.214	−1.397	−0.051	−0.341
PROD_14	−0.058	−0.380	0.014	0.092
13. Self-evaluation of ICT utilization and information management				
SELF_U	0.328***	2.146***	0.345***	2.287***
14. Perception of the FTA participation of Japan				
FTA	0.045	0.293	0.059	0.394
15. Age of representatives				
AGE_R	−0.065*	−0.425*	−0.036	−0.237
16. Educational background of representatives				
EDU_2 (specialized schools)	0.298**	1.950**	0.293**	1.939**
EDU_3 (vocational colleges)	0.246*	1.613*	0.289**	1.913**
EDU_4	−0.214	−1.401	−0.198	−1.309
EDU_5	−0.029	−0.188	−0.033	−0.217

(continued)

Table 5 (continued)

	$N = 195$		$N = 183$	
	Parameter	Marginal effect	Parameter	Marginal effect
EDU_6	−0.240	−1.567	−0.156	−1.031
EDU_7	0.075	0.492	−0.002	−0.017
17. Non-agricultural experience of representatives				
NAGRI	0.006	0.038	0.021	0.142
_cons	0.641		−0.092	
N	195			183
Pseudo-R^2	0.148		0.146	
Log likelihood	−459.061		−432.347	
Lndelta	−1.716**		−1.882**	
AIC	1060.122		1004.694	
BIC	1292.505		1229.358	

Note ***, **, * denote statistically significance level of 1%, 5%, 10% respectively

References

Bucci, G., Bentivoglio, D., & Finco, A. (2019). Factors affecting ict adoption in agriculture: A case study in italy. *Quality—Access to Success, 20*(S2), 122–129.

Cameron, A. C., & Trivedi, P. K. (1986). Econometric models based on count data: Comparisons and applications of some estimators and tests. *Journal of Applied Econometrics, 1*(1), 29–53. https://doi.org/10.1002/jae.3950010104

Carrer, M. J., de Souza Filho, H. M., & Batalha, M. O. (2017). Factors influencing the adoption of Farm Management Information Systems (FMIS) by Brazilian citrus farmers. *Computers and Electronics in Agriculture, 138*, 11–19. https://doi.org/10.1016/j.compag.2017.04.004

Ehiakpor, D. S., Danso-Abbeam, G., & Mubashiru, Y. (2021). Adoption of interrelated sustainable agricultural practices among smallholder farmers in Ghana. *Land Use Policy*, *101*(November 2020), 105142. https://doi.org/10.1016/j.landusepol.2020.105142

EU-JAPAN CENTRE FOR INDUSTRIAL COOPERATION ECOS GmbH. (2021). *Smart farming technology in Japan and opportunities for EU companies*. ECOS. https://www.ecos.eu/files/content/downloads/publikationen/REPORT_Smart_Farming.pdf

Fountas, S., Carli, G., Sørensen, C. G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., Liakos, B., Canavari, M., Wiebensohn, J., & Tisserye, B. (2015). Farm management information systems: Current situation and future perspectives. *Computers and Electronics in Agriculture, 115*, 40–50. https://doi.org/10.1016/j.compag.2015.05.011

Isgin, T., Bilgic, A., Forster, D. L., & Batte, M. T. (2008). Using count data models to determine the factors affecting farmers' quantity decisions of precision farming technology adoption. *Computers and Electronics in Agriculture, 62*(2), 231–242. https://doi.org/10.1016/j.compag.2008.01.004

Knierim, A., Kernecker, M., Erdle, K., Kraus, T., Borges, F., & Wurbs, A. (2019). Smart farming technology innovations—Insights and reflections from the German Smart-AKIS hub. *NJAS—Wageningen Journal of Life Sciences, 90–91*(October), 100314. https://doi.org/10.1016/j.njas.2019.100314

Knowler, D., & Bradshaw, B. (2007). Farmers' adoption of conservation agriculture: A review and synthesis of recent research. *Food Policy, 32*(1), 25–48. https://doi.org/10.1016/j.foodpol.2006.01.003

MAFF (Ministry of Agriculture Forestry and Fisheries). (2020). *Agriculture and Forestry Census in 2020 (in Japanese).*

MAFF (Ministry of Agriculture Forestry and Fisheries). (2022). *Smart agriculture (in Japanese).* https://www.maff.go.jp/j/kanbo/smart/attach/pdf/index-69.pdf

Mi, J., Nanseki, T., Chomei, Y., Uenishi Y., & Nguyen, T. L. (2021). Determinants of ICT and smart farming technology adoption by agricultural corporations in Japan. In *The 10th The Asian Society of Agricultural Economists International Conference.* http://www.asae2020.pku.edu.cn/index.htm

Nanseki, T. (2019). *Smart agriculture practice in rice-farming and perspective of farm in next-generation (in Japanese).* (T. Nanseki, Ed.). Yokendo, Tokyo, Japan.

Nanseki, T. (2021). *Agricultural corporations as seen from fact data: Profile, business operation, strategy and innovation (in Japanese).* Agriculture and Forestry Statistics Publishing Inc.

Nanseki, T., Chomei, Y., & Matsue, Y. (2016). *Rice farm management innovation and smart agriculture in TPP era: Farming technology package and ICT applications (in Japanese).* (T. Nanseki, Y. Chomei, & Y. Matsue, Eds.). Yokendo, Tokyo, Japan.

Ogata, Y., Nanseki, T., & Chomei, Y. (2019). Factor analysis of agricultural corporation managers' consciousness of ICT cost-effectiveness (in Japanese). *Agricultural Information Research, 28*(1), 1–12. https://doi.org/10.3173/air.28.1

Paxton, K. W., Mishra, A. K., Chintawar, S., Roberts, R. K., Larson, J. A., English, B. C., Lambert, D. M., Marra, M. C., Larkin, S. L., Reeves, J. M., & Martin, S. W. (2011). Intensity of precision agriculture technology adoption by cotton producers. *Agricultural and Resource Economics Review, 40*(1), 133–144. https://doi.org/10.1017/S1068280500004561

Rahelizatovo, N. C., & Gillespie, J. M. (2004). The adoption of best-management practices by Louisiana Dairy Producers. *Journal of Agricultural and Applied Economics, 36*(1), 229–240. https://doi.org/10.1017/s1074070800021970

Simmons, P., Winters, P., & Patrick, I. (2005). An analysis of contract farming in East Java, Bali, and Lombok, Indonesia. *Agricultural Economics, 33*(SUPPL 3), 513–525. https://doi.org/10.1111/j.1574-0864.2005.00096.x

Zhang, S., Sun, Z., Ma, W., & Valentinov, V. (2020). The effect of cooperative membership on agricultural technology adoption in Sichuan, China. *China Economic Review, 62*(August 2019), 101334. https://doi.org/10.1016/j.chieco.2019.101334

Chapter 15
Innovation Implementation and Its Determinants in Japanese Agricultural Corporations

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1 Introduction

Japanese agricultural management has been described as smaller in scale compared to Europe and the US. However, the percentage of Japanese agricultural corporations out of the total agricultural management is nearly the same as that of Germany and higher than that of Switzerland, France, Spain, and Italy (Nanseki, 2019, p. 337). In such agricultural corporation management, aside from the introduction of information and communications technology (ICT) in production management and business management, innovations such as processing and direct sales of agricultural goods that were produced are being promoted. Such innovative practices may significantly impact agricultural and rural structures in the future. Nanseki (2021) showed the state of innovation implementation in Japanese agricultural corporations using four types of innovation: product, process, marketing, and organizational innovation, as

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classified by OECD (2005). All of them were adopted by less than 50% of agricultural corporations. Most corporations (41.9%) implemented product innovation, particularly “producing and selling new or significantly improved goods”.

Therefore, it is important to understand the factors driving the adoption of these innovations to enhance innovation implementation and change agricultural structures. In this regard, Feder et al. (1985) reviewed the factors affecting innovation adoption in agriculture at the micro-level, using individual technologies as a proxy for agricultural innovations. Läpple et al. (2015) and Castillo-Valero and García-Cortijo (2021) presented such factors by treating innovation adoption in agriculture as overall innovation adoption. However, studies that consider innovation adoption in Japanese agricultural corporations as overall innovation and do not specify individual innovations do not exist to the best of our knowledge. Moreover, among the four types of innovation, product innovation is adopted by most Japanese agricultural corporations (Nanseki, 2021) as well as by Japanese firms (OECD, 2009). Therefore, this chapter aims to determine the factors associated with the implementation of product innovation in Japanese agricultural corporations.

The next section describes data collection and the empirical model. It is followed by the results and discussion section, which presents general information on Japanese agricultural corporations and the factors affecting the implementation of product innovation. The final section concludes the paper.

2 Data and Methodology

2.1 Data

The data for this study was collected from the “Questionnaire on Business Development and Innovation in Agricultural Corporation Management,” conducted by the authors in 2019 by mailing the questionnaire on agricultural corporations nationwide to 2,885 corporations. They collected the names of such corporations by independently searching the related websites (such as the Japan Association of Agricultural Corporations) and existing literature. By December of the same year, responses were received from 505 corporations (response rate: 17.5%). However, the number of valid answers to each item varied. An outline of the survey’s results is presented in Nanseki (2021). Product innovation was divided into two categories in the questionnaire: (1) starting to produce and sell new or significantly improved goods and (2) launching new or significantly improved services. Notably, 504 corporations answered for the first category, and 505 corporations answered for the second one. However, the number of valid observations with the available data of all the variables used for analysis of this study was 308.

2.2 Empirical Model

This study used the following probit model to determine whether a corporation implemented product innovation as following:

$$Y^* = \beta_0 + X\beta + e \quad (1)$$

$$\text{with } Y = 1 \text{ if } Y^* > 0 \text{ and } Y = 0 \text{ if } Y^* \leq 0$$

Here, Y^* is an unobserved or latent variable, and Y is an observed variable of Y^*. $Y = 1$ if the corporation implemented product innovation that means that the corporation started to offer new or significantly improved goods or services and 0 otherwise. X is the full set of explanatory variables that include a range of characteristics of agricultural corporations, such as main product, sales and profit, self-evaluation of their ability to innovate, and their representative's profile (Table 1). Further, β represents the set of parameters, and e is independent of X and has a standard normal distribution.

3 Results and Discussion

3.1 Characteristics of the Japanese Agricultural Corporation and Its Implementation of Product Innovation

The result of the basic analysis showed that the rate of implementing product innovation in Japanese agricultural corporations was 50.0% ($n = 154$) (Table 2). This finding suggests that 50.0% of corporations started to provide at least one of the two following types of product innovation: new or significantly improved products or services in the three years before the survey. More details on the distribution of corporations implementing product innovation based on their categories are shown in Table 3. Notably, corporations implement product innovation in different ways. Some product innovations can be creating food-residue-based feed, Omega-3 eggs in livestock corporations, the rice turned into ready-to-eat meals, or rice corporations cultivating a new variety. Some corporations may launch innovative services such as direct selling to cafeterias, providing tourist farms, paying the hometown tax, organizing events at farm stores, creating farmers' markets, and offering guidance on GLOBAL G.A.P.

Regarding the characteristics of agricultural corporations shown in Table 2, some common characteristics are observed as follows. A total of 86.1% of the corporations ($n = 265$) were stock companies and limited companies established on the guidelines of the Companies Act. A total of 89.9% of the corporations ($n = 277$) were qualified to own agricultural land. Although agricultural corporations were

Table 1 Description of variables

No	Variable	Description	Unit	Expected sign	Reference
I	Dependent variable				
	Product innovation (PI)	It equals one if a corporation started to produce and sell new or significantly improved goods or products, and/or launched new or significantly improved services in the three years before the survey. Otherwise, it equals zero	Dummy		
II	Independent variables				
1	Type of corporation	There are four types of corporations. 1 = Limited company; 2 = Stock company; 3 = Agricultural producers' cooperative corporation; 4 = Others	Categorical	+/–	
2	Own land	It equals one if a corporation is qualified to own farmland. Otherwise, it equals zero	Dummy	+	
3	Region	The region where the head office is located. There are seven regions. 1 = Hokkaido; 2 = Tohoku; 3 = Kanto; 4 = Hokuriku; 5 = Kinki and Tokai; 6 = Chugoku and Shikoku; 7 = Kyushu and Okinawa	Categorical	+/–	
4	Age of corporation	The number of years since the establishment of the corporation	Years	+/–	Ns: Castillo-Valero and García-Cortijo (2021)

(continued)

Table 1 (continued)

No	Variable	Description	Unit	Expected sign	Reference
5	Agricultural experience of corporation	The number of years since the corporation started engaging in agricultural activities	Years	+/−	
6	Background of corporation	There are seven categories. 1 = A farmer established the corporation of only one person corporation; 2 = A farmer jointly established the corporation with other members; 3 = A Farmer established the corporation in collaboration with non-farmers and companies from other industries; 4 = A non-farmer entered agriculture as an individual and established the corporation; 5 = The company mainly deals in a separate/different business, but it has entered agriculture as a new business; 6 = The parent/main company or group company has established a new corporation and entered agriculture; 7 = Others	Categorical	+/−	
7	Regular employees	The total number of regular employees in the corporation	Persons	+	Castillo-Valero and García-Cortijo (2021); Hashi and Stojčić (2013) as firm size

(continued)

Table 1 (continued)

No	Variable	Description	Unit	Expected sign	Reference
8	Annual sales	The sales revenue generated in latest accounts before the survey. 1 = Less than 30 million yen; 2 = 30–50 million yen; 3 = 50–100 million yen; 4 = 100–300 million yen; 5 = 300–500 million yen; 6 = 500–1,000 million yen; 7 = 1,000–1,500 million yen; 8 = 1,500–2,000 million yen; 9 = Over 2,000 million yen	Categorical	+	+ Läpple et al. (2015) in terms of farm area
9	Profit margin	The profit margin earned in latest accounts before the survey. 1 = 0% (Break-even); 2 = 1–5%; 3 = 5–10%; 4 = 10–15%; 5 = 15–20%; 6 = Over 20%; 7 = Deficit	Categorical	+/−	
10	Growth stage	The corporation's growth stage. 1 = Starting; 2 = Growing; 3 = Mature; 4 = Recession; 5 = 2nd starting; 6 = 2nd growing; 7 = 2nd mature; 8 = 2nd recession; 9 = Others	Categorical	+/−	
11	Sales target	The sales the corporation aims to earn in the next five years compared to their current sales. 1 = Same; 2 = 1.2 times; 3 = 1.5 times; 4 = 1.8 times; 5 = 2.0 times; 6 = Over 2 times but less than 3 times; 7 = 3 times or more; 8 = Lesser; 9 = No target	Categorical	+	

(continued)

Table 1 (continued)

No	Variable	Description	Unit	Expected sign	Reference
12	Profit margin target	The profit margin the corporation aims to achieve in the next five years. 1 = 0% (Break-even); 2 = 1–5%; 3 = 5–10%; 4 = 10–15%; 5 = 15–20%; 6 = Over 20%; 7 = No target	Categorical	+/−	
13	Main product	It represents the agricultural product that accounted for more than 60% of the corporation's total annual sales There are 14 categories: 1 = Paddy rice; 2 = Wheat; 3 = Beans and coarse cereals; 4 = Open ground vegetable; 5 = Facility vegetable; 6 = Flowers and foliage plants; 7 = Fruiter; 8 = Mushroom; 9 = Livestock products; 10 = Mixed; 11 = Others	Categorical	+/−	
14	Self-evaluation in new product and technology development	Self-evaluation of the ability to innovate. 1 = Weaker than others; 2 = Slightly weaker than others; 3 = Neither weaker nor stronger than others; 4 = Slightly stronger than others; 5 = Stronger than others	Likert scale	+	
15	FTA participation	Self-evaluation of the Free Trade Agreements (FTA) participation of Japan. 1 = Big crisis; 2 = Crisis; 3 = Neither crisis nor chance; 4 = Chance; 5 = Big chance	Likert scale	+/−	
16	Age of representative	The age of the corporation's representative. 1 = 10–20; 2 = 20–30; 3 = 30–40; 4 = 40–50; 5 = 50–60; 6 = 60–70; 7 = Over 70	Categorical	–	Läpple et al. (2015), Feder et al. (1985)

(continued)

Table 1 (continued)

No	Variable	Description	Unit	Expected sign	Reference
17	High school	If the corporation's representative graduated high school, it equals one. Otherwise, it equals zero	Dummy	+/−	
18	Vocational school	If the corporation's representative graduated vocational school, it equals one. Otherwise, it equals zero	Dummy	+/−	
19	Educational institution	If the corporation's representative graduated from an educational institution, it equals one. Otherwise, it equals zero	Dummy	+/−	
20	Junior college	If the corporation's representative graduated junior college, it equals one. Otherwise, it equals zero,	Dummy	+/−	
21	University	If the corporation's representative graduated university, it equals one. Otherwise, it equals zero	Dummy	+/−	
22	Graduate school	If the corporation's representative graduated from graduate school, it equals one. Otherwise, it equals zero	Dummy	+/−	
23	Other type of education	If the corporation's representative completed some other type of education, it equals one. Otherwise, it equals zero	Dummy	+/−	
24	Non-agricultural experience of representative	The values range from 1 to 6: 1 = None; 2 = 1–5 years, 3 = 5–10 years; 4 = 10–15 years; 5 = 15–20 years; 6 = 20–25 years	Categorical	+/−	+ (Feder et al., 1985); –(Läpple et al., 2015)

Table 2 Descriptive results on the implementation of product innovation and explanatory variables (Nanseki, 2021)

No	Variable	Unit	Mean	Std. Dev	Min	Max	Numbers of corporations
I	Dependent variable						
	Product innovation (PI)	Dummy	0.500	0.501	0	1	154
II	Independent variables						
1	Type of corporation	Categorical					
	1 = Limited company		0.416	0.494	0	1	128
	2 = Stock company		0.445	0.498	0	1	137
	3 = Agricultural producers' cooperative corporation		0.130	0.337	0	1	40
	4 = Others		0.010	0.098	0	1	3
2	Own land	Dummy	0.899	0.301	0	1	277
3	Region	Categorical					
	1 = Hokkaido		0.026	0.159	0	1	8
	2 = Tohoku		0.192	0.394	0	1	59
	3 = Kanto		0.143	0.350	0	1	44
	4 = Hokuriku		0.101	0.301	0	1	31
	5 = Kinki and Tokai		0.127	0.333	0	1	39
	6 = Chugoku and Shikoku		0.166	0.372	0	1	51
	7 = Kyushu and Okinawa		0.247	0.432	0	1	76
4	Age of corporation	Years	20.110	14.196	1	109	–
5	Agricultural experience of corporation	Years	30.734	31.687	0	319	–
6	Background of corporation	Categorical					
	1 = A farmer established the corporation of only one member corporation		0.416	0.494	0	1	128

(continued)

Table 2 (continued)

No	Variable	Unit	Mean	Std. Dev	Min	Max	Numbers of corporations
	2 = A farmer jointly established cooperation with other members		0.286	0.452	0	1	88
	3 = A farmer established the corporation in collaboration with non-farmers and companies from other industries		0.039	0.194	0	1	12
	4 = A non-farmer entered agriculture as an individual and established a corporation		0.055	0.229	0	1	17
	5 = The company mainly deals in a separate/different business, but it has entered agriculture as a new business		0.075	0.263	0	1	23
	6 = The parent/main company or group company has established a new corporation and entered agriculture		0.084	0.278	0	1	26
	7 = Others		0.045	0.209	0	1	14
7	Regular employees	Persons	17.045	35.348	1	352	–
8	Annual sales	Categorical					
	1 = Less than 30 million yen		0.075	0.263	0	1	23
	2 = 30–50 million yen		0.101	0.301	0	1	31
	3 = 50–100 million yen		0.227	0.420	0	1	70
	4 = 100–300 million yen		0.386	0.488	0	1	119
	5 = 300–500 million yen		0.075	0.263	0	1	23

(continued)

Table 2 (continued)

No	Variable	Unit	Mean	Std. Dev	Min	Max	Numbers of corporations
	6 = 500–1,000 million yen		0.049	0.216	0	1	15
	7 = 1,000–1,500 million yen		0.039	0.194	0	1	12
	8 = 1,500–2,000 million yen		0.016	0.127	0	1	5
	9 = Over 2,000 million yen		0.032	0.178	0	1	10
9	Profit margin	Categorical					
	1 = 0% (Break-even)		0.104	0.306	0	1	32
	2 = 1–5%		0.321	0.468	0	1	99
	3 = 5–10%		0.192	0.394	0	1	59
	4 = 10–15%		0.127	0.333	0	1	39
	5 = 15–20%		0.042	0.201	0	1	13
	6 = Over 20%		0.019	0.138	0	1	6
	7 = Deficit		0.195	0.397	0	1	60
10	Growth stage	Categorical					
	1 = Starting		0.081	0.274	0	1	25
	2 = Growing		0.347	0.477	0	1	107
	3 = Mature		0.179	0.384	0	1	55
	4 = Recession		0.068	0.252	0	1	21
	5 = 2nd starting		0.149	0.357	0	1	46
	6 = 2nd growing		0.120	0.326	0	1	37
	7 = 2nd mature		0.042	0.201	0	1	13
	8 = 2nd recession		0.003	0.057	0	1	1
	9 = Others		0.010	0.098	0	1	3
11	Sales target	Categorical					
	1 = Same		0.127	0.333	0	1	39
	2 = 1.2 times		0.318	0.467	0	1	98
	3 = 1.5 times		0.273	0.446	0	1	84
	4 = 1.8 times		0.029	0.169	0	1	9
	5 = 2.0 times		0.120	0.326	0	1	37
	6 = Over 2 times but less than 3 times		0.055	0.229	0	1	17

(continued)

Table 2 (continued)

No	Variable	Unit	Mean	Std. Dev	Min	Max	Numbers of corporations
	7 = 3 times or more		0.058	0.235	0	1	18
	8 = Lesser		0.010	0.098	0	1	3
	9 = No target		0.010	0.098	0	1	3
12	Profit margin target	Categorical					
	1 = 0% (Break-even)		0.058	0.235	0	1	18
	2 = 1–5%		0.214	0.411	0	1	66
	3 = 5–10%		0.338	0.474	0	1	104
	4 = 10–15%		0.195	0.397	0	1	60
	5 = 15–20%		0.120	0.326	0	1	37
	6 = Over 20%		0.055	0.229	0	1	17
	7 = No target		0.019	0.138	0	1	6
13	Main product	Categorical					
	1 = Paddy rice		0.205	0.404	0	1	63
	2 = Wheat		0.003	0.057	0	1	1
	3 = Beans and coarse cereals		0.010	0.098	0	1	3
	4 = Open ground vegetable		0.110	0.314	0	1	34
	5 = Facility vegetable		0.143	0.350	0	1	44
	6 = Flowers and foliage plants		0.039	0.194	0	1	12
	7 = Fruiter		0.097	0.297	0	1	30
	8 = Mushroom		0.036	0.186	0	1	11
	9 = Livestock production		0.146	0.354	0	1	45
	10 = Mixed		0.117	0.322	0	1	36
	11 = Others		0.094	0.293	0	1	29
14	Self-evaluation in new product and technology development	Likert	2.805	1.025	1	5	–
	1 = Weaker than others		0.110				34
	2 = Slightly weaker than others		0.253				78

(continued)

Table 2 (continued)

No	Variable	Unit	Mean	Std. Dev	Min	Max	Numbers of corporations
	3 = Neither weaker nor stronger than others		0.412				127
	4 = Slightly stronger than others		0.169				52
	5 = Stronger than others		0.055				17
15	FTA participation	Likert	2.851	1.003	1	5	–
	1 = Big crisis		0.104				32
	2 = Crisis		0.214				66
	3 = Neither crisis nor chance		0.471				145
	4 = Chance		0.149				46
	5 = Big chance		0.062				19
16	Age of representative	Categorical	5.292	1.199	2	7	–
	1 = 10–20		0.000				0
	2 = 20–30		0.003				1
	3 = 30–40		0.081				25
	4 = 40–50		0.198				61
	5 = 50–60		0.208				64
	6 = 60–70		0.357				110
	7 = Over 70		0.153				47
17	High school	Dummy	0.532	0.500	0	1	164
18	Vocational school	Dummy	0.094	0.293	0	1	29
19	Educational institution	Dummy	0.143	0.350	0	1	44
20	Junior college	Dummy	0.049	0.216	0	1	15
21	University	Dummy	0.321	0.468	0	1	99
22	Graduate school	Dummy	0.032	0.178	0	1	10
23	Other type of education	Dummy	0.026	0.159	0	1	8
24	Non-agricultural experience	Categorical	3.328	1.980	1	6	–
	1 = None		0.250				77
	2 = 1–5 years		0.198				61
	3 = 5–10 years		0.140				43

(continued)

Table 2 (continued)

No	Variable	Unit	Mean	Std. Dev	Min	Max	Numbers of corporations
	4 = 10–15 years		0.081				25
	5 = 15–20 years		0.049				15
	6 = 20–25 years		0.282				87

Note $N = 308$; \$1–109 yen (in 2019 from https://www.stat-search.boj.or.jp/ssi/cgi-bin/famecgi2)

Table 3 Distribution of corporations implementing product innovation (PI) based on their category (Nanseki, 2021)

Category	Description	Frequency	Percentage
PI_only product	If a corporation started providing only new or significantly improved products, it equals one. Otherwise, it equals zero	105	34.1
PI_only_services	If a corporation started providing new or significantly improved services, it equals one. Otherwise, it equals zero	16	5.2
PI_both product and service	If a corporation started providing new or significantly improved products and services, it equals one. Otherwise, it equals zero	33	10.7
PI_None	If a corporation had not yet started to provide new or significantly improved products and services, it equals one. Otherwise, it equals zero	154	50.0
Total		308	100.0

Note $N = 308$

established based on various backgrounds, particularly those from non-agricultural sectors that recently joined the agriculture sector. Notably, 41.6% of the corporations ($n = 128$) originated from a farmer who had established a one-person corporation. Corporations that began with a farmer jointly establishing the corporation with other members followed next (28.6%, $n = 88$). Considering sales revenue as an economic indicator, most corporations (38.6%, $n = 119$) earned 100 to 300 million yen in sales revenue, followed by the corporations generating 50 to 100 million yen (22.7%, $n = 70$). Interestingly, 243 corporations (78.9%) had sales revenue up to 300 million yen. However, 85.3% of corporations ($n = 269$) aimed to achieve at least 1.2 times their current sales in the next five years. This finding suggests that future sales will see a significant change. Furthermore, most corporations (33.8%, $n = 104$) seek a profit margin of 5–10%. In addition, paddy rice accounted for more than 60% of most corporations' total annual sales (20.5%, $n = 63$), followed by facility vegetables and mixed products (14.3%, $n = 44$ and 11.7%, $n = 36$, respectively).

Corporations were asked to evaluate whether their ability to produce new products or technologies is stronger or weaker than that of others. Resultingly, the mean value of this self-evaluation was 2.805 on a scale ranging from 1 (weaker than others) to 5 (stronger than others). This result indicates that, on average, corporations perceive their ability to innovate at a level lower than neither weaker nor stronger than the ability of others. Of these, 69 corporations (22.4%) evaluated this ability as being at least slightly stronger than that of others.

The study also collected data on the representatives of corporations, particularly their age, education, and non-agricultural experience. Notably, their ages varied from 20 to over 70 years old, with most representatives (35.7%, $n = 110$) between the ages of 60 and 70. Their education was analyzed based on different levels. Most representatives (53.2%, $n = 164$) completed high school, 99 representatives (32.1%) graduated from university and 44 (14.3%) from an educational institution. Furthermore, 29 representatives (9.4%) completed vocational school, 15 (4.9%) attended junior college, followed by 10 (3.2%) who finished graduate school, and 8 (2.6%) who gained some other type of education. Finally, 75% of them ($n = 231$) had at least one year of experience in non-agricultural activities.

3.2 Determinants of Implementing Product Innovation

The objective of this study is to unfold the factors driving the implementation of product innovation in Japanese agricultural corporations by the characteristics of agricultural corporations and the profile of corporation representatives. The results are presented in Table 4.

First, the value of the likelihood ratio chi-square was 116.2 and significant at the 1% level. This finding suggests that the current estimated model is statistically significantly better than a model without any explanatory variables. Moreover, the pseudo R^2 was 0.277, and the correctly classified percentage was 72.9%.

Second, factors determining the implementation of product innovation in Japanese agricultural corporations can be observed in Table 4. The sign of the coefficients showed the relationship between the variable and innovation implementation. If the sign of a coefficient is positive, it means that one unit increase in the variable will increase the probability of implementing the product innovation in agricultural corporations. Conversely, if the sign of a coefficient is negative, it means that a one-unit increase in the variable will reduce the probability of implementing the product innovation. However, all continuous variables are non-significant in this study. The categorical variables are transformed into dummy variables and expressed conditionally in the base group, which is the first group in the categories. Table 4 shows that the coefficients of three categories under the variable Annual sales (300–500 million yen, 500–1,000 million yen, and over 2,000 million yen) were significantly positive. This finding signifies that corporations whose sales revenue stands between 300 million yen and 1 billion yen and those earning more than 2 billion yen tend to implement product innovation more than those generating sales

Table 4 Factors associated with the implementation of product innovation (Nanseki, 2021)

No	Variable	Coef.	Std. err	*z*	$P > \lvert z \rvert$	[95% Conf. interval]	
1	Type of corporation (1 = Limited company is the base group)						
	2 = Stock company	−0.011	0.238	−0.050	0.964	−0.477	0.455
	3 = Agricultural producers' cooperative corporation	−0.005	0.348	−0.010	0.989	−0.688	0.678
	4 = Others	−0.429	1.105	−0.390	0.698	−2.595	1.738
2	Own land (Dummy)	0.151	0.342	0.440	0.660	−0.520	0.821
3	Region (1 = Hokkaido is the base group)						
	2 = Tohoku	0.156	0.617	0.250	0.800	−1.054	1.366
	3 = Kanto	0.394	0.633	0.620	0.533	−0.846	1.635
	4 = Hokuriku	1.169*	0.676	1.730	0.084	−0.157	2.494
	5 = Kinki and Tokai	1.064	0.657	1.620	0.105	−0.224	2.352
	6 = Chugoku and Shikoku	0.207	0.628	0.330	0.741	−1.023	1.438
	7 = Kyushu and Okinawa	0.424	0.607	0.700	0.485	−0.766	1.615
4	Age of corporation (Years)	0.000	0.009	−0.030	0.978	−0.017	0.017
5	Agricultural experience of corporation (Years)	−0.001	0.003	−0.470	0.637	−0.008	0.005
6	Background of the corporation (1 = A farmer established the corporation of only one member/single corporation is the base group)						
	2 = A farmer jointly established the cooperation with other members	0.182	0.263	0.690	0.490	−0.334	0.697
	3 = A Farmer established the corporation in collaboration with non-farmers and companies from other industries	−0.867	0.546	−1.590	0.113	−1.937	0.204
	4 = A non-farmer entered agriculture as an individual and established the corporation	−0.680	0.504	−1.350	0.178	−1.668	0.309
	5 = The company mainly deals in a separate/different business, but it has entered agriculture as a new business	−0.477	0.479	−0.990	0.320	−1.416	0.463
	6 = The parent/main company or group company has established a new corporation and entered agriculture	0.138	0.414	0.330	0.739	−0.673	0.949
	7 = Others	−0.366	0.524	−0.700	0.484	−1.393	0.660
7	Regular employees (Persons)	−0.002	0.004	−0.460	0.648	−0.011	0.007

(continued)

Table 4 (continued)

No	Variable	Coef.	Std. err	z	P > |z|	[95% Conf. interval]	
8	Annual sales (1 = Less than 30 million yen is the base group)						
	2 = 30–50 million yen	0.289	0.484	0.600	0.550	−0.660	1.238
	3 = 50–100 million yen	0.493	0.422	1.170	0.243	−0.334	1.319
	4 = 100–300 million yen	0.517	0.409	1.260	0.207	−0.285	1.318
	5 = 300–500 million yen	1.883***	0.588	3.200	0.001	0.730	3.036
	6 = 500–1,000 million yen	1.557**	0.655	2.380	0.017	0.273	2.840
	7 = 1,000–1,500 million yen	−0.827	0.783	−1.060	0.291	−2.362	0.708
	8 = 1,500–2,000 million yen	1.406	0.890	1.580	0.114	−0.338	3.150
	9 = Over 2,000 million yen	1.671*	0.889	1.880	0.060	−0.070	3.413
9	Profit margin (1 = 0% (Break-even) is the base group)						
	2 = 1–5%	−0.796**	0.350	−2.280	0.023	−1.481	−0.111
	3 = 5–10%	−1.208***	0.394	−3.070	0.002	−1.979	−0.436
	4 = 10–15%	−0.615	0.443	−1.390	0.165	−1.484	0.254
	5 = 15–20%	−0.564	0.546	−1.030	0.302	−1.634	0.507
	6 = Over 20%	−1.156	0.867	−1.330	0.182	−2.856	0.543
	7 = Deficit	−0.551	0.369	−1.490	0.136	−1.275	0.174
10	Growth stage (1 = Starting is the base group)						
	2 = Growing	−0.249	0.417	−0.600	0.550	−1.067	0.569
	3 = Mature	−0.344	0.473	−0.730	0.468	−1.271	0.584
	4 = Recession	−0.271	0.557	−0.490	0.626	−1.363	0.820
	5 = 2nd starting	0.014	0.492	0.030	0.978	−0.950	0.977
	6 = 2nd growing	−0.825	0.504	−1.640	0.102	−1.813	0.163
	7 = 2nd mature	−0.716	0.674	−1.060	0.288	−2.038	0.605
	8 = 2nd recession	0.000	(empty)				
	9 = Others	−0.068	0.867	−0.080	0.937	−1.768	1.631
11	Sales target (1 = Same is the base group)						
	2 = 1.2 times	0.186	0.334	0.560	0.577	−0.468	0.841
	3 = 1.5 times	0.665*	0.374	1.780	0.075	−0.068	1.398
	4 = 1.8 times	1.774**	0.738	2.400	0.016	0.328	3.220
	5 = 2.0 times	0.782*	0.445	1.760	0.079	−0.091	1.655
	6 = Over 2 times but less than 3 times	0.584	0.564	1.030	0.301	−0.522	1.690
	7 = 3 times or more	1.056*	0.577	1.830	0.067	−0.076	2.187
	8 = Lesser	0.310	1.171	0.270	0.791	−1.985	2.606
	9 = No target	0.000	(empty)				
12	Profit margin target (1 = 0% (Break-even) is the base group)						
	2 = 1–5%	0.270	0.498	0.540	0.587	−0.705	1.246

(continued)

Table 4 (continued)

No	Variable	Coef.	Std. err	z	$P > \|z\|$	[95% Conf. interval]	
	3 = 5–10%	0.880*	0.497	1.770	0.077	−0.094	1.854
	4 = 10–15%	1.056*	0.540	1.950	0.051	−0.003	2.115
	5 = 15–20%	0.544	0.589	0.920	0.355	−0.610	1.699
	6 = Over 20%	0.814	0.652	1.250	0.211	−0.463	2.092
	7 = No target	0.164	1.008	0.160	0.870	−1.811	2.140
13	Main product (1 = Paddy rice is the base group)						
	2 = Wheat	0.000	(empty)				
	3 = Beans and coarse cereals	2.037*	1.128	1.810	0.071	−0.174	4.248
	4 = Open ground vegetable	−0.629	0.403	−1.560	0.118	−1.419	0.160
	5 = Facility vegetable	−0.771*	0.403	−1.920	0.055	−1.561	0.018
	6 = Flowers and foliage plants	0.488	0.624	0.780	0.434	−0.734	1.710
	7 = Fruiter	0.484	0.416	1.160	0.244	−0.331	1.299
	8 = Mushroom	0.887	0.582	1.530	0.127	−0.253	2.027
	9 = Livestock production	−0.752*	0.430	−1.750	0.081	−1.596	0.092
	10 = Mixed	−0.142	0.357	−0.400	0.691	−0.842	0.558
	11 = Others	0.043	0.397	0.110	0.913	−0.735	0.822
14	Self-evaluation in new product and technology development	0.323***	0.106	3.050	0.002	0.115	0.531
15	FTA participation	0.056	0.099	0.570	0.570	−0.138	0.251
16	Age of representative	−0.043	0.092	−0.470	0.640	−0.223	0.137
17	High school	−0.114	0.227	−0.500	0.616	−0.559	0.331
18	Vocational school	−0.430	0.334	−1.290	0.198	−1.085	0.225
19	Educational institution	−0.387	0.333	−1.160	0.246	−1.041	0.266
20	Junior college	0.102	0.441	0.230	0.818	−0.762	0.965
21	University	−0.112	0.251	−0.450	0.655	−0.603	0.380
22	Graduate school	−0.128	0.568	−0.220	0.822	−1.241	0.986
23	Other type of education	−0.646	0.722	−0.890	0.371	−2.061	0.770
24	Non-agricultural experience	−0.022	0.063	−0.350	0.730	−0.145	0.101
	Constant	−1.576	1.288	−1.220	0.221	−4.100	0.948

Note $N = 303$ (Five observations were not used in the probit model because they belonged to the categories that predict failure/success perfectly); $1–109 yen (in 2019 from https://www.stat-search.boj.or.jp/ssi/cgi-bin/famecgi2)
, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively; Log likelihood = –151.921; LR Chi-Square (73) = 116.2; Pseudo $R^2 = 0.277$; percent correctly classified = 72.9%

revenues lower than 30 million yen. From this result, it can be concluded that higher annual sales amount of the corporation as an economic scale factor contributed to the likelihood of innovation implementation. This finding was consistent with that of Läpple et al. (2015), who found that larger-sized farms tend to implement innovation more, measuring farm size by the utilizable agricultural area However, our conclusion does not hold for all categories denoting high sales revenues.

Notably, the coefficients of four categories under the variable Sales target, namely 1.5 times, 1.8 times, 2.0 times, and 3.0 times or more, were significantly positive. This finding indicates that corporations seeking sales higher than 1.5 times their current sales in the next five years are more likely to adopt product innovation than corporations wanting their sales to remain the same. However, corporations seeking sales 2 times more but less than 3 times their current sales are exceptions to this result. Furthermore, the coefficients of target profit at 5–10% and 10–15% were significantly positive as well (Table 4). This result suggests that corporations targeting profit margins between 5 and 15% have a higher probability of implementing product innovation than corporations seeking to break even. The final variable that had a significantly positive coefficient was Self-evaluation in new product and technology development. It means that the corporations that self-evaluated themselves as being stronger than others tend to implement more product innovation. It is a reasonable result because corporations that find their ability to innovate as being strong can innovate their products and engage more in innovative practices (Sauer & Vrolijk, 2019).

Contrastingly, the coefficients of profit margin from 1–5% and 5–10% were significantly negative. This shows that corporations with a profit margin of 1–10% are less likely to implement product innovation than corporations breaking even. The coefficients of facility vegetable and livestock products as corporations' main products were also significantly negative. This implies that the corporations mainly dealing in facility vegetables or livestock tend to not implement the production innovation than those whose main product is rice.

The results discussed above show that all determinants of implementing product innovation pertain to the characteristics of corporations. That is, the profile of the representative does not affect the implementation. Especially, age had no effect, considering that the aging population is a crucial concern in Japanese agriculture. This result differs from that of previous studies (Feder et al., 1985; Läpple et al., 2015), which found that older farmers tend to adopt fewer agricultural innovations and technologies. They show that old farmers believe that innovating might not be effective at their age, considering the time and money invested and the payoff from innovating. In this regard, this study shows that the representative's age does not deter the corporation because the corporation could continue its business more easily (MAFF, 2019).

4 Conclusion

To summarize, product innovation is implemented by 50.0% of Japanese agricultural corporations. They continue to multiply because of easier employment and business continuity (MAFF, 2019). Moreover, they have changed the agricultural sector. Especially, the rate of implementing product innovation of the Japanese agricultural corporations tends to increase in corporations generating sales revenues between 300 million yen to less than 1 billion yen and those with sales from 2 billion yen and above. The corporations targeting more than 1.5 times their current sales tend to implement product innovation more than those seeking the same as their current sales. However, corporations that aim for more than two times but less than three times their current sales are exceptions. The corporations with a target profit margin of 5–15% are more likely to implement product innovation than those intending to break even. The corporations with higher self-evaluation in new product and technology development tend to implement more product innovation.

Overall, these results imply that: (1) corporations might require suitable annual sales to innovate; (2) innovating farms aim to grow and set high targets; (3) innovations are stimulated by higher self-evaluation in new product and technology development. Therefore, these factors should be considered to promote product innovation in Japanese agricultural corporations. The researchers intend to expand their research to other types of innovation (process, marketing, and organizational) in the future to present the determinants of implementing agricultural innovation extensively.

References

Castillo-Valero, J. S., & García-Cortijo, M. C. (2021). Factors that determine innovation in agrifood firms. *Agronomy, 11*(5). https://doi.org/10.3390/agronomy11050989

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survery. *Economic Development and Cultural Change, 33*(2), 255–298. http://www.jstor.org/stable/1153228

Hashi, I., & Stojčić, N. (2013). The impact of innovation activities on firm performance using a multi-stage model: Evidence from the Community Innovation Survey 4. *Research Policy, 42*(2), 353–366. https://doi.org/10.1016/j.respol.2012.09.011

Läpple, D., Renwick, A., & Thorne, F. (2015). Measuring and understanding the drivers of agricultural innovation: Evidence from Ireland. *Food Policy, 51*(2015), 1–8. https://doi.org/10.1016/j.foodpol.2014.11.003

MAFF (Ministry of Agriculture Forestry and Fisheries). (2019). FY2018 summary of the annual report on food, agriculture and rural areas in Japan. https://www.maff.go.jp/e/data/publish/attach/pdf/index-160.pdf

Nanseki, T. (2019). *Smart agriculture practice in rice-farming and perspective of farm in next-generation* (T. Nanseki, ed.). (p. 363.). Yokendo Co. Ltd. (in Japanese).

Nanseki, T. (2021). *Agricultural corporations as seen from fact data: Profile, business operation, strategy and innovation.* Agriculture and Forestry Statistics Publishing (in Japanese).

Nguyen, T. L., Nanseki, T., Chomei, Y., Uenishi Y., & Mi, J. (2021). Determinants of the product innovation implementations in Japanese agricultural corporations. In *The 10th ASAE (The Asian*

Society of Agricultural Economists) International Conference. http://www.asae2020.pku.edu.cn/index.htm

OECD. (2005). Oslo manual: Guidelines for collecting and interpreting innovation data. In *OECD and Eurostat Publication* (3rd ed.). OECD Publishing. https://doi.org/10.1787/9789264013100-en

OECD. (2009). *Innovation in firms: A microeconomic perspective*. https://www.oecdilibrary.org/docserver/9789264056213en.pdf?expires=1625537110&id=id&accname=oid008387&checksum=FA127BBDC2970407F2B1F3AEF8EBACE8

Sauer, J., & Vrolijk, H. (2019). Innovation and performance–evidence at micro level. *Applied Economics, 51*(43), 4673–4699. https://doi.org/10.1080/00036846.2019.1597252

Appendix
The Role of Education, Institutional Settings and ICT on the Integrated Production Development in Spain

Winston Esteban Marte, Teruaki Nanseki, and Fernando Bienvenido

Introduction

In recent years, consumers' concern on product quality and demand on application of good agricultural practices (GAP), good manufacturing practices (GMP), and environmental conservation have been increasing all over the world. This is the case of developed nations such as Japan, Germany, United Kingdom, France, Belgium, Holland, Italy, Denmark, the United States of America and Canada among others. These issues are not only faced by farmers from agricultural product export countries such as Spain and the Dominican Republic, but also by Japanese farmers. This is especially true for Almeria's farmers, who export fruits and vegetables to European markets during its cold seasons as well as for Dominican oriental vegetable farmers though they export during the whole year and not only to European markets but also to the United States of America and Canadian markets.

Almeria is located by the Mediterranean sea, in the southeast of Spain, and holds the largest concentration of greenhouses in the world (Acebedo et al., 2009). This is a favorable factor for the development and proliferation of pest and plague in the area. That may call not only for a rational use of pesticides to manage pests but also for the adoption and/or application of cultural measures and biological control methods. Such crop management practices, among others, addressed to make best use

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of available resources and to reduce emissions of agro-chemicals to the environmental are ways to assure agricultural sustainability and food safety (Haverkort et al., 2008).

In order to successfully address these issues accurate agricultural policies are required. Nonetheless, the existence itself of an agricultural policy does not assure its successful implementation. Factors such as educational programs, institutional settings as well as the development of information and communication technology (ICT) tools may play a significant role in accomplishing policy objectives. Education is expected to have a positive impact on all types of activities including agriculture. Therefore, educated farmers are expected to be better farm managers, more receptive to adopt new technologies, and to keep up with market trends and institutional policy changes. These factors may play an important role in improving productive efficiency, assuring food safety and good agricultural practices. Similarly, the coordinated and cooperative work of all stakeholders and institutions related to a policy may contribute to the accomplishment of their roles, and therefore policy objectives as well.

Thus, the objectives of this chapter are to describe the role of educational programs, institutional settings and information and communication technology tools on integrated production (IP) developments in Almeria. To consider the necessity of integrated production and the role of above factors, the transfer of this agricultural system (IP) to other countries is discussed as well. As a case of other countries, the Dominican Republic is selected because of similar cultural and agricultural features with Spain. Some of the cultural similarities include spoken language (Spanish) and religious believe (Christian-catholic). While both countries, Spain and the Dominican Republic, are facing similar market requirements (GAP, GMP, traceability, environmental protection) to produce and export to European markets agricultural products such as green pepper, chili pepper, melon, eggplant, bitter melon, green beans, and tomatoes.

Outline of the Study Site and Survey Method

The research site of this chapter corresponds to the province of Almeria, which is located in the region of Andalucía, in the south of Spain. Since the regional economy mostly relies on agriculture and there has been a pressure/requirement regarding food quality, safety, and good agricultural practices from countries such as Germany, Italy, France, Holland, and England, the government of Andalucía has decided to focus on agriculture as a development tool. As for 2009, in the region of Andalucía around 375,000 ha were cultivated under IP protocols, sharing 63% of the total area under IP in Spain.

The region devotes some 365,000 ha every year to the production of vegetables and fruits, sharing about 35% of the national production. The province of Almeria is leading the production of tomato, watermelon, melon, cucumber, eggplant, green beans, zucchini, and pepper (Salazar et al., 2002). Annual production of these vegetables and fruits is greater than 3 million tons and export value amounts to more than

€2,000 million per year (Acebedo et al., 2009). In this province, there are approximately 16,000 farmers producing fruits and vegetables in 30,000 ha of plastic covered greenhouses. This indicates that the average greenhouse area per farmer is 1.87 ha. While the total area expected to be under IP for 2009–2010 campaign was estimated to be 18,000 ha. Meanwhile, the number of IP certified farmers was 4,000 suggesting an average farm size of 4.50 ha for IP certified farmers (Ministry of Agricultura and Fishery of Andalucía, 2010). Thus, IP certified farmers were cultivating areas over 2 times larger compared to IP non-certified farmers.

The information provided in this chapter comes from two surveys carried out during 12–25 September 2008 and 13–23 November 2009. These surveys were done by the authors and consisted of bibliographical search and face to face interviews of each one of the IP stakeholders, which include farmers, farmers' cooperative leaders, technicians, officials of the Ministry of Agriculture and Fishery of Andalucía, researchers from the University of Almeria, the El Ejido city hall officials, and the IFAPA institute, which is responsible for farmers and technicians training on IP.

Background and Development of Integrated Production (IP) in Almeria

Integrated Production (IP) is an agricultural production system that used natural methods and natural mechanisms of production to manage pests and diseases, taking into account the protection of the environment and the farm economy, with social responsibility. IP not only takes into consideration operations at the farm level but also at packaging, processing, and labeling (Ministry of Agriculture and Fisher of Andalucía, 2010).

During the decades of the 60's and 70's, the regional government of Andalucía promoted the formation and development of agricultural cooperatives in order to gather farmers since they were mostly small farmers. The purpose of this policy was to help farmers to reduce production costs, improve product quality and safety, and commercialize greater volumes of products not only in national market (Spain) but also in international markets (mainly the UK, France, and Germany). However, with an inefficient extension service, an increasing demand on product quality and safety, and destination country markets demands on good agricultural practices toward agricultural sustainability, a production system that assures better product quality and safety and environmental sustainability was required. Under such circumstances, the regional government of Andalucía decided to start Integrated Production in 1990.

In the European Union (EU) there is an institutional framework that provides guidelines on integrated production systems. The main institutions are the International Organization for Biological and Integrated Control of Noxious Animals and Plants (IOBC), located in Switzerland, the Integrated Vegetable Production organizations (IVP), and the European Initiative for Sustainable Development in Agriculture (EISA), which is based in Brussels and was found in 2001. The IVP and EISA are committed to agricultural sustainability considering economic viability, environmental responsibility, and social acceptability of farms. These two institutions have developed guidelines with specific principle and practices on the management of crop protection, nutrient, soil, energy, water, and natural habitats (Haverkort et al., 2008).

In Almeria, Spain, IP regulations are within the guidelines framework provided by IVP and EISA. Two regulations outline the main content of IP in Horticulture. One establishes the general framework for horticultural products and the other is specific for each crop (tomato, watermelon, melon, cucumber, eggplant, green beans, zucchini, and pepper). These norms are in line with other quality certification systems such as Naturane, AENOR, and Global-GAP, but also include more demanding regulations and provide users tools to assure product quality and safety and production requirements.

This agricultural production system is freely accepted by farmers following some requirements, such as registration at the Andalucían Integrated Production Register, presence of technical service validated by the regional government, farm activities records, annual farm plan, and weekly submission of a report on sanitary conditions and measures taken.

Usually, farmers get registered through groups of integrated production (called "APIs"), though they are able to register individually. These APIs can be either formed within an agricultural cooperative or a group of farmers may just gather together themselves and form an API. The APIs have to send the regional government information on the different activities taking place at the farms and the government uses this information for follow up and monitoring purposes. Every API has to hire qualified technicians (approved by the Ministry of Agriculture and Fishery of Andalucía) to direct each one of the stages during production, handling, manipulation, and processing. The technical service is responsible for providing guidance on plant nutrition, soil, management, pest and disease management, quality assurance, traceability, and norms and rules fulfillment.

Key Factors for IP Developments

In order to accomplish the objectives of any policy or new-program, the active participation and role fulfillment of each agent and/or organization involved is required. The main stakeholders engaged in IP include farmers and production cooperatives, technical service providers, certification entities, the regional government, commercialization cooperatives, manipulating cooperatives and companies, exporters& traders, transport companies, distribution companies, research institutions, and technological solutions providers. Fig. A1 shows the most active stakeholders and organizations engaged in IP and the collaborative and coordinated work of each one toward IP development.

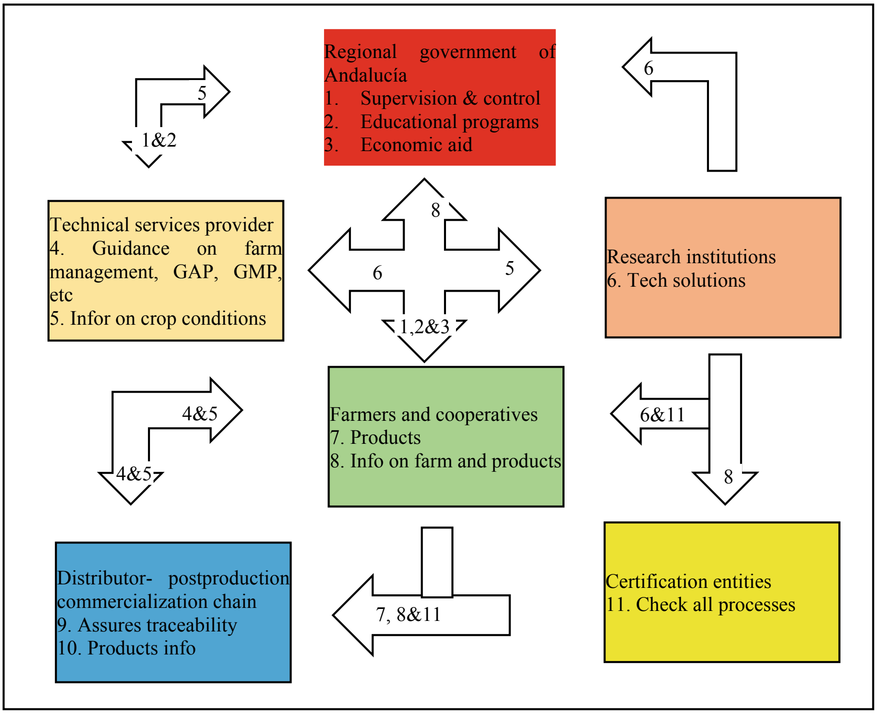

Fig. A1 Information flow of the main stakeholders and organizations of IP

Groups of Integrated Production

Since the most the farmers hold relatively small farms, the assurance of exportable amounts, certified quality and protection of the environment would be difficult to be accomplished by individual small farmers. Therefore, the active participation of farmers in the formation of APIs within production cooperatives has been making significant contribution toward addressing these issues. This new agricultural system has been well accepted by farmers.

Technical Service Providers

The provision of technical services by companies and/or division of cooperatives to APIs plays an important role in the successful implementation of IP protocol, addressing pest and disease management, fert-irrigation guidance, production quality and safety assurance, traceability achievement, and norm and rules fulfillment (GAP, GMP) as shown in Fig. A2. To be able to provide technical assistance to the APIs, these technicians have to take and approve a training program on IP, provided by the

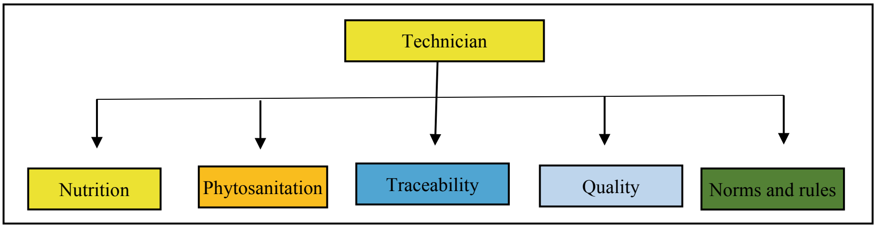

Fig. A2 Technical service staff responsibilities

regional government or other institutions that are registered for this purpose. After approving the training, the technicians receive a certificate that grants them the rights to provide technical assistance to APIs or to any other farm under IP. As for 2008–2009 campaign, around 250 technicians have approved the courses on IP in Almeria province (Acebedo et al., 2009). A qualified technician can provide technical assistance to a maximum of 60 ha and has to visit every farm under supervision at least once a week. Furthermore, every technical recommendation has to be written down on the farm record book and signed by the technician at the moment of recommendation and by the farmer when the action is taken (this information is stored in a general database owned and managed by the Ministry of Agriculture and Fishery of Andalucía too). That is, both farmer and technician are taking responsibility for any action taken at the field.

Certification Entities

Every certification entity must be formally accredited to the European Norm (EN) or standard EN45011 and registered in the Ministry of Agriculture and Fishery of Andalucía. Certification entities check whethera farmer/group (API) is effectively implementing and achieving IP protocol and objectives. This check includes production practices, handling processes, and marketing of each API. This check is carried out by analyzing stored information in the databases and directly visiting fields. If there is not any issue on compliance of IP protocol, then the farmer of API may be granted of a certificate.

Regional Government

The regional government of Andalucía, through its Ministry of Agriculture and Fishery, takes actions on the implementation of IP regarding supervision and control, educational programs and licensing system, and provision of economic aids.

Supervision and Control

The Ministry of Agriculture and Fishery of Andalucía decides on the inclusion of new farmers in IP, technical advisors, and certification entities. It looks over the certification provided to farmers by certification entities. This check is randomly carried out by Ministry technician via surprise visits and includes at least 30% of the IP operators annually.

Educational Programs and Licensing System

The second important function performed by the Ministry of Agriculture and Fishery of Andalucía regards to the provision of educational programs and licenses. Field technical advisors, manipulation center technicians, and technical staff of certification entities have to take and approve some compulsory courses on IP. An outline of the courses provided to technicians is given in Table A1. Further, IP courses for farmers and operators are also provided. The main course provided to farmers and operators is the phytosanitary applicator ID which consists of two levels, basic (white ID) and qualified (orange ID), with a duration of 25 and 72 hours, respectively.

Table A1 Outline of content of educational program (training) for technicians

1. Commercialization of agrochemicals and plan of use
2. National program of insect control and economic aid
3. National and regional laws regarding economic aid for IP
4. Technical service competence on obligations and control of operators
5. Descriptive report on farm exploitations
6. Biological control in protected agriculture
7. Risk management on horticultural protected agriculture
8. IP crops fert-irrigation management in protected agriculture
9. IP crops management
10. Labor risk prevention
11. Agrochemicals plan management
12. Integrated pest management on horticultural protected agriculture
13. Agricultural residues management
14. Pest and disease identification on the fields
15. IP AEN certification
16. IP horticultural crops baby plant management
17. IP norms and regulations
18. Farm management

Fig. A3 Qualified ID for manipulating pesticides

EU regulations require government authorization to manipulate and apply pesticides. Therefore, the government of Spain has adopted the issuance of a phytosanitary applicator ID card. Since there is a legal requirement to have one of these IDs to manipulate and apply pesticides, farmers have to take and approve at least the basic level course. Actually, some 8,000 farmers have taken and approved the basic course for manipulating and applying pesticides while around 400 farmers and/or operators have taken and approved the qualified level course (Ministry of Agriculture and Fishery of Andalucía, 2009). Out of the 8,400 farmers who have taken and approved the courses on applying and managing pesticides, some 4,000 farmers have been granted an IP certification as for 2009. That is 47% of the phytosanitary applicator ID grantee farmers were certified under IP protocols. A picture of a qualified ID is shown in Fig. A3.

In order to get the certification and/or ID, participants of IP courses must participate in at least 90% of the classes for basic courses and 95% for specialization courses. The issuance of certification and ID is upon the approbation of specific exams (Ministry of Agriculture and Fishery of Andalucía, 2010). Usually, these courses are provided at Institute for Agricultural Research, Agrarian and Fishery Formation (IFAPA), universities, and other research institutes facilities.

Economic Aid

Economic aid is provided to APIs and manipulators. This aid is mainly addressed to cover a maximum of 50% of new cost on technical advisors, new control methods such as biological control, certification processes, traceability systems implementation, and improvement on the transformation chain. As for the 2009–2010 campaign, the aid devoted to new control methods per crops was between €900/ha and €3,000/ha for melon & watermelon and green pepper, respectively (Ministry of Agriculture and Fishery of Andalucía, 2010). The main objective of this economic aid is to promote system adoption by farmers and/or operators. Once an API or a manipulator receives this economic aid, it must fulfill all the requirements when the certification entities and the Ministry of Agriculture and Fishery of Andalucía carry out control checks. These incentives are reduced every year after the adscription of the farmers to the IP protocol, disappearing once the farmers master the application of the IP protocols.

Distributor-Postproduction Commercialization Chain

Similarly important has been the assurance of traceability and the comprehensibility translation of huge amounts of information on product quality and safety and production process requirements to consumers by the commercialization chain (commercialization cooperatives, manipulating cooperatives and companies, exporters and traders, transport companies and distribution companies).

Research Institutions

Since Almeria' agriculture is characterized by a large concentration of greenhouses in a relative small area high demand on product quality and environmental protection, faces competition from northern African countries which have 10 times cheaper labor force costs; research efforts have been needed to cope with these issues. In this sense, research institutions such as public universities, research institutes and private research institutions have been working together, with the aim of solving pest and plague management issues, developing new techniques, testing and evaluating new techniques at experimental fields, and developing different software packages to manage all the information generated by IP.

Biological Control

The IFAPA and other research institutions have been carrying out research on pest management, focusing on the development of biological control techniques. There has been a consistent search for identifying new parasitoids and beneficial insects. This has resulted in the development of illustrated pest management guides, which help farmers and technician to identify pest and beneficial insects. The consistent research efforts aimed at managing pests have been playing a significant role on meeting consumer requirements on food safety and protecting the environment.

Laboratory for Pesticide Residue Analysis

There are several laboratories for pesticide residue analysis, the most important one being founded by the University of Almeria and the El Ejido town hall. At these laboratories, agricultural and food analyses are being carried out. Generally they include pesticide, nutrient solution, agricultural water, crop leaf, fertilizer, and soils and substrate analyses. The later includes pesticide residue, microbiological control, drinking water, nutrition, heavy metals, and quality control analysis. Usually, farmers send some samples of their crops to be analyzed before sending their products to cooperatives and/or manipulation center (always previous to the arrival of the products to final markets). In addition, cooperatives and the regional government take some random samples to be analyzed on the presence of pesticide residues and microbiological agents. As an example, the Saint Isidro Agricultural Cooperative, which has gathered with 1,750 farmers, holds around 4,000 ha, and produces around 1.2 million tons of tomatoes annually, carries out over 40,000 pesticide residues tests annually in order to assure product quality and safety.

Information and Communication Technology (ICT) Developments

The University of Almeria, among other research institutions, had an important role of developments of ICT tools for supporting IP. Table A2 shows the set of ICT tools, including their main functions and users, for IP normative implementation in Almeria. The availability of ICT tools is facilitating the administrative control by the regional government, adoption by farmers, technical support by technicians, and management and assurance of traceability by the distributor-postproduction commercialization chain. The ICT tools PRIM and PRIM-Movil are facilitating the adscription of farmers or API to the IP protocol. These two ICT tools along with SIG-PAC and TRIANA support the control activities carried out by the regional government and certification entities in order to secure the fulfillment of the IP protocol. While ICT tools such a RAID, SIFA, and SAEPI offer actual technical information on pest management to technician and farmers. This information is helping technicians (mainly) and farmers on the day-to-day decision making. At the same time, the ICT tools ERP Agro-Management and ERP-Agro-Traceability are translating and transferring to consumers huge amounts of information on production quality, production process, and production requirements in a comprehensive manner. The development of ICT tools has been one of the key factors for securing the successful implementation of the IP normative by the regional government.

Table A2 Set of ICT tools used in IP

ICT tools	Functions	Main users
PRIM and PRIM-Movil	Adscription of a farmer or API to the IP protocol	Farmers (APIs), regional government, and technicians
SIG-PAC	Geographic Information System about the plots under the IP protocol	Regional government and certification entities
TRIANA	Storage and manage all the information about the procedures applied on the IP plots and farms (data stored by the certified filed technicians and used by the certification bodies and the administration)	Regional government and certification entities, technicians
RAID-SIFA-SAEPI	Information and support to the technicians (mainly) and farmers on pest management, Geographical information about the pest for the Government	Technicians and regional government
ERP-Agro-Management	Management of farms, cooperatives and manipulation companies	Distributor-postproduction commercialization chain
ERP-Agro-Traceability	Full traceability of the products from the farm plots to the final consumers	Distributor-postproduction commercialization chain

Discussion and Implications to Other Countries

The Role of Education, Institutional Settings and ICT

Since consumer concern on product quality, safety, and production and handling processes is one of the main issues in market trends worldwide, the adoption of a system such as IP may be useful to address these challenges for countries when marketing their products, especially at international markets. This is a reason why we describe the role of educational programs, institutional settings, and information and communication technology tools on the development of integrated production in Almeria, Spain in this chapter.

The availability of ICT tools such as administrative, technical support, and private management and traceability have significantly contributed to control and secure the accrue application of IP rules by the regional government and certification entities. They also facilitate the adoption of IP by farmers through the groups of integrated production (APIs), and to translate huge amounts of information in a comprehensive manner so that consumers are able to verify product quality, safety, and production requirements.

IP has not only been provided for the normative framework but also for educational programs and institutional settings. Farmers are trained on pest, pesticides, and labor risk management while technicians are capacitated on a wider range including product quality, safety, and certification norms at both farm and processing center levels.

The development of ICT tools, the provision of educational programs along with the cooperation and coordinated work of all the stakeholders and organizations involved in IP is bringing about the successful application and development of this agricultural system.

Implications to Other Countries

To consider the necessity of integrated production and the role of above factors, the transfer of integrated production system to other countries is also discussed. As a case study, the discussion and implications provided below are focused on the Dominican Republic exportable fruit and vegetable sector. Vegetable and fruit production play a significant role in both Spanish and Dominican agricultural sectors. Further, farmers in Almeria, Spain as well as in the Dominican Republic are facing similar issues and challenges on product quality, safety, and production requirements when exporting to international markets.

Dominican fruit and vegetable farmers have been facing competition when exporting to European and the United States markets. This is especially true for oriental vegetable and protected agricultural farmers who export most of their production (fruit and vegetables) to the United States, Canada, and EU markets. These markets are not only highly competitive but also demand high quality products, fulfillment of good agricultural and manufacturing practices, and availability of a traceability system, among other environmental protection requirements. Oriental vegetable and protected agricultural vegetable production are significant components of Dominican fruit and vegetable exports. These two sources of vegetable exports combined surpass 100 million USD/year and provide employment for over 50,000 workers at the different stages of production, processing, packaging, and exporting (Martínez et al., 2007; Ministry of Agriculture of the Dominican Republic, 2010).

Nonetheless, there have been several cased in which the presence of pest and pesticide residues have been found in vegetables and fruits exported from the Dominican Republic to international markets. During the period 2004–2006, there were 49 cases where the Food and Drugs Administration of the United States (FDA) reported the presence of pesticide residues in fruit and vegetables from the Dominican Republic. While for the year 2007, 2008, and 2009, residues of pesticides and pests were found in 469, 50 and 29 containers, respectively (Ministry of Agriculture of the Dominican Republic, 2010). This is not only negatively affecting the image of Dominican vegetables at international markets but also causing economic lost to farmers. Martínez et al. (2007) report that this economic loss for producers in estimated to be USD 1,656,000. Therefore, there is a need for the establishment of an agricultural system such as IP, which assures product quality, safety, environmental protection, and social responsibility. Similar to the IP system, this would require the cooperative and coordinated work of each agent and organization involved in oriental vegetable production in the Dominican Republic, which includes farmers, the Dominican Association of Oriental Vegetable Exporters, processors, the Ministry of Agriculture of the Dominican Republic, public (IDIAF) and private (UCATECI, UAFAM) research institutions, certification entities, international cooperation organization such as the Technical Mission of Taiwan, and transport companies. Since educational programs have been playing a key role in the establishment and development of IP in Almeria, where farmers may have a better and higher educational background compared to oriental vegetable farmers, the provision of educational programs for both technicians and farmers, regarding pests, diseases, labor risk management, product quality certification norms, among other relevant contents is required.

The Ministry of Agriculture of the Dominican Republic has been ruling out some policies aimed at securing fruit and oriental vegetables, fruits and related export products (PROVOFEX) were established too. More recently, in 2009 the prohibition of 10 pesticides and restrictions of 17 other pesticides that can only be used under the supervision of a technician of the Ministry of Agriculture was adopted. Likewise, good agricultural practices and good manufacturing practices have been adopted for exporting oriental vegetables (Mejia, 2010).

The export pre-inspection program has three main components, pre-harvest inspection to check the level of pests infestation (thrips), pre-inspection at the processing and packaging centers to assure product management requirements, and pre-inspection at airports to finally verify product requirements and issue a phytosanitary certificate (Ministry of Agriculture of the Dominican Republic, 2010). The export pre-inspection program and the PROVOFEX have 81 technicians devoted to directly assist oriental fruit and vegetables farmers on pest management and good agricultural practices. Further, there are 30 inspectors who supervise processing and packaging activities. These technicians have been assisting and training farmers on pest management and good agricultural and manufacturing practices. That may be the reason why the number of cases, where pest and pesticides residues have been detected in oriental fruits and vegetables, has been decreasing since 2007. However, these programs and other related policies have not been provided with economic aid to promote the adoption of new technologies and techniques such as the introduction of biological control methods, which are relatively expensive and require consistent work for establishment. Therefore, economic aid to encourage farmers to adopt new technologies and techniques such as biological control methods are at the cornerstone of assuring product quality and environmental conservation, which are strongly demanded by international markets.

The establishment of a system such as IP in the Dominican Republic may generate, like in Almeria, huge amount of information. Therefore, the development of information and communication technology tools that support the control and supervision by the Ministry of Agriculture of the Dominican Republic and certification entities, the technical support given by technician, the management of information related to products quality, processing, manipulation, traceability, and production process, may be one of the key components.

Concluding Remarks

The objectives of this chapter were to describe the role of educational programs, institutional settings, and ICT tools on the development of integrated production in Almeria, Spain and to discuss the transfer of this system (IP) to other countries-the Dominican Republic as a case study. IP is an agricultural system that takes into account operations at farm, processing, packaging, and labeling levels. The IP regulations are derived from the guidelines of the integrated farming framework developed by the Integrated Vegetable Production (IVP) organizations and the European Initiative for Sustainable Development in Agriculture (EISA). Further, IP rules are in agreement with other certified quality norms such as Naturane, AENOR, and Global-GAP, but also include more demanding regulations. These systems allow customers to be assured of product quality, safety, and that production requirements were adhered to. The background, key factors for IP development and the main features have been discussed.

The successful implementation of the IP normative in Almeria, Spain is a result of the cooperative and coordinated work of each one of the stakeholders and organizations involved. The cooperative and coordinated work enable provision of educational programs to farmers and technical staff the development of ICT tools to manage information, and the provision of economic aid to promote IP adoption.

Similar to the case of Almeria, the application and/or adoption of a system like IP in the vegetable and fruit sector in any country including the Dominican Republic allows farmers to improve product quality, safety and production requirements. Even though the government has been making some effort toward assuring the safety and production requirements of vegetables and fruits, these efforts have been mainly focused on the provision of regulations in many countries. However, our study shows that education, institutional settings and ICT tools are necessary to promote IP.

The establishment of a normative framework providing educational programs not only for farmers but also for technicians, as well as the provision of economic incentives for the development and adoption of new technologies is at the cornerstone of improving the quality and safety of agricultural products and agricultural sustainability. The ICT tools enable stakeholders to manage related information. In this sense, ICT has an important role for promoting IP.

Appendix References

Acebedo, M., Tunez, S., & Bienvenido, F. (2009). Use of information technologies in integrated production (IP) in Europe: The Almeria's Case. In *The Fifth International*

Symposium on Intelligent Information Technology in Agriculutre, National Engineering Research Center for Information Technology in Agriculture (NERCITA), Beijing.

Haverkort, A. J., Jansen, D. M., de Ruijter, F. J., & Verhagen, A. (2008). From food safety guidelines to quantifies sustainability indicators: A transition to good practices schemes in food production in Europe. *Outlook on Agriculture, 37*(1), 37–45. https://doi.org/10.5367/000000008783883591

Martínez, C., Jiménez, J., & Wu, P.-L. (2007). Los Vegetales Orientales en la República Dominicana. In *IDIAF*.

Mejia, O. (2010). *Disminuye devolución de furgones de EU*. https://otca.gob.do/disminuye-devolucion-de-furgones-de-eu/#:~:text=Santo Domingo.,ha bajado de manera significativa.

Ministry of Agriculture of the Dominican Republic. (2010). *Resolucion No.11/97*. http://www.agricultura.gob.do

Ministry of Agriculture and Fishery of Andalucía. (2010). http://www.juntadeandaluca.es/agriculturaypesca/portal/areas-tematicas/agricultura/sanidad-vegetal/produccion-integrada/index.html

Salazar, J., M., Navarro del Aguila, L. F., Aliaga, J., & Leon, M. (2002). *"El Sector Productor-Commericalizador de Frutas y Hortalizas de Almeria, Cuadarado, I., Economia y Gestion de la Calidad en la Agricultura Bajo Plastico", Fundacion para la Investigacion Agraria en la Provincia de Almeria, Almeria.*

List of Original Publications Related to the Chapters

Chapter 2
Khoy, R., Nanseki, T., & Chomei, Y. (2015). Impacts of organic rice farming on production performance in Cambodia—An application of propensity score matching. *Japanese Journal of Farm Management, 53*(2), 85–90. https://doi.org/10.11300/fmsj.53.2_85.

Chapter 3
Nguyen, L. T., Nanseki, T., & Chomei, Y. (2020). The impact of VietGAHP implementation on Vietnamese households' pig production. *Environment, Development and Sustainability, 22*(8), 7701–7725. https://doi.org/10.1007/s10668-019-00543-w.

Chapter 4
Ho, B. Van, Nanseki, T., & Chomei, Y. (2019). Profit efficiency of tea farmers: Case study of safe and conventional farms in Northern Vietnam. *Environment, Development and Sustainability, 21*(4), 1695–1713. https://doi.org/10.1007/s10668-017-0073-z.

Chapter 5
Li, D., Nanseki, T., & Hotta, K. (2011). Measurement of wheat production efficiency and the determinants in different counties of Hebei Province, China—A model based on two-stage DEA. *Japanese Journal of Farm Management, 49*(2), 111–116. https://doi.org/10.11300/fmsj.49.2_111.

Chapter 6
Linh, T. T., Nanseki, T., & Chomei, Y. (2015). Identification of information sources influencing the technical inefficiency of crop farmers in Vietnam. *Asian Journal of Science and Technology*, *6*(8), 1677–1683. http://www.journalajst.com/sites/default/files/issues-pdf/2356.pdf.

T. Nanseki (ed.), *Agricultural Innovation in Asia*,
https://doi.org/10.1007/978-981-19-9086-1

Chapter 7
Southavilay, B., Nanseki, T., & Hotta, K. (2011). Farm organization in the Maize Commodity Chain: A case study in Lao PDR. *Japanese Journal of Farm Management*, *49*(2), 170–175. https://doi.org/10.11300/fmsj.49.2_170.

Chapter 8
Alwarritzi, W., Nanseki, T., & Chomei, Y. (2015). Analysis of the actors influencing the technical efficiency among oil palm smallholder farmers in Indonesia. *Procedia Environmental Sciences*, *28*, 630–638. https://doi.org/10.1016/j.proenv.2015.07.074.

Chapter 9
Zhou, H., Nanseki, T., Hotta, K., & Shinkai, S. (2010). Traceability system in Chinese dairy products: An analysis of consumers' preference on products information. *Japanese Journal of Farm Management*, *48*(1), 130–135. https://doi.org/10.11300/fmsj.48.1_130.

Chapter 10
Lhing, N. N., Nanseki, T., Hotta, K., & Shinkai, S. (2010). An Impact Assessment of the Perfomance of PACT Microfinance Program on Rural Households: A Case Study of Dry zone Area in Central Myanmar. *Japanese Journal of Farm Management*, *48*(1), 124–129. https://doi.org/10.11300/fmsj.48.1_124.

Chapter 11
Diansari, P., D., Nanseki, T., & Chomei, Y. (2014). Relationship Between Dietary Diversity and Perceived Food Security Status in Indonesia - A Sase of Households in the North Luwu of South Sulawesi Province. *Journal of the Faculty of Agriculture, Kyushu University*, *59*(2), 399–404. https://doi.org/10.5109/1467653.

Chapter 12
Li, D., & Nanseki, T. (2022). Review of the Practice, Promotion, and Perspective of Smart Agriculture in China, *Journal of the Faculty of Agriculture, Kyushu University, 67*(2), 227–237. http://hdl.handle.net/2324/4797830.

Chapter 13
Nanseki, T., Li, D., & Chomei, Y. (2022). Impacts and Policy Implication of Smart Farming Technologies on Rice Production in Japan. *Journal of the Faculty of Agriculture, Kyushu University, 67*(2), 219–225.http://hdl.handle.net/2324/4797829.

Chapter 14
Mi, J., Nanseki, T., Chomei, Y., Uenishi, Y., & Nguyen, L. T. (2022). Determinants of ICT and Smart Farming Technology Adoption by Agricultural Corporations in Japan. *Journal of the Faculty of Agriculture, Kyushu University, 67*(2), 249–262. http://hdl.handle.net/2324/4797832.

Chapter 15
Nguyen, L. T., Nanseki, T., Chomei, Y., Uenishi, Y., & Mi, J. (2022). Determinants of Product Innovation Implementation in Japanese Agricultural Corporations. *Journal of the Faculty of Agriculture, Kyushu University, 67*(2), 239–247. http://hdl.handle.net/2324/4797831.

Appendix Chapter
Marte, W. E., Nanseki, T., & Bienvenido, F. (2011). The role of education, institutional settings and ICT on the integrated production development in Almeria, Spain. *Agricultural Information Research, 20*(2), 66–73. https://doi.org/10.3173/air.20.66.

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T. Nanseki (ed.), *Agricultural Innovation in Asia*, https://doi.org/10.1007/978-981-19-9086-1