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Preface

Japan has a high population density, large number of part-time farmers and limited agricultural land when compared to other rice exporting countries in the New World. This is due to its unique history and geomorphic characteristics. On the other hand, many innovative professional farms, family-owned or company-owned, have grown in Japan in the recent decades. Some of them come from traditional family-run farms while others come from non-agricultural sectors. This shows that agriculture in Japan has two faces.

At present, the government feels that there are other problems, such as a low food self-sufficiency rate and a decreasing and aging labor force. By 2019, agricultural work population at farm household was 1.68 million, reduced by 0.925 million than that in 2010. The ratio of those aged more than 65 was 70.20%, increased by 8.61% since 2010. The average age of agricultural work population at farm household was 67, increased by 1.2 years in the ten years. By 2030, agricultural labor force is forecasted to reduce to 1 million. In 2018, the food self-sufficiency rate calculated by calories was 37.8%. Even though agricultural labor force includes many part-time farmers and food self-sufficiency rate is not always a suitable indicator for considering the future policy of agriculture and food, these issues are still important for the Japanese society.

To alleviate the impact of the above problems on agriculture, the Japanese government proposed the goal of building agriculture into a “growth industry.” Following the decision to promote a “smart society” in the Fifth Basic Plan of Science and Technology in January 2016, the “future investment strategy” established the goal of “building the world’s top level smart agricultural system.” It proposed that “the penetration rate of digital agriculture should reach more than half of the production and operation entities” by 2025. In 2019, the prime minister’s office released the “promotion plan of field assembly of agricultural new technology,” which cleared the policy obstacles for applying new agricultural technology. At the same time, the Ministry of agriculture, forestry and fisheries (MAFF) started to promote the combination of knowledge and technology accumulated by related industries, accelerate the use of smart agricultural technologies including robots and information and communication technology (ICT), upgrade production and circulation systems, and activate agricultural innovations. In the financial budget of 2019, the “smart agriculture extension project” was set up, with a special fund of 5 billion JPY, equivalent to 30% of the smart agriculture value in 2018.

Rice is the staple crop in Japan and has index values higher than those of other agricultural products. In 2019, Japan’s total rice output was 1.74 billion JPY, accounting for 19.2% of the total agricultural output. Rice consumption contributed 22% of food calories, and rice had a self-sufficiency rate of 97%. As an integral part of the strategy to promote agriculture and economic growth, the Japanese government decided to enhance the international competitiveness and market share of Japanese rice. One of the major policy measurements is to promote the adoption of ICT and other smart agricultural technologies. It contributes to save labor and material inputs, reduce production costs, and increase the productivity of paddy fields. The strategy for Japan’s Rejuvenation, issued in June 2013, proposed a 10-year objective of reducing rice production cost by 40%, from 267 JPY per hectare in 2011.

There are an increasing number of innovative farms in Japan and the average annual sales of farm companies are around two million JPY. In terms of physical size, rice farms of over 100 hectares are not rare in Japan anymore. Most of them produce different varieties of rice using different cultivation regimes and mill, process, and sell directly to consumers as well as to supermarkets and food processing companies. Some of them are introducing new technologies including ICT and smart agriculture technologies.

Smart agricultural technologies have been rapidly promoted and applied in rice production in collaboration with innovative rice farms. For instance, IoT sensors, cloud systems, and automation devices of rice farm operations have been developed and applied in real farms involved in the “NoshoNavi1000” project. The authors of this book analyzed big data measured using smart combine harvesters, paddy field sensors, and other indoor equipment with sensors of rice yield in Ibaraki Prefecture and Ishikawa Prefecture. The technologies greatly facilitated the data collection of rice yield, water content, and other information during rice production and harvest. This book presented an analytical framework of big data in agriculture and shows the empirical results for rice farm innovation.

To assist farmers in optimizing rice cultivation management, many companies and research institutes have collected and analyzed large volume of data. However, most of that data was not collected from real farms. The image data collected by an unmanned aerial vehicle (UAV) is one such example for analyzing rice growth and providing technical guidance to farmers in precision topdressing. Another example is a square-meter-unit grid meteorological information system to support farmers in predicting pests and diseases. However, the impact of the information on improving rice yield and quality are not clear yet. These effects can be measured through real farm production practices, using appropriate methods and models based on quantitative analysis, as shown in this book.

The empirical analysis of big data and multiple models, integrated with multidisciplinary theories and methods, has become an important approach for studying smart agriculture. Most of the previous studies collected data from the paddy fields of scientific and experimental facilities. They did not reflect the actual situation of the farms, or they considered the individual farms or even the region as a unit, and hence ignored the natural and managerial differences among the fields. Moreover, only a few smart technologies were used, and they cannot fully reflect the contribution of smart agriculture in improving production efficiency. In addition, the selection of quantitative analysis methods did not show the mainstream approaches of production efficiency analysis, and the characteristics of smart agricultural production.

In this book, the determinants of rice production efficiency were analyzed using field data of rice farms in Japan. The farms have paddy fields varying from 30 hectares to 170 hectares. They are large-scale farms in Japan comparing to the national average acreage of 2.99 hectare by 2019, although their scales may be common or even small in countries like Australia, the US, and many other American countries. It differed from most of the other studies that were based on the experimental field data or the farmers. This book put forward more realistic and targeted countermeasures and suggestions. The data collection adopted the Japanese smart rice production model "NoshoNavi1000" (agricultural expert navigation in 1000 paddy fields), which has been in use for many years and reflects the main elements and basic characteristics of smart agriculture. For example, using IoT technologies, such as laser levelers and soil sensors, to collect paddy field information; using farming visualization systems to improve work accuracy and efficiency; using farming evaluation and planning systems to optimize rice planting and transplanting to obtain the optimal combination of rice varieties and cultivation regimes; using IC tags, global positioning system (GPS), mobile phones, and other mobile terminals to record field operation information in the farming visualization system (FVS); combining the digital images of crop canopy and leaf color map captured by UAVs to accurately determine the range of chlorophyll value; introducing the "best topdressing determination model" to determine the topdressing amount at the early stages based on leaf color value; using smart combine harvester to collect rice yield and water content, and the rice grain component analysis machine to determine the hardness and viscosity of rice.

Based on rice yield, quality, and other factors, this book summarized the data composition, collection process, and variable measurement methods of these topics, the main results of data envelopment analysis (DEA), path analysis, principal component analysis (PCA), multivariate and Tobit regressions, variance analysis and other models; and the effects of applying quantitative analysis in optimizing rice production. The main purpose is to provide practical reference for replication in improving rice yield and quality and theoretical reference for future studies.

This book consists of the major findings of the big data analysis of the "NoshoNavi1000" projects on smart rice farming in Japan. We aim to build the big data on rice farming, by incorporating the results of soil analysis, growth investigation, environmental observation of air temperature, water temperature, water depth, cultivation and management records, yield, and quality analysis. In addition to the analysis on this large database, we develop and demonstrate the new generation large-scale rice farming technology system, integrated with agricultural machineries, field sensors, visualized farming, and skill-transferring system.

Two books based on the results of the "NoshoNavi1000" projects have been published in Japanese. They are namely: "Smart agriculture practice in rice-farming and perspective of farm in next-generation" (Nanseki, 2019) and "Rice farm management innovation and smart agriculture in TPP era: farming technology package and ICT applications" (Nanseki, et al., 2016). These results were contributed by many rice farmers, local government agencies for agricultural science and technology promotion, high-tech companies, academic institutes, and universities from around the country. All the contributors showed an eagerness for managerial innovation and for exploring smart agriculture and the empirical mining of the data from rice farming. We held many on-farm demonstrations and representations in Japan, where we were encouraged to continue the exploration and extension of smart technologies. The feedback from the farms show the significance of empirical analyses in improving the productivity and incomes of rice farmers.

Based on the series of published papers and books, we decided to carefully select and compile the major findings on big data analysis, to share our academic and practical experiences from the projects. We would be immensely pleased to contribute theoretically and practically toward adoption of smart technologies in agriculture anywhere in the world.

Fukuoka, Japan — Teruaki Nanseki
Changsha, China — Dongpo Li
October 2020

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Contents

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Smart Rice Farming, Managerial Model and Empirical Analysis

Dongpo Li, Teruaki Nanseki, and Yosuke Chomei

This chapter reviewed the connotations and research approaches of smart agriculture and agricultural production efficiency, summarized the composition of a smart rice production model, "Noshonnavi1000." The adoption of this smart rice farming model was in accordance with the GAP objectives, and it was used to collect data from large-scale rice farms and support empirical analyses of production efficiency determinants through models reflecting the main streams of production efficiency analysis: path analysis explored the determinants from the perspective of marginal effect, while data envelopment analysis decomposed production efficiency into technical and scale efficiency. This chapter summarized the constitution of the research consortium of the series projects and organization of the following chapters, thus provided the general scenario of this book.

1 Introduction

In Japan, rice is the most important staple crop. By 2019, it accounted for the largest proportion of 19.4% in the gross agriculture output. Although it has increased slightly since 2015, the gross production of rice has been decreasing in recent decades, while the production cost remains high. In this context, the Japanese government decided to

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promote efficient and competitive rice production. The Japan Revitalization Strategy released in 2013 envisaged a 40% reduction in the costs of rice production in the next 10 years (PMJHC 2014). To this end, adoption of advanced technologies and optimized farm management is essential for agricultural development. Since the 1990s, smart farming technologies have been used widely in developed countries to monitor and analyze farming conditions and yields and optimize farm management accordingly (Nanseki et al. 2016).

Japanese cuisine was designated to UNESCO's intangible cultural heritage list on December 4, 2013. The government hopes to enhance its global recognition by boosting the exports of Japan's agricultural products including rice. However, rice farming in Japan is beset by high production costs, in addition to market fluctuations, climate change, and other uncertainties. In 2011, the average costs of rice production in Japan amounted to 266.7 JPY per kg, much higher than that in the US, with 52 JPY per kg as sampled in California (Fig. 1).

The number of farm households, especially the part-time ones, have been decreasing over the previous decades. In 1960, the total number of farm households was 6.07 million, of which 2.08 million were full-time farms. In 2010, the two numbers reduced to 2.53 and 0.45 million, respectively (MAFF 2011). In contrast, agricultural production corporations, have shown a dramatic growth from 2,740 in 1970 to 19,213 in 2019 in almost all the agricultural sectors (MAFF 2020, Fig. 2). In 2015, the title of "agro-corps" were to "corporations qualified to own farmland," to show their competence in possessing and transacting farmland like a farm household. Their dramatic increasing is mainly since unlike small farm household, agro-corps have the advantage of superior managerial ability, easier access to credit, diversified business development, better welfare, and sufficient HR. Agro-corps represent the

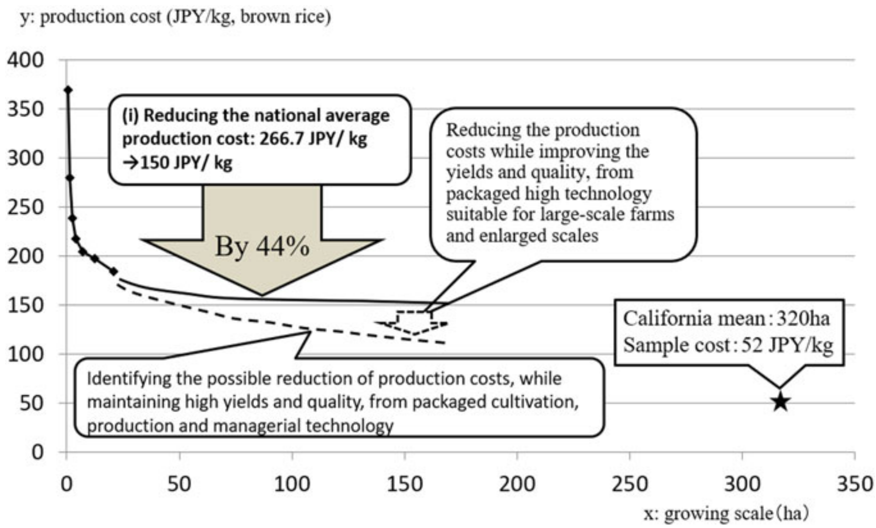


Fig. 1 Scale and production costs of rice in Japan, 2011 (*Source* Nanseki [2019])

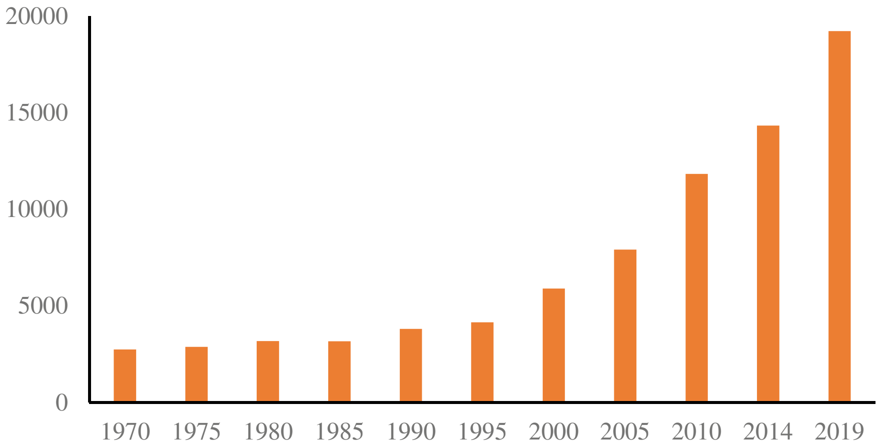


Fig. 2 Number of Japanese agro-corps (corporations qualified to own farmland) in 1970–2019 (*Source* MAFF 2020)

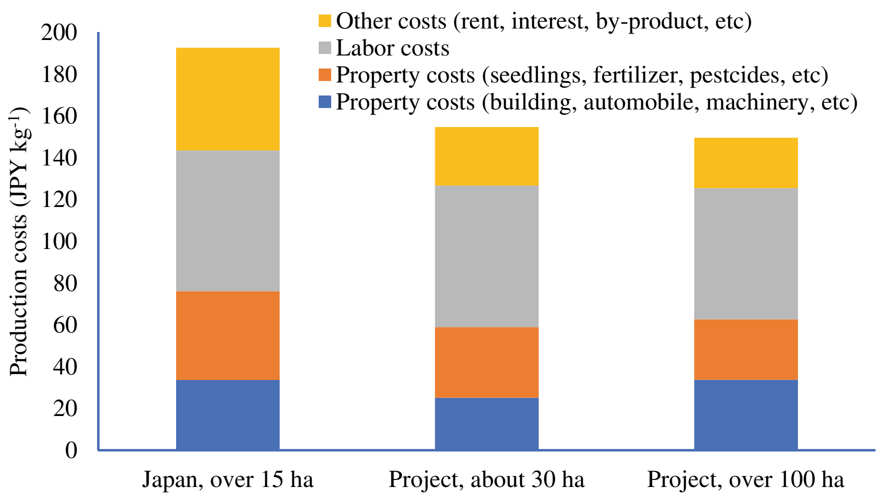
future trend of agricultural development in Japan, including rice production, to which more attention needs to be paid.

Recently, smart technologies have been used widely applied in developed countries, to monitor and analyze farming condition, yields, and optimize farm management accordingly (Nanseki et al. 2016). Therefore, to increase Japan's rice exports, it is necessary to establish an innovative technological system within the large-scale rice farms and to establish proactive rice farm management that can deal with uncertainties. Another critical issue is the organization and integration of cultivation, production, and business management. In this way, differentiate Japanese rice from imported ones, with low production costs, high quality, and added value.

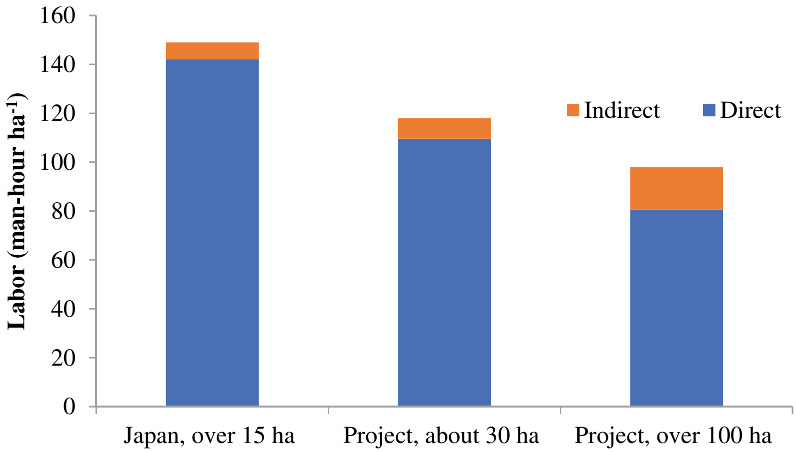
2 Concepts and Framework

2.1 Cost Reduction in Rice Production

The cost of rice production is mainly comprised of the property costs and labor costs (Fig. 3a). In farms scaled over 15 hectares, the average production cost of sorted rice was 193 JPY per kilogram. In our research consortium, the average cost per kg decreased to 155 JPY and 150 JPY, in farms scaled to 30 hectares and over 100 hectares, respectively, and the average labor hours reduced simultaneously (Fig. 3b). The cost typically decreases when farming scale increases, by adopting new management and technologies (Fig. 4). Nevertheless, it is difficult to further reduce production cost by merely increasing scale without any technological innovation. Hence, it is



(a) Rice production costs on different farms



(b) Man-hours in rice production on different farms

Fig. 3 Total cost and labor hours of rice production large-scale farms, on the average of nation-level of Japan and member farms of the research project. **a** Rice production costs on different farms. **b** Man-hours in rice production on different farms (*Source* Nanseki et al. 2016, pp. 9–10)

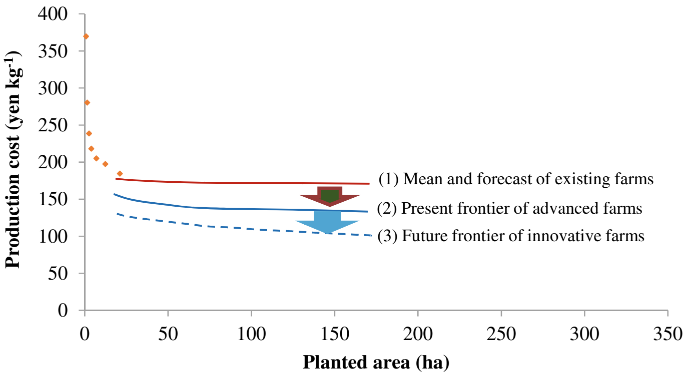


Fig. 4 Planted area expansion and rice production cost reduction in Japan (*Source* Nanseki et al. 2016, p. 5)

essential to adopt smart technologies to increase yield for an efficient and competitive rice production.

2.2 *Smart Farming Technology*

Smart agriculture refers to the agricultural production mode that uses Internet of things (IoT), artificial intelligence, cloud computing, big data and other modern information technologies, to deeply integrate with agriculture to realize information perception, precise management and smart control in the whole process of agricultural production, and has the functions of agricultural visual diagnosis, remote control, disaster warning (Laurens et al. 2019; Kang et al. 2019). Smart Farming contributes to better actions in farming, as well as monitoring data and decision-making by using ICTs. Smart farming focus on whole farm management not only production process. This has become increasingly complex due to data fusion, and the analysis needs to be conducted using partial or complete automation.

As illustrated in Fig. 5, the smart farming technologies summarized in this book were drawn from three stages: (1) field-specific data on farming, meteorology, soil, and cropping was collected and visualized using FVS and planning and management supporting system (PMS), (2) big data analysis and visualization in the cloud center, and (3) optimized production and operational management against the risks of meteorological and market changes. The application of these technologies result in stabilizing and improving yield and quality, by visualizing soil properties and meteorology, using high-precision cultivation that can respond to meteorological changes, and efficient operation using visualized information technology, agro-machineries, labor, and inputs.

As shown in Fig. 6, the FVS cloud system is a key component of smart farming technologies and it constitutes three components. (1) The mobile app collects data

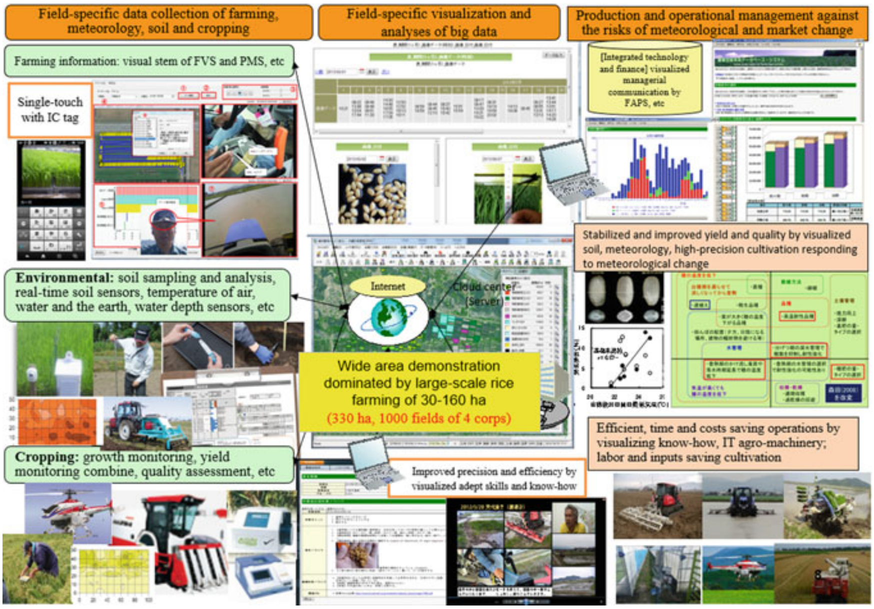


Fig. 5 Development and demonstration of new generation large-scale rice farming technological system integrating with agro-machinery, field sensors, visualized farming, and skill-transferring system (*Source* Nanseki et al. 2016, p. 167)

on farming and crop growth using the IC tag, built-in camera, and GPS. The data and comments can be shared online via collaborating software, like Facebook. (2) The server system stores, processes, and analyzes the data of the scattered fields and displays the results in the form of tables, graphs, and maps. The field-specific and longitudinal data (e.g., every 10 min, hour, day, or month) are easy to be inquired and displayed when necessary. (3) The sensor system for the paddy fields integrates the smart network communication module and the environmental sensor system monitors and records depth and temperature of water. An alarm message is sent to the mobile handsets when the data crosses the threshold value. Through the linked graphs, the longitudinal data of the paddy fields can be checked easily. More information can be read and displayed, by just touching the IC tags on the sensor box using the FVS mobile App (Nanseki et al. 2016).

In our studies, the initial data of raw rice yield and moisture was collected using the smart combine harvester, where a small matchbox-sized sensor was installed in the input slot of the grain tank. The sensor measured the grain flow rate, while a much larger load cell was set at the bottom to measure the total grain weight in the tank. This innovation enabled real-time, precise, and low-cost monitoring and removes any bias out of the grain tank filling state—if the tank was filled or not. Meanwhile, the smart combine harvester can detect the threshing or screening yield loss through loss sensors and minimize it by automatic operation. Finally, the field-specific data was conveyed through GNSS to the cloud server, which was shared

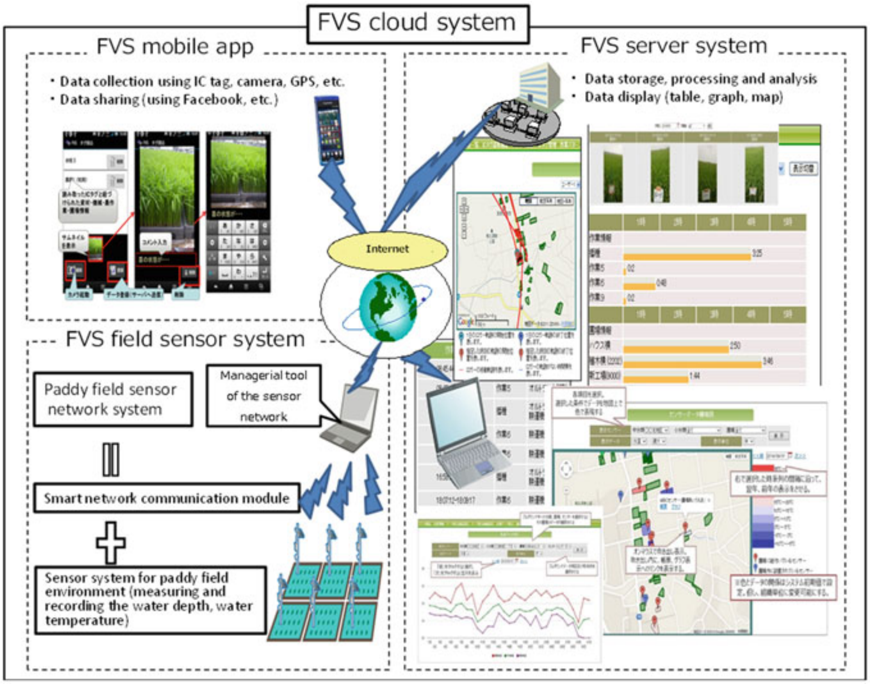


Fig. 6 Image of the FVS cloud system combining the paddy field sensors (*Source* Nanseki et al. 2016, p. 170)

by the companies, institutes, and farms. Thereafter, the yield, moisture content, and farming time were automatically mapped using Google maps. The maps are essential for the farms to capture yield variation among the fields, and to update their farming plans accordingly (Nanseki et al. 2016).

2.3 Rice Yield and Measurement

Furthermore, the yield of paddy with 15% moisture was calculated using the weight of raw paddy and the average moisture content. Brown rice was then sampled and estimated after hulling; the sorted brown rice retains only grains thicker than 1.85 mm. Finally, rice yield was estimated in terms of the sampled weight of milled rice (i.e., the fluffy white-yellow rice with the bran and germ removed) and full-grain rice (Fig. 7). In Japan, rice yield is measured by the sorted brown rice, while in many other countries, rice yield is measured mainly by paddy weight. The unsorted and sorted brown rice, along with the average weights of the milled and full-grain rice, can also indicate rice quality, which links to the market value.

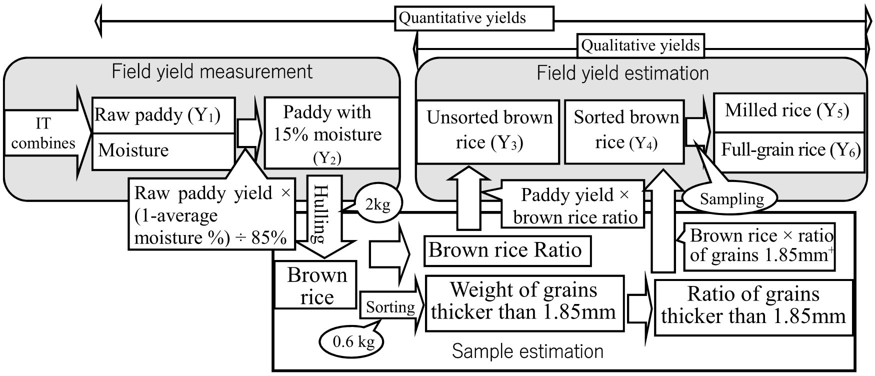


Fig. 7 Process of estimating rice yield from raw paddy to milled and full-grain rice (*Source* Nanseki 2019, p. 166)

3 Managerial Models of Smart Rice Farming

In this section, we outlined the managerial models of smart rice farming as proposed in "NoshoNavi1000", series research projects that we conducted along with other coordinating institutes. Furthermore, we examined how the new managerial models, using ICT, can contribute to the major objectives of good agricultural practices (GAP), such as security for people, environmental protection, and food safety. Finally, we explored the possibility and significance of introducing these managerial models of smart rice farming to China and other East Asian countries.

3.1 Adopting Practical Rice Cultivation Technology

This was mainly conducted by four agricultural production corporations, that are implementing advanced large-scale rice production in Japan. We summarized the findings that can contribute to the development of management and personnel training. Furthermore, we extended these findings to domestic rice farming, in collaboration with the institutions that extend farming models in different climatic and field conditions.

3.2 Developing Innovative Production Technology

(1) Farming systems using smart combine harvesters of Yanmar Co., Ltd., and other institutes. To sample the grain in each field, it was necessary to equip the smart combine harvester with yield and moisture sensor. Meanwhile, further restructuring was needed to install the real-time data collection units to map the fields using soil sensor data obtained separately. Finally, data collection and mining were conducted for increasing yields, quality, and productivity.
(2) Visualization system using the information obtained from cropping and management sensors (from the agricultural technology promotion center of Shiga Prefecture). Collecting growth information with UAVs during the rice growing season, to create a trial management index that combines the information on soil diagnosis, yields, quality, among others, to achieve higher yield and quality.
(3) Low-cost rice cultivation technology using high-density seedlings, dissemination, and technical assistance, from the agricultural experiment station of agriculture and forestry research center of Ishikawa Prefecture. To reduce costs of nursery materials, manual and managerial labor while ensuring yield and quality, high-density seedlings and cultivation techniques were adopted, through cooperation with the production corporations. In addition, the technical guidance and extension activities of high-density seedling cultivation techniques was provided simultaneously.
(4) Labor-saving fertilization technology, from the agricultural center of Ibaraki Prefecture. In the paddy fields scaled over 100 hectares, farming yields and economic efficiency were assessed, with labor-saving cultivation technology being applied to various breeds in different cropping seasons, including the technological demonstration of drifting the dissolved fertilizer from the water inlet, by adopting ICT technologies with smart agricultural machineries, field sensors, visualization farming systems, and so on.
(5) Evaluating the benefits of preventing high-temperature injury through the application of rice cultivation technology against climate changes, from Kyushu Okinawa agricultural research institute of NARO. Firstly, we verified the effect and managerial benefits of weather-aware top-dressing. Then, the risks of negative impact on yield, quality, and taste were evaluated, in the case of incorrect weather prediction.

3.3 Developing Innovative Managerial Technology

(1) Mapping field-specific information integrated with smart agricultural machinery, to promote commercialization and dissemination of the analysis methods in Sorimachi company. We created the cloud database on farming and growth, using the data collected by smart agricultural machinery that have the functions of GPS and growth monitoring. In this way, we provided the information to map and analyze the mechanical operation time and yields within each

farm. Furthermore, using the data collected above, demonstration tests were conducted on each farm.

(2) Soil mapping based on soil sensors from Tokyo University of Agriculture and Technology. Firstly, we conducted the trial improvement of soil sensors towed by a tractor and perform soil measurement and analysis using soil sensors after harvest. Furthermore, methods of soil mapping were developed and demonstrated to show the variations within each field, using the data obtained above. In addition, the data of the mapped soil with different ingredients was shared with other research institutions and agro-corps.

(3) Supporting cultivation management through information collection technology and PMS by the central agricultural research of NARO. We reviewed the labor-saving approaches in the multi-point measurement of leaf color and water depth in the fields, which are needed by the demonstrating production corporations. In this way, we supported cultivation management through the integration of information on water depth, leaf color measurement, and growth prediction. The data collected this way was integrated with the existing PMS. We further demonstrated the efficiency of supporting cultivation management by integrating the data of meteorological observations, growth prediction model services, and PMS.

(4) Information collection and visualization technologies integrated with FVS and the wide-area environmental information observation system of the paddy fields from Kyushu University. The FVS cloud was applied over the 1000 fields of the four agro-corps to collect, visualize, and manage the information on soil, growth, yields, and quality. Then, in collaboration with the agricultural technology promotion center of Shiga Prefecture and NARO, we demonstrated the effectiveness of data collection and visualization techniques in large-scale rice production. In addition, we explored the applicability of the precise information observation system with far-reaching width, using the data on water and soil temperature and water depth in the 1000 fields. Finally, we developed and demonstrated the innovative approaches of collecting and visualizing data in large-scale rice farms, integrated with the FVS cloud.

(5) Building and analyzing the big data on rice farming, the optimal production system based on farming-systems analysis and planning support system (FAPS) by Kyushu University. We built a database on rice farming, considering the results of soil analysis, growth investigation, observation of air and water temperature, water depth, cultivation and management records, yields, and quality analysis. This was conducted in the 1000 fields of the four corporations, in cooperation with Yanmar, NARO, and other institutes. In addition to the analysis on this database, we developed and demonstrated the approaches of the optimal production system with the application of FAPS.

4 Smart Rice Farming Models and GAP

4.1 GAP and Major Objectives

GAP has been adopted worldwide to deal with the problems related to agriculture, food, and environment. The objectives of GAP are (1) security for people—improved worker and consumer conditions, enhanced Agricultural Family welfare, and improved food security; (2) environmental protection—no contamination of water and soil, rational handling of agrochemicals, increased concern for biodiversity; (3) food safety—healthy food, which is not contaminated and of higher quality to improve nutrition and food consumption;(4) animal welfare—animal care and adequate feeding (Fig. 8).

GAP is generally promoted through regulations (e.g., food safety policies), subsidies (e.g., agricultural environment policies), trading standards (e.g., farm certifications), guidelines, and educational activities. The promoting institutions of GAP are international organizations, national and local governments, private companies, and organizations of logistics, agriculture. GAP is achieved through independent certification, independent supervision of public institutions and business partners, internal supervision by farm unions, and self-management of farms (Nanseki 2011a). The major GAPs are: the General Standards and Principles for Food Hygiene formulated

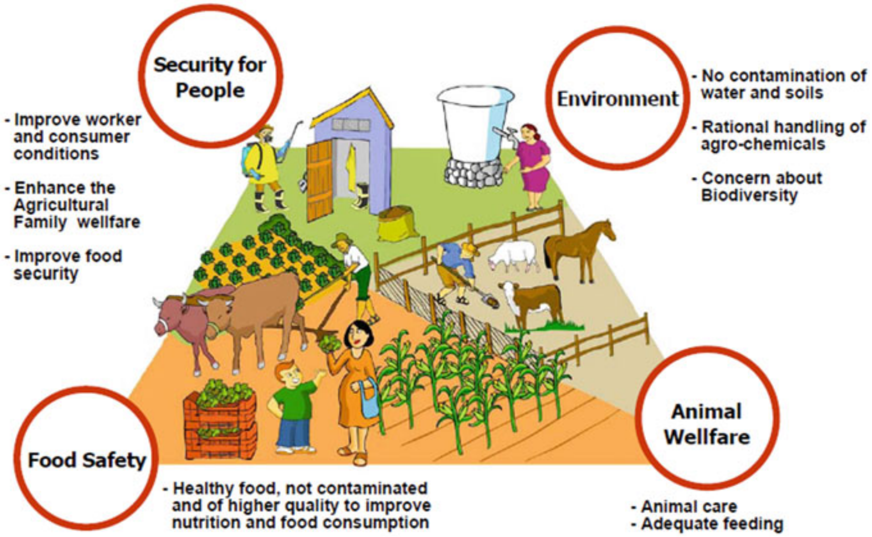


Fig. 8 Four major objectives of GAP (*Source* FAO [2007] Guidelines on "Good Agricultural Practices for Family Agriculture")

by Codex Alimentarius commission, the agricultural environment protecting GLOBALGAP (the former EUREPGAP) formulated by the EU, and the GAPs of China, Korea, and other countries (Nanseki 2011b).

In Japan, the promotion of GAP has been an important agricultural policy, to improve the reliability and reputation of local products, through higher quality and safety. There are a variety of GAPs: the JGAP of Japan GAP Association, GAP guidelines of the MAFF, and the local GAP of the Saitama Prefecture (Nanseki 2011a, b). A part of JGAP has been identified as equivalent with the international standard of GLOBALGAP. By the end of 2016, there were 3,954 farms certified by JGAP, an increase of 150% in 3 years.

4.2 Impact of the Smart Models to GAP

In our studies, the practices of the smart rice farming models introduced were in accordance with the GAP objectives, as summarized in Table 1.

(1) Security for people. Regarding safe work processes, farms like Butta Agricultural Production Corp. have introduced a standard work manual on the process of agricultural affairs. In the smart combine harvester developed by Yanmar (Fig. 9), cameras were equipped to record the process of operation from different angles. Further, technical improvements have been made for safer operation, including an emergency switch to stop the engine, automatic stop of the engine in case of wrong operation or clogging, etc. There have also been some endeavors to make work easier and, hence, save on labor by adopting high-performance machinery like the smart combine mentioned above and larger land compartments; equipping smart combine harvesters with functions for monitoring yields, moisture, soil, etc.; diversifying the harvesting seasons by combining multiple rice breeds; reducing the number of nursery boxes with high-density seedlings; shipping using flexible containers; adopting intensive work processes that comprise planting, fertilizing, and weeding, etc.

(2) Environmental protection. The major practices to optimize the use of fertilizers are: high-density fertilization using a GPS broadcaster; fertilization from seeding stage in the nursery box; drifting dissolved fertilizer over paddy fields by the water inlet; improving fertilization efficiency based on soil analysis data and real time soil sensors; and fertilization diagnosis using UAV.

The cultivation improvements included the introduction and extension of special cultivation using chicken manure for fertilization, iron coating and flooded direct seeding. Water protection practices included the adoption of automatic taps to save water and precision irrigation management on temperature, depth, etc., the major sensors for precision irrigation management are shown in Fig. 10. Soil improvements mainly included precision soil analysis, real time soil sensors and land flatting using a laser leveler.

(3) Food safety. Though agricultural production is the source of food supply chains, it is also one of the riskiest stages. As the staple crop of Japan, rice quality

Table 1 Practices of the smart models in accordance with GAP objectives

Objective	Topic	Practice
Security for people	Safer work	Standardized work manual on agricultural affairs
		Safer mechanical operation using video recording, technical improvements
	Easier work	Adopting high-performance machinery and larger land compartments
		Adopting smart combine harvester for monitoring yields, moisture, soil, etc.
		Diversified harvesting seasons by combining multiple rice breeds
		Reducing number of nursery boxes with high-density seedlings
		Paddy shipments using flexible containers
		Intensive work including planting, fertilizing, weeding, etc.
Environmental protection	Fertilizer optimization	High-density fertilization using GPS broadcaster
		Fertilization from seeding stage in the nursery box
		Drifting dissolved fertilizer in paddy fields by the water inlet
		Efficient fertilization using soil analysis and real time soil sensors
		Fertilization diagnosis using UAV
	Cultivation improvement	Special cultivation using chicken manure
		Iron coating and flooded direct seeding
		Herbicide-free cultivation by adopting rice-duck farming system
	Water protection	Adoption of automatic taps to save water
		Precision irrigation management on water temperature, depth, etc.
	Soil improvement	Precision soil analysis and real time soil sensors

(continued)

Table 1 (continued)

Objective	Topic	Practice
		Land flatting using laser leveler
Food safety	Crop monitoring	Reducing chalky rice using precision fertilization and irrigation
		Adopting cultivation regimes to reduce chalky rice
		Forecasting the bust of leafhopper
		Growth diagnosis using UAV
		Mobile crop observation equipment
	Ensuring grain quality	Shortening the drying time using far-infrared dryer
		Reducing chalky rice by adopting color sorters

Fig. 9 Rice harvest using a smart combine harvester in a large-scale farm of Kinki Region, Japan (*Source* Photograph by the authors)

Fig. 10 Paddy sensor and meteorological sensor for precision irrigation

is essential for ensuring food safety. In the smart rice farming models of our studies, practices concerning food safety consist of two aspects. On the one hand, crop monitoring was conducted, including reduction of chalky rice using precision fertilization and irrigation; adopting cultivation regimes to reduce chalky rice; forecasting the bust of leafhopper; growth diagnosis using UAV, and adoption of mobile crop observation equipment (e.g., smart phones).

On the other hand, a variety of practices were adopted to ensure grain quality, including shortening of drying time using far-infrared dryers and reducing chalky rice by adopting color sorters, etc. Based on the research projects of “NoshoNavi1000”, the managerial models of smart rice farming can be summarized as having the following features: research consortiums including cooperation of universities, public research and development institutes, technology companies, and agricultural production corporations; implemented by large rice production corporations scaled to 30–150 hectares, scattered across Japan with different climatic and natural conditions and farming status; integration of smart agricultural machinery, field sensors, visualization farming, and skill-transferring system; and funding from the public budget.

The managerial models of smart rice farming included adopting practical rice cultivation technology, developed production technology, and innovative managerial technology. These aspects were divided into several sub-projects conducted by different institutions.

4.3 Discussion on Overseas Extension

Asia is the most important producer of rice. FAO estimated the rice production in 2014 at 744.4 million metric tons, within which Asia accounted for 90.5% with 673.6 million metric tons (FAO 2014). The major Asian rice producing countries, like China, India, Thailand, are less developed in dealing with production uncertainties like droughts, pests, extreme weather, and so on. Thus, it is important to extend the smart rice farming models formulated in this project abroad, especially to the neighboring Asian countries of Japan.

The models can be extended through: corporation between universities, academies, or R&D institutions, hence preparing for information exchange and personnel training; business cooperation between companies, farming corporations from Japan and abroad or direct overseas expansion of these organizations. As it is like "NoshoNavi1000", comprehensive extension by research projects with the consortium consisting of policymakers, researchers, and industry personnel relating to rice production is possible. In future, this may be funded by the Overseas Economic Cooperation Fund (OECF), Japan International Cooperation Agency (JICA), among other organizations.

5 Data and Empirical Analyses

5.1 Project and the Research Consortium

In the early stage, we conducted the studies on an urgent extension project funded by the MAFF, from April 2014 to March 2016. It aimed to develop and demonstrate smart rice farming models, implemented by agricultural production corporations, with the help of smart agricultural machinery, field sensors, visualization farming,

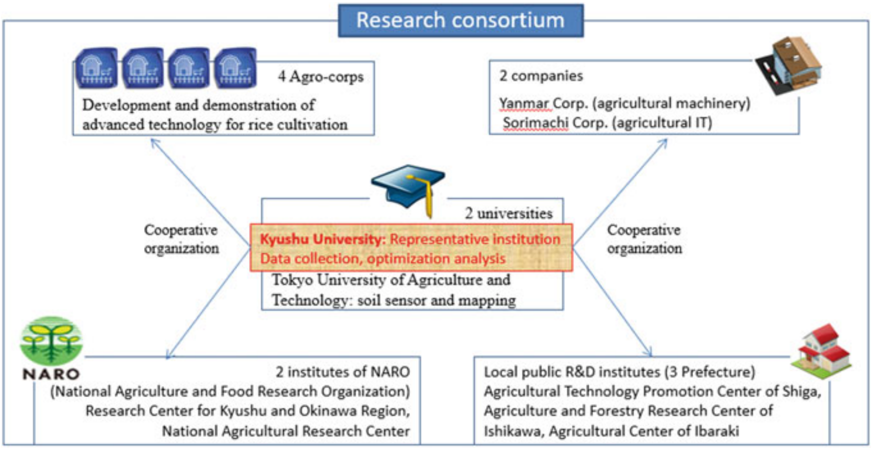


Fig. 11 Research consortium of the project

and skill-transferring system. The project was represented by Kyushu University, in cooperation with four agricultural corps to be introduced later, two technological companies (Yanmar Corp., Sorimachi Corp.), two institutes of NARO (Research Center for Kyushu and Okinawa Region, National Agricultural Research Center), three local public R&D institutes (Agricultural Technology Promotion Center of Shiga Prefecture, Agriculture And Forestry Research Center of Ishikawa Prefecture, Agricultural Center of Ibaraki Prefecture), and Tokyo University of Agriculture and Technology (Fig. 11).

5.2 *Study Areas and Objectives*

As shown in Fig. 12, this book studies 4 regions across Japan: Kyushu (AGL Corp., Aso City of Kumamoto Prefecture), Kinki (Fukuhara Farm Co. Ltd., Hikone City of Shiga Prefecture), Hokuriku (Butta Agricultural Production Corp., Nonoichi City of Ishikawa Prefecture), and Kanto (Yokota Farm Co. Ltd., Ryugasaki City of Ibaraki Prefecture).

Table 2 summarizes the features of the four farms of the research consortium. All of them are current "corporations qualified to own farmland", and they were "agricultural production corporations (agro-corps)" in the former system before 2015. This project aimed to (1) reduce production costs of brown rice to 150 JPY per kilogram, by 44% from the national average of 266.7 JPY per kilogram, and (2) obtain high yield, quality, and added-value, with the ratio of return to production to be improved to 2–2.5.

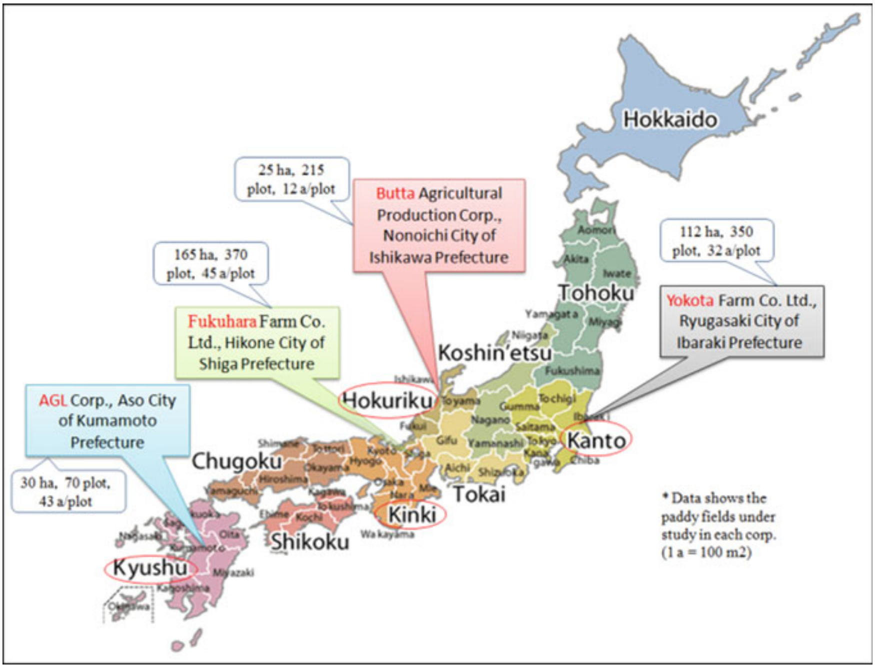


Fig. 12 Location of the 4 agricultural corporations

5.3 Sample and Statistical Analyses

Studies summarized in this book used the data of the 1000 paddy fields scaled to 330 hectares, from four farming corporations scattered in different regions of Japan. The yields defined in Fig. 7, nominated as Y_1 through Y_6, were used as the output variables. To be in accordance with international studies, the yield of paddy with 15% moisture (Y_2) is the most-widely used measurement in the studies (Table 3).

The inputs included: (1) Field attributes. The paddy fields vary area as revealed by the coefficient of variance, from 200 m^2 to 21,148 m^2 with an average of 3238 m^2. Farming conditions were evaluated by farm managers, considering the differences in height, water depth, water leakage, former crop, water inlet, soil fertility, illumination, and herbicide application.

(2) Production management. The proxy variable of transplanting or sowing date was converted by defining the earliest date as 1 for all the sampled paddy fields. The nitrogen quantities taken were weighted means calculated according to the amount and corresponding nitrogen content of compost, compound chemical fertilizer, ammonium sulfate, and urea fertilizers.

(3) Stage-specific growth indices. This stages cover panicle-forming, full-heading, 10 days following full-heading, and maturity. The growth indictors included the chlorophyll meter value of soil and plant analyzer development (SPAD), number

Table 2 Four farms of the research consortium of NoshoNavi 1000

Farm (Region)	F (Kinki)	Y (Kanto)	B (Hokuriku)	A (Kyushu)
Form (Year)	Limited company (1994)	Limited company (1996)	Stock company (2001)[a]	Stock company (2006)
Capital	8 million JPY	3 million JPY	10 million JPY	2 million JPY
Sales (2014)	380 million JPY	130 million JPY	146 million JPY	69 million JPY
Staff[b]	18	18	22	6
Acreage (ha)	165	125	30	30
Rice[c] (ha)	157 (for process and new purposes[d]: 70)	125 (for process: 27.2, feed 3.9, reserve 12.3)	28 (for process: 0.9)	21.2 (for feed: 4.7)
Other crops[c] (ha)	Vegetable fruiter 15	–	Radish 1.1, eggplant 0.3	Maize 0.6
Entrusted[c] (ha)	Rice 30, wheat 15, Soy 5	Rice 20	Rice 1.6	Rice 10.6
Philosophy	Honest, harmonious	For the smiles of all	Quality, value, and life	Delivering happiness
Purpose	Quality and high-yield rice, sustainable low cost	Large scale, low cost, breeding the elites	Quality, delicious, low cost	High income, low cost
Advantage	Plain area, large scale	Consolidated plots	High-yielding tech	Compost fertilizing
Disadvantage	Limited and young labor, vulnerable to market fluctuations	Relying on staff ability	Outskirts area, limited scale, unstable staff	Semi-mountainous area, poor in HR cultivation
Features	Large scale, multi-variety, schemed production, joint rice, vegetable, and fruit, multiple ages in staff composition	Large scale, multi-variety, schemed production, cost-saving tech of direct seedling, etc., self-sale of rice and cookies	All first-grade rice, precision field cultivation and water use, by-products sale from self-operating shop	Joint rice and livestock production, fertilizing by soil-investigation, organic farming, selling straw

[a]Founded as a limited company since 1988; [b]Number of persons including officers, workers, and long-term part-time employees; [c]Data of 2015; [d]Include rice used to process noodle, Japanese liquor, desserts, sushi, and animal feed
Source Nanseki et al. (2016, pp. 24–39)

Table 3 Summary of the empirical results on determinants of rice yield in different measurements

No	Determinant[a]	Yield[b]	Variety[c]	Plots	Model	Farm[d]
1	**Field area**, farming conditions, **transplanting or sowing date**, **fertilizer nitrogen**, SPAD, **panicle number**, **culm length**, LPV, rice variety (**Akidawara**), cultivation regime (**direct sowing**), soil type	Y_2	T	351	Multivariate regression	Y (2014)
2	**Field area**; temperature, solar radiation, **fertilizer nitrogen**, transplanting or sowing date, **panicle number**, **culm length**, soil properties (**magnesia**, **potassium**), cultivation regimes (**organic transplanting**)	Y_2	K	126	Multivariate regression	Y (2014)
3	**Rice variety**, **cultivation regime**, **transplanting or sowing date**, **nitrogen fertilizer**, **field area**	Y_2	T	351	ANOVA	Y (2014)
4	**Transplanting or sowing date**, **field area**, farming condition, **nitrogen fertilizer**, SPAD, **panicle number**, culm length, LPV, soil properties (**lime/magnesia**, **humus**, **magnesia**, **potassium**), rice variety (**Akidawara**), cultivation regime (**well-drained direct sowing**), soil type	Y_1–Y_4	T	351	Correlation, Multivariate regression	Y (2014)
5	**Field area**, **fertilizer nitrogen**, **panicle number**, **culm length**, soil properties (**potassium saturation**, **magnesia saturation**), cultivation regime (**organic transplanting**)	Y_2	K	126	Path analysis, correlation analysis	Y (2014)
6	**Farming conditions**, **temperature**, **solar radiation**, **nitrogen fertilizer**, soil properties (**base saturation**, **inorganic nitrogen**), **panicle number**, **culm length**	Y_2	K	117	Path analysis, correlation analysis	Y (2014–2015)

(continued)

Table 3 (continued)

No	Determinant[a]	Yield[b]	Variety[c]	Plots	Model	Farm[d]
7	**Field area**, **fertilizer nitrogen**, **temperature**, **solar radiation**, **panicle number**, **culm length**, **soil fertility, farm**	Y_2	K	301	Path analysis, correlation analysis	Y&B (2014)
8	**Temperature**, solar radiation, fertilizer nitrogen, **panicle number**, **culm length**, soil fertility, **field area**, **farming conditions**, cultivation regime (**same in the last two years, organic transplanting**)	Y_4, Y_4/Y_2, Y_6/Y_2	K	117	Multivariate regression, correlation analysis	Y (2014–2015)
9	**Field area**, **soil fertility**, **farming condition**, **nitrogen fertilizer**, **solar radiation**, **panicle number**, stage-specific **water depth and water temperature**	Y_1–Y_6	K	110	DEA, Tobit regression	Y (2015)
10				122		B (2015)

[a]The significant yield determinants are bolded; [b]Yield of raw paddy (Y_1), paddy with 15% moisture (Y_2), unsorted brown rice (Y_3) and sorted brown rice (Y_4), milled (Y_5) and full-grain rice (Y_6); [c]T and K denote the total seven rice varieties and Koshihikari, respectively; [d]Numbers in ( ) indicate the year of data collected

of stems or panicles per hill, culm length, and individual and community leaf plate value (LPV) by stage of panicle growth for the forming, heading, 10 days following full-heading, and maturity stages, and panicle length for just the maturity stage.

(4) Average temperature and solar radiation of 20 days following heading, as this stage is vital for starch accumulation (Asaoka et al. 1985). With global warming and climate change, there is increasing concern regarding the impact of temperature and solar radiation on crop growth and yield among scholars (e.g., Ohsumi and Yoshinaga 2014). In our research projects, we adopted precision devices to collect continuous data on temperature and solar radiation every hour.

(5) Soil property analysis. Soil has been established as an important determinant for paddy yield by many prior studies (e.g., Tsujimoto et al. 2009), for its permeability, heat-preservation, and large amounts of nutritive material that is closely correlated with grain yield, from the surface to the deeper soil layers. Soil properties are considered on five aspects: (1) fertility and texture, including pH, electrical conduction, cation exchange capacity, humus, and phosphate absorption coefficient; (2) saturation, constitution, and exchangeable amount of the base, by potassium, lime, and magnesia; (3) inorganic nitrogen in the form of ammonium and nitrate; (4) effective phosphoric and silicic acid; and (5) amount of other elements, including manganese, free iron oxide, soluble zinc, and copper.

(6) Irrigation management was measured in terms of water depth and temperature for the four stages of the total growth duration. The detailed information is to be provided in chapters "Production Efficiency and Irrigation of 110 Paddy Fields in Kanto Region" and "Two-Stage DEA of 122 Paddy Fields in Hokuriku Region".

In addition, we included the variety and cultivation regime (method) to analyze the determinants of rice yield, like some of the previous studies, like Nishiura and Wada (2012), Muazu et al. (2014). Soil type may affect rice growth and yield from the perspective of nutrition content, water drainage and conservation, and aeration (CSSJ 2002, p. 210). Therefore, a dummy variable named soil type was formulated, with binary values of gray lowland soil and peat soil (Table 2). The summary statistics of these variables have been provided in the following sections.

6 Framework and Organization of This Book

6.1 General Outline of the Empirical Analyses

A series of empirical models were utilized to estimate the impact of the independent variables, including the discrete and continuous variables on rice yield in different forms. The major empirical models used were multivariate regression with yield and logarithmic continuous determinants, 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 used to analyze production efficiency and the significant determinants for individual paddy fields.

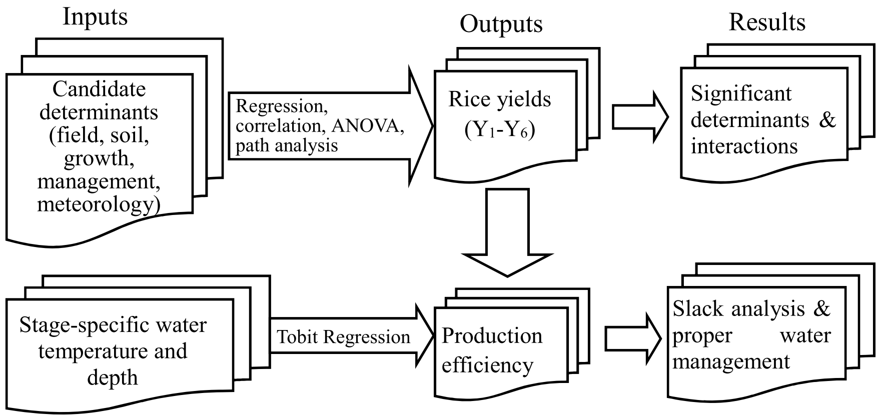


Fig. 13 General scenario of estimating the results in the empirical analyses summarized in this book

The analyses were performed using IBM SPSS 23.0, IBM Amos 23.0, and DEAP 2.0.

As illustrated in Fig. 13, the empirical analyses summarized in this book has mainly three parts. The inputs consist of the candidate determinants summarized above and the stage-specific water temperature and depth. The outputs comprise the rice yields of Y_1 through Y_6 as defined in Fig. 7, and the measured DEA production efficiency. The results are shown in terms of significant yield determinants, interactions among the outputs and inputs, and slack analysis to reduce the inefficient outputs and inputs. The rest of this section shows the major findings of these results.

6.2 *Book Organization*

Based on the above outline, the contents of this book are organized as follows (Fig. 14). Using the data from 351 paddy fields of farm Y located in Kanto Region, chapter "Variation in Rice Yields and Determinants among Paddy Fields" examines the variation and determinants of rice yields among individual fields. Chapter "Impact of Rice Variety and Cultivation Regime through ANOVA" estimates the impact of the varieties and cultivation practices on paddy yield, while chapter "Identifying the Rice Yield Determinants among Comprehensive Factors" explores the determinants of paddy yield measured by smart combine harvester. We used paddy yield with 15% moisture (Y_2) and the ratio of full grains (RFG) to present yields from the quantitative and qualitative perspectives, respectively. In chapter "Path Analysis on the Interacting Determinants and Paddy Yield", path analysis is conducted to identify the determinants of paddy yield, using the data of 301 fields in two farms, and 117

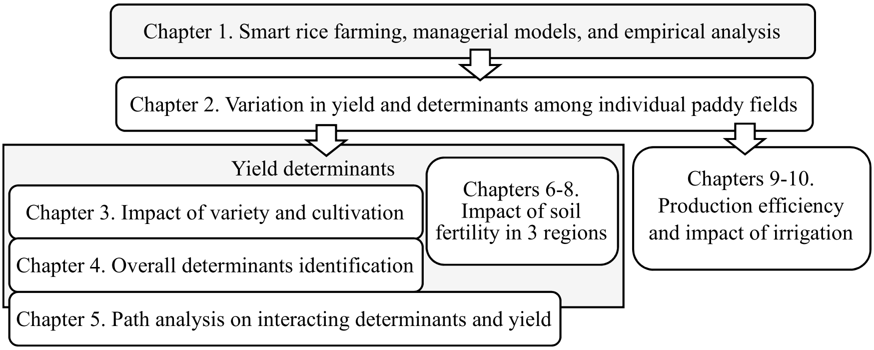


Fig. 14 Organization of this book

fields sampled in 2014–2015 from farm Y. Chapters "Impact of Soil Fertility in 92 Paddy Fields of Kanto Region"–"Impact of Soil Fertility in 116 Paddy Fields of Kinki Region" analyze the effects of nitrogen fertilizer and soil chemical properties on rice yield, using the data of 92 fields from farm Y in Kanto Region, 93 fields from farm B in Hokuriku Region, and 116 fields from farm F in Kinki Region. Chapters "Production Efficiency and Irrigation of 110 Paddy Fields in Kanto Region" and "Two-Stage DEA of 122 Paddy Fields in Hokuriku Region" adopt a two-stage DEA model to specify the technical efficiency and impact of irrigation management on rice yield, using the data from of 110 fields from farm Y in Kanto Region and 122 fields from farm B in Hokuriku Region, respectively. In this way, the book presents an overall image of rice production using smart technologies, in large-scale farms at the field level. In the analyses, a variety of empirical models and methods were used, which are the popular approaches to explore the yield determinants of rice and other crops.

In the conclusion, the main findings concentrate on increasing yield, and hence the efficiency and competitiveness of rice production. The key points for higher rice yield, identified by the empirical analyses are: adopting a suitable variety; earlier transplanting or sowing and, hence, a longer period for vegetative accumulation; sufficient nitrogen application, temperature, and solar radiation; and appropriate field areas. Yield can be increased through scale enhancement (i.e., proportionally augmenting all the inputs), while a higher production efficiency can be achieved through saved inputs. Water temperature affects technical efficiency more than water depth; the 25 days from heading to grain filling is important for improving technical efficiency through proper irrigation.

With respect to the open topics, future studies can consider a deeper exploration of determinants, like the determinants of water temperature, construction of soil quality index to include the significance of individual properties. DEA models can be expanded to incorporate non-discretionary variables—the stage-specific average and the corresponding daily ranges of air temperature and solar radiation. Furthermore, with data accumulation, the panel data sets can be used in more empirical models, such as the Malmquist DEA and pooled multivariate regression, to identify more effects and interactions of the yield determinants.

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Variation in Rice Yields and Determinants Among Paddy Fields

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This chapter identified the variation and determinants of rice yield measured by the smart combine harvester, from among different rice yields within large-scale farms. Apart from to the paddy yield with 15% moisture, we studied the variations in the concerning ratios for unsorted and sorted brown rice as well. The sample included 351 fields from a farm corporation scaled over 113 hectares, located in the Kanto region of Japan. The candidate determinants were the field area and condition, nitrogen amount, time of transplanting or seeding, stage-specific growth indicators of chlorophyll content, number of panicles, plant height, and leaf plate value. In addition, soil properties, average temperature, and solar radiation were incorporated. Meanwhile, the varieties, cultivation practices, and soil types were adopted as dummy variables. The empirical analysis was conducted using multivariate linear regression, with logarithmic transformations of the continuous variables. The result indicated that panicle numbers in the full-heading stage and transplanting or sowing time were the most important continuous determinant, following by nitrogen amount, humus

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content, and so forth. Within the significant discrete determinants, Akidawara and Milky queen were found to be the productive and unproductive varieties, respectively, while the well-drained direct sowing was found to negatively affecting yield.

1 Introduction

Since coming back to power in 2012, the government has been pushing forward policies on proactive agriculture, forestry, and fisheries to increase the efficiency and competitiveness within these sectors in Japan. In agriculture, it is essential to reduce production costs and improve yields, through fiscal subsides for adopting efficient technologies, equipment, managerial models, among the others. To increase rice yield and reduce average production costs, the government declared that by 2018, the acreage reduction of rice adopted since the early 1970s will be abolished, to expand efficient production and exports along with improved international competitiveness (Nikkei 2013).

As the staple crop in Japan, rice accounted for the largest proportion in the gross agricultural output at 21.03% in 2013 (MAFF 2014a). After the post-war high economic growth, the extensive adoption of a western diet changed Japanese food consumption habits with increasing amounts animal products, such as meat, dairy products, eggs, oils, and fats. Together with the increasing share of the elderly and a decreasing population in general, the average annual consumption of sorted brown rice decreased from 111.7 kg per capita in 1965 to 55.2 kg per capita in 2014 (MAFF 2014b). Simultaneously, rice production also decreased and contributed to a reduction in agricultural growth to a large extent (Ohizumi 2014).

In Japan, rice yield is measured by the sorted brown rice grains with a thickness of no less than usually 1.70 mm. In 2014, the yield of sorted brown rice was 8.43 million metric tons, a decrease of 40.27% from 11.83 million metric tons in 1985. During the same period, the planted area of paddy decreased by 45.58%, from 2.29 million hectares to 1.57 million hectares. Since 2000, the average yield of sorted brown rice has been stagnant at approximately 5300–5400 kg per hectare. In 2014, the average yield of sorted brown rice was 5360 kg per hectare (E-Stat 2015), while in the US it was 7263 kg per hectare (USDA 2014). Paddy production in Japan is plagued with high costs. In 2014, the average production costs of sorted brown rice in Japan was 256.9 JPY per kilogram (MAFF 2016), much higher than that of the US, which was a mere 35 JPY per kilogram on average (USDA 2014). Note that, unlike Japan, rice yield in many other countries like the US, China, and Korea is measured by paddy weight—the raw rice grain without threshing the hull. Thus, for a better comparison, the above rice yield of the US was converted from paddy to sorted brown rice, using the ratio 1:0.8 (MAFF 2014d; Yaguchi 2012). As aforementioned in chapter "Smart Rice Farming, Managerial Model and Empirical Analysis", the Japan Revitalization Strategy of 2014 aims to cut the costs of paddy production by 40% in the next 10 years (PMJHC 2014).

In the last few decades, agricultural production corporations have had a dramatic growth, from 2,740 in 1970 to 14,333 in 2014 (MAFF 2014c) and have become significant paddy producers. The major reasons for this growth are that unlike family management, agricultural production corporations possess larger arable lands and stronger managerial abilities, easier access to credit, diversified business development, better welfare, and sufficient human resources. Nevertheless, such large-scale farms usually have scattered fields, with different scales, soil properties, altitudes, humidity levels, daylight hours, and so on (JSAI 2014, p. 128). At the same time, to deal with the problems related to agriculture, food, and environment, GAP has been adopted widely in Japan. With respect to paddy production, GAP can improve people's working and consuming conditions, provide environmental protection through appropriate application of agrochemicals, address the concerns over biodiversity, and ensure food safety that is free of contamination and nutritionally balanced (Li et al. 2014). In this circumstance, to increase the yield with saved costs of paddy production subject to GAP, ICT has been adopted and promoted, to process the enormous amount of information in sectors of innovational cultivation, production and managerial technologies (Nanseki 2015; JSAI 2014).

This book incorporated the research findings of "NoshoNavi1000", series projects funded by the Japanese Ministry of Agriculture, Forestry and Fisheries (MAFF). Represented by Kyushu University, the project consortium includes four agricultural production corporations with 1000 paddy fields scaled over 330 hectares in total, two technology companies, five research institutes, and two universities (Nanseki 2015). It aimed to develop and demonstrate smart paddy agriculture models, implemented by agricultural production corporations, with the integration of ICT agricultural machinery, field sensors, visualization farming, and skill-transferring system. In this chapter, we investigated the variation in and determinants of rice yield, from among 351 fields at different planting stages, from a large-scale farm in Ibaraki Prefecture, Kanto Region, Japan. Unlike most previous studies that used experimental data, we used actual yield data measured by the smart combine harvester in the fields of a large-scale farm, with the cooperation of farm managers and field-work practitioners.

2 Materials and Methods

2.1 Yield Measurement and Estimation

According to the Japan's standards of brown rice inspection (MAFF 2014e), the paddy yield used in the following analyses was converted using 15% of moisture content. The paddy before the conversion is called *raw paddy*, the weight and moisture content of which were monitored directly by the smart combine harvester equipped with GNSS (Isemura et al. 2015), and compared against the estimated weight of brown rice by sampling. Table 1 shows the calculation of rice yield for

Table 1 Calculation of rice yields and summary statistics

Field	Raw yield (kg)	Average moisture (%)	Total paddy yield[a] (kg)	Field area (ha)	Average paddy yield[a] (kg/ha)	Unsorted brown rice/paddy (%)	Unsorted brown rice (kg/ha)	Sorted/Unsorted brown rice (%)	Sorted brown rice (kg/ha)
	a	b	c = a(100−b)/85	d	e = c/d	f	g = e×f/100	h	g × h/100
No. 1	7894.10	20.80	7355.40	1.03	7079.99	75.80	5366.64	90.88	4877.20
No. 2	7555.40	23.30	6817.50	1.04	6557.18	75.00	4917.90	91.00	4475.29
…	…	…	…	…	…	…	…	…	…
N	351	351	351	351	351	345	345	349	344
Min.	103.60	1.61	100.10	0.02	3484.44	70.61	3427.81	79.42	3074.65
Max.	13388.40	31.60	12871.60	2.11	9945.93	83.80	7918.93	97.52	7462.00
Mean	2383.68	21.91	2189.89	0.32	6904.42	77.87	5383.80	92.44	4976.76
Std.D.	2384.19	3.26	2191.54	0.34	833.32	2.50	666.00	2.93	624.58
CV (%)[b]	100.02	14.89	100.08	105.88	12.07	3.22	12.37	3.17	12.55

[a]Yield converted by moisture content of 15%; [b]The CV (coefficient of variation) represents the ratio of the standard deviation to the mean and it is a statistic to compare the degree of variation among the data series

all 351 fields. Incidentally, rice yield is determined by four factors: panicle number, spikelet number per panicle, ratio of filled grains, and grain weight (CSSJ 2002).

In Japan, rice yield, as mentioned earlier, refers to the weight of sorted brown grains, while it is measured by weight of paddy grains in other countries. The difference is due to a complex process of measuring rice yield, which incorporates different concepts and ratios. Following the process shown in Fig. 7 of chapter "Smart Rice Farming, Managerial Model and Empirical Analysis", we estimated paddy yield with 15% moisture, using the data of raw paddy and average moisture, measured by the smart combine harvester. Then, 2 kg of paddy from each field was sampled and hulled, based on which the weight of the brown rice was measured. The ratio of brown rice and, hence, the yield of unsorted brown rice were estimated in succession for each paddy field. At the same time, the hulled samples were sent to the laboratory in Kyushu University, where using another sample of 0.6 kg for each field, the brown rice grains thicker than 1.85 mm were sorted out through a grain-sorting machine. Finally, the yield of the sorted brown rice was estimated by multiplying the weight of brown rice with the ratio of sorted grains. For each field, the calculation of rice yield and summary statistics of concerning indices are shown in Table 1.

2.2 Explanatory Variables

To summarize the production and present the candidate yield determinants in the sampled fields, we built an indicator system of 48 continuous variables, from the perspective of field area and condition, nitrogen amount, and time of transplanting or seeding for the stage-based growth indicators. In addition, soil properties, average temperature, and solar radiation were incorporated to show the impact of natural conditions. The summary statistics are shown in Table 2.

(1) Field property. There were significant variations among the paddy fields as revealed by the coefficient of variance, from 200 to 21148 m^2 with an average of 3238 m^2. The scores for the fields were evaluated by farm managers, considering the differences in height, water depth, water leakage, former crop, amount of inlet water, soil fertility, illumination, and herbicide application.
(2) Production management. The proxy variable of transplanting date was converted by encoding April 14 as 1 and June 22 as 70 for all 351 fields. The nitrogen amounts measured were average weights calculated according to the amount and corresponding nitrogen content, including compost, compound chemical fertilizer, ammonium sulfate, and urea fertilizers.
(3) Stage-specific growth indices. The different growth stages included panicle-forming, full-heading, 10 days following full-heading, and maturity. The growth indicators included the chlorophyll meter value of the SPAD, number of stems or panicles per hill, plant height, and individual and community LPV by the stage of panicle growth for the forming, heading, 10 days following full-heading, and maturity stages, as well as panicle length for only the maturity stage.

Table 2 Summary statistics of the continuous explanatory variables

Variable	Min	Max	Mean	Std. D.	CV (%)	R[e]
Field area (m^2)	200.00	21148.00	3237.70	3428.18	105.88	−0.165***
Score of field evaluation[a]	0.00	38.90	32.13	4.56	14.18	−0.076
Date of transplanting/sowing[b]	1.00	70.00	33.66	13.98	41.55	−0.221***
Nitrogen from fertilizers (kg/ha)[c]	14.00	148.83	66.09	20.02	30.29	0.065
SPAD in panicle-forming stage	26.30	63.30	36.06	4.26	11.82	0.185***
Stems per hill in panicle-forming stage	13.80	34.60	24.34	4.18	17.15	0.236***
Plant height in panicle-forming stage (cm)	57.70	112.70	86.66	10.38	11.98	−0.226***
Individual LPV in panicle-forming stage	2.60	6.00	4.39	0.58	13.31	0.248***
Community LPV in panicle-forming stage	2.00	6.00	4.29	0.73	17.05	0.231***
SPAD in full-heading stage	24.60	50.70	35.60	4.17	11.72	0.142***
Panicles per hill in full-heading stage	13.30	42.40	23.52	4.36	18.55	0.191***
Plant height in full-heading stage (cm)	79.50	117.60	102.61	6.71	6.54	0.157***
Individual LPV in full-heading stage	2.60	6.20	4.47	0.67	14.98	0.121**
Community LPV in full-heading stage	2.00	6.00	4.31	0.73	17.02	0.225***
SPAD 10 days after full-heading	20.10	46.80	34.93	3.86	11.05	0.207***
Panicles per hill 10 days after full-heading	12.60	33.30	23.23	3.92	16.89	0.037
Plant height 10 days after full-heading (cm)	80.90	124.20	106.08	6.27	5.91	0.282***
Individual LPV 10 days after full-heading	2.00	6.00	4.05	0.75	18.42	0.265***
Community LPV 10 days after full-heading	2.00	6.00	4.02	0.74	18.40	0.299***
SPAD in maturity stage	12.80	42.30	31.31	4.71	15.04	0.305***

(continued)

Table 2 (continued)

Variable	Min	Max	Mean	Std. D.	CV (%)	R^e
Individual LPV in maturity stage	1.00	6.40	3.18	0.79	24.79	0.254***
Community LPV in maturity stage	1.00	6.00	3.13	0.82	26.22	0.198***
Panicles per hill in maturity stage	12.80	33.50	23.12	3.86	16.72	0.072
Panicle length in maturity stage (cm)	16.90	23.80	19.99	1.23	6.14	−0.067
Plant height in maturity stage	65.60	99.30	83.95	5.87	7.00	−0.076
Average temperature (°C)[d]	23.42	27.49	25.91	1.01	3.88	−0.173***
Average solar radiation (MJ/m^2)[d]	12.80	22.91	18.81	3.00	15.94	−0.032
pH	5.42	6.56	6.12	0.18	3.01	−0.134**
EC (ms/cm)	0.03	0.18	0.08	0.03	34.77	0.149***
Humus (%)	1.46	12.33	5.63	1.81	32.15	0.127**
Phosphate absorption coefficient (mg/100 g)	574.08	2689.26	1464.16	301.57	20.60	0.086
CEC (meq/100 g)	5.69	31.43	18.29	4.64	25.34	0.073
Ammonium nitrogen (mg/100 g)	0.16	2.27	0.65	0.28	42.63	−0.080
Nitrate nitrogen (mg/100 g)	0.21	3.15	1.25	0.63	50.49	−0.034
Effective phosphoric acid (mg/100 g)	1.02	29.45	7.74	5.26	67.90	0.213***
Exchangeable potassium (mg/100 g)	9.07	54.09	21.62	6.91	31.96	−0.077
Exchangeable lime (mg/100 g)	90.91	561.62	303.25	79.77	26.30	0.046
Exchangeable magnesia (meq/100 g)	18.40	128.24	65.07	17.92	27.55	0.092*
Potassium saturation (%)	0.94	6.16	2.60	0.80	30.70	−0.166***
Lime saturation (%)	28.43	96.80	59.45	7.28	12.24	−0.082
Magnesia saturation (%)	9.97	36.29	17.97	3.91	21.74	−0.004
Lime/magnesia	1.96	5.41	3.41	0.62	18.03	−0.092*
Magnesia/potassium	2.64	18.62	7.54	2.74	36.35	0.110**

(continued)

Table 2 (continued)

Variable	Min	Max	Mean	Std. D.	CV (%)	R[e]
Exchangeable manganese (%)	0.13	19.76	5.03	3.11	61.89	0.060
Soluble zinc (%)	2.50	76.69	8.70	6.37	73.15	−0.137**
Soluble copper (%)	0.54	10.99	5.84	1.97	33.65	−0.026
Free iron oxide (%)	0.32	3.42	1.73	0.57	32.71	0.073
Available silicic acid (mg/100 g)	6.70	68.54	29.54	11.47	38.84	−0.086

[a]Evaluation items include variables for height difference, water depth, water leakage, former crop, amount of water inlet, unevenness of soil fertility, illumination, and herbicide application; [b]The earliest date is April 14 = 1, while the latest date is June 22 = 70; [c]Calculation is based on the amount of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizers, and the corresponding nitrogen content; [d]Data of 20 days since full-heading; [e]Pearson's correlation with sorted brown rice; ***, **, * denote significant at 0.01, 0.05 and 0.10 levels, respectively

(4) Temperature and solar radiation. We adopted precision devices to collect continuous data of temperature and solar radiation. The data shown in Table 2 was the average of 20 days following heading, as this span of time is vital for starch accumulation (Asaoka et al. 1985).
(5) Soil property analysis. There were five aspects of soil properties considered: (1) fertility and texture including pH, EC, CEC, humus, and phosphate absorption coefficient; (2) saturation, constitution, and exchangeable amount of the base, by potassium, lime and magnesia content; (3) inorganic nitrogen in the form of ammonium and nitrate; (4) effective phosphoric and silicic acid; (5) amount of other elements, such as manganese, free iron oxide, soluble zinc, and copper.

We included the rice variety and cultivation regime to analyze the determinants of rice yield, like previous studies, including Nishiura and Wada (2012), Muazu et al. (2014), Ju et al. (2015). Soil properties can affect rice growth and yield in terms of nutrition content, water drainage and conservation, and aeration (CSSJ 2002). Therefore, we investigated the soil types of the sampled fields by referring to the Soil Information Navigation System of Japan (NIAES 2015). A dummy variable named *soil type* was formulated, with the binary values of *gray lowland soil* and *peat soil*. The summary statistics of these variables were provided in the following section.

2.3 Statistical Analysis

The impact of the independent variables, including the discrete and continuous variables, on the yield of sorted brown rice was analyzed using multivariate regression. The values of yield and the continuous variables were natural logarithmic transformations to enable an easier interpretation of the regression coefficients in terms of elasticity (Gujarati 2015). All the analyses were performed using SPSS 23.0 for

Windows, and the Backward procedure was used to select the significant determinants of the ultimate model.

2.4 Variation in the Yields and Ratios

(1) Correlation and variation

As shown in Table 1, the coefficients of variation (CVs) of average yield per hectare, including those of the paddy with 15% moisture, unsorted brown rice, and sorted brown rice, vary from 12 to 13%. In contrast, the ratio CVs of both the unsorted brown rice against paddy and the unsorted brown rice over sorted brown rice, were around 3%. Thus, there was greater fluctuation in the yields than the ratios. With respect to the correlation coefficients, the yield of sorted brown rice is significantly correlated with the other four indicators shown in Table 3. Among them, the coefficients of the two yields were greater than 0.95, much higher than those of the two ratios. This indicated that when comparing ratios, the yield of sorted brown rice is more linearly related to the yield of paddy and unsorted brown rice. Figure 1 plots the yield of the sorted brown rice and other yields and ratios, and the yields are scattered close to the estimated regression line, related to the yield of sorted brown rice.

(2) Variation among rice varieties

The variety of Akidawara had the highest value of both the paddy yield converted by 15% moisture (7303 kg per hectare) and ratio of the unsorted brown rice in the

Table 3 Pearson's correlation of the yields and ratios

Yield and ratio	Paddy with 15% moisture (kg/ha)	Unsorted brown rice/paddy (%)	Unsorted brown rice (kg/ha)	Sorted/unsorted brown rice (%)	Sorted brown rice (kg/ha)
Paddy yield of 15% moisture (kg/ha)	1.000				
Unsorted brown rice/paddy (%)	0.071	1.000			
Yield of unsorted brown rice (kg/ha)	0.963[***,a]	0.334[***]	1.000		
Sorted/Unsorted brown rice (%)	0.001	−0.267[***]	−0.067	1.000	
Sorted brown rice (kg/ha)	0.951[***]	0.263[***]	0.969[***]	0.178[***]	1.000

[a, ***] Implies significant at the 0.01 level

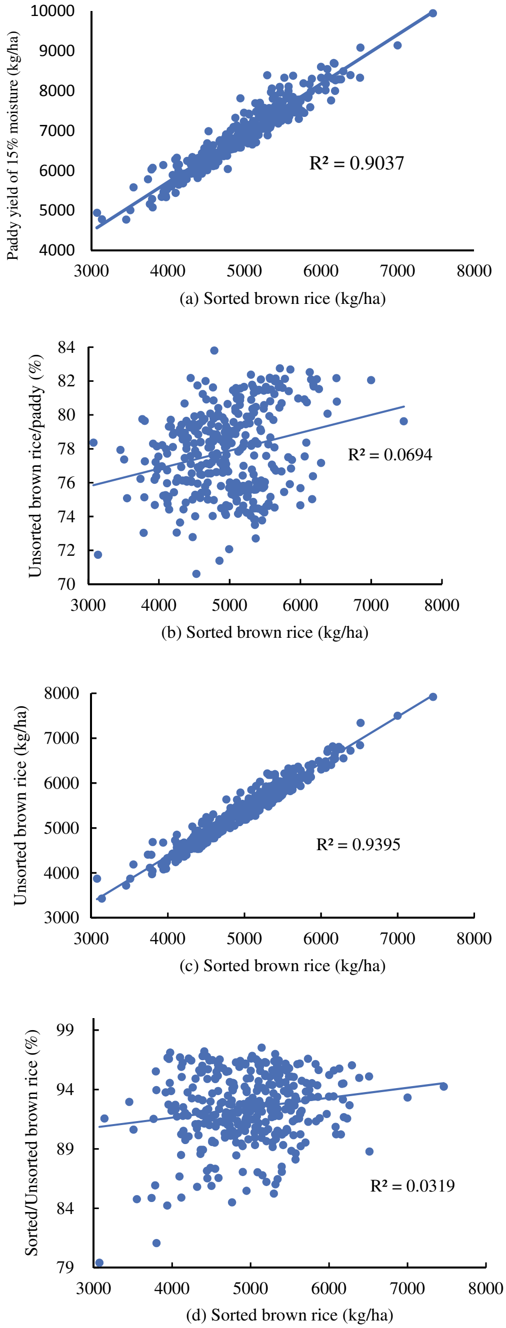


Fig. 1 Sorted brown rice yield and other yields and ratios of the 351 paddy fields of farm Y. **a** Sorted brown rice (kg/ha). **b** Sorted brown rice (kg/ha). **c** Sorted brown rice (kg/ha). **d** Sorted brown rice (kg/ha)

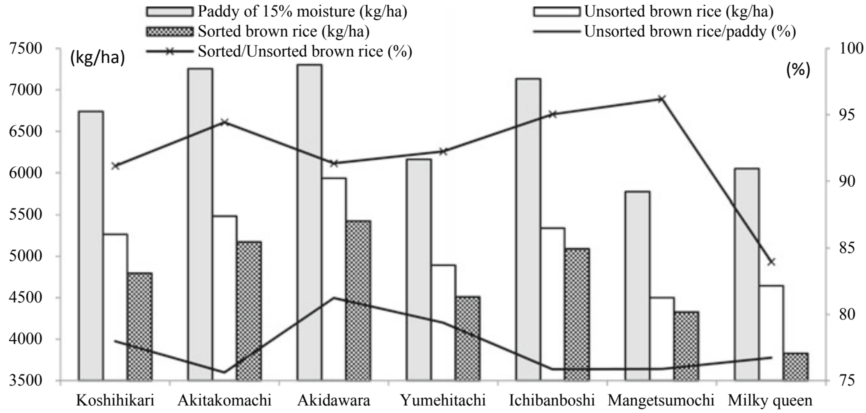


Fig. 2 Rice yields and ratios among rice varieties in 351 fields of farm Y. **a** Panicles per hill in full-heading stage. **b** Date of transplanting/sowing (day). **c** Lime/magnesia. **d** Nitrogen from fertilizers per ha (kg). **e** Community LPV in panicle-forming stage **f** Humus (%). **g** Exchangeable potassium (mg/100 g). **h** Exchangeable manganese (%)

paddy (81%). Consequently, its yield of unsorted brown rice was the highest valued at 5934 kg per hectare. Simultaneously, Akidawara yielded the highest amount of sorted brown rice with 5426 kg per hectare, despite the lowest ratio of sorted brown rice against unsorted brown rice, which was merely 91%. It was then followed by the varieties of Akitakomachi, Ichibanboshi, Koshihikari, and Yumehitachi. While both are relatively low-yielding varieties, Mangetumochi had a higher yield of both paddy and unsorted brown rice than Milky queen. The former also yielded more sorted brown rice per hectare than the latter, thanks to a higher ratio of sorted brown rice to the unsorted brown rice (Fig. 2).

(3) Variation among cultivation regimes or practices

The conventional transplant had the highest yield per hectare, measured in forms of both paddy (7053 kg) and sorted brown rice (5105 kg). This was followed by the yields of submerged direct sowing, at 6940 kg per hectare and 5057 kg per hectare, respectively. Submerged direct sowing yielded the highest amount of unsorted brown rice, at 5619 kg per hectare, with the highest ratio of 81% of unsorted brown rice to paddy. Well-drained direct sowing had the highest ratio of 97% sorted brown rice within the unsorted grains, while its average yield of 4846 kg of sorted brown rice per hectare had the third highest rank, due to the lowest paddy yield (Fig. 3).

(4) Variation among soil types

There were some discrepancies between the two soil types, with respect to all the yields and ratios. In general, rice planted in the gray lowland soil yields more than the peat soil, while the average ratios of the latter were higher than the former. In the fields with gray lowland soil, the yields per hectare of paddy, unsorted rice, and sorted brown rice were 7069 kg, 5464 kg, and 5030 kg, which is 2.6, 1.6 and

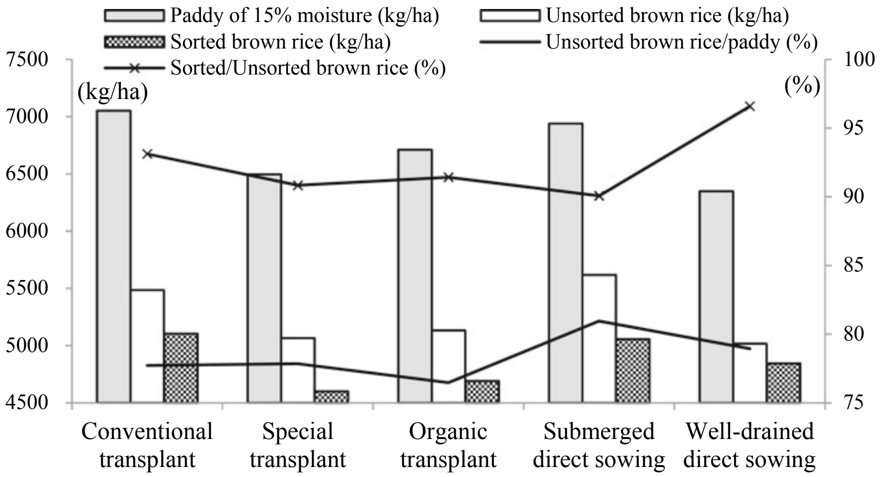


Fig. 3 Rice yields and ratios among cultivation regimes

1.2% higher than that of peat soil, respectively. At the same time, gray lowland soil gives 77.5% of unsorted brown rice in paddy and 92.2% of sorted brown rice in the unsorted ones, on average. Both ratios were lower than that of the fields in peat soil, although the differences were no more than 0.5% (Fig. 4).

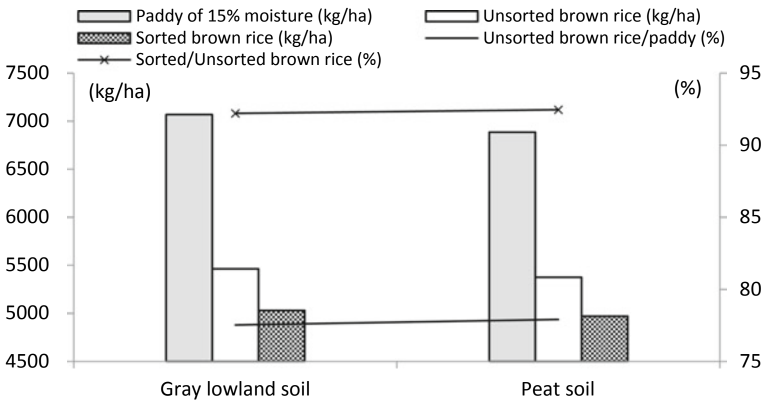


Fig. 4 Rice yields and ratios among soil types

3 Result and Discussion

As mentioned above, rice yield in Japan is mainly measured by the weight of sorted brown grain, which is causally related to the milled rice sold in the market. For each continuous variable, we presented the Pearson's correlation coefficient and its significance with sorted brown rice yield in Table 3. These coefficients measured the linear association between each determinant and the yield, showing how strongly the two variables are linearly related and can be used as a reference in identifying the determinants of some variables. However, the correlation coefficient may lead to illusory results as it shows only a bilateral relationship, without considering the influence of other variables. Therefore, to identify the yield determinants of sorted brown rice, we need to conduct multivariate regression analysis. In this case, we can get significant models and determinants and partial correlation coefficients, which show the pure impact when other variables are held constant (Gujarati and Porter 2010). To amplify the relationships among yield and the determinants, logarithmic transformation was adopted for the continuous variables.

3.1 Results of the Multivariate Regression

In the initial multivariate regression model, the independent variables included all the continuous and discrete variables shown in Table 2. For each discrete variable, a dummy variable was formulated taking the value of 1 or 0 to indicate the presence or absence of a categorical effect. According to the result of the final model, 9 continuous and 3 discrete variables were included in the final model (Table 4). The adjusted R^2 value denoted that 37.5% of the variation in the independent variable can be explained by 12 significant independent variables for this sample of 334 paddy fields. The significant F and t values showed that, both the model and each dependent variable made a difference in identifying the variation. The variance inflation factors (VIF) of all the dependent variables were less than 10; hence, eliminating the probability of collinearity. In the regression standardized residual plot shown in Fig. 5, the expected cumulated probability increases closely as the observed cumulated probability increases. This indicated that there is no heteroscedasticity in the final model (Carter et al. 2012).

In Table 4, column B contains the unstandardized estimated regression coefficients. For each continuous variable (X_{i}), the coefficient is the elasticity of yield with respect to X_i. For instance, the positive coefficient of X_1 and the negative coefficient of X_2 implied that yield can be increased by either more panicles per hill in the full-heading stage or earlier transplanting or sowing. For a certain level, a 1% increase in panicle number can increase the yield by 0.196%, while a 1% decrease in the transforming or sowing date value can increase the yield by 0.053%, holding other variables constant. For a more precise calculation, the estimated yield increased by $1.01^{0.196}-1 = 0.195\%$ and $1.01^{-0.053}-1 = -0.053\%$, respectively (Wooldridge

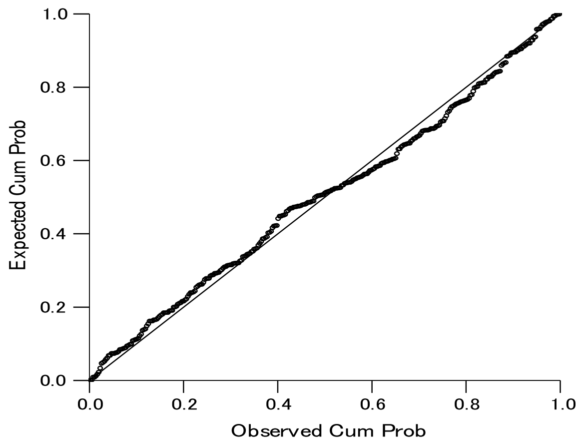
Table 4 Result of the Log-linear Multivariate Regression estimation

Independent variable[a]	B[b]	Δ%[c]	Std. B	Contribution (%)[d]	t	VIF
(Constant)	7.803				37.053	
Panicles per hill in full-heading stage (X_1)	0.196***	0.195	0.297	14.558	4.860	1.995
Date of transplanting/sowing (X_2)	−0.053***	−0.053	−0.212	10.371	−2.931	2.785
Lime/magnesia (X_3)	−0.100***	−0.100	−0.145	7.120	−2.830	1.408
Nitrogen from fertilizers per hectare (X_4)	0.046**	0.046	0.107	5.232	1.983	1.549
Community LPV in panicle-forming stage (X_5)	0.065**	0.065	0.100	4.880	2.120	1.178
Humus (X_6)	0.036*	0.036	0.098	4.811	1.657	1.875
Field area (X_7)	0.014*	0.014	0.090	4.415	1.719	1.467
Exchangeable potassium (X_8)	−0.034*	−0.034	−0.086	4.194	−1.661	1.417
Exchangeable manganese (X_9)	0.014*	0.014	0.079	3.847	1.670	1.180
Akidawara (D_1)	0.153***	16.537	0.484	23.706	9.102	1.509
Milky queen (D_2)	−0.201***	−18.198	−0.197	9.658	−4.174	1.191
Well-drained direct sowing (D_3)	−0.236**	−21.025	−0.147	7.210	−2.422	1.971

Dependent Variable (Y): Natural log of sorted brown rice yield; Valid $N = 334$
$R = 0.631$, $R^2 = 0.398$, Adjusted $R^2 = 0.375$; $F(12, 321) = 17.682^{***}$

[a]Natural log values of X_i, [b,]***, ** and *Imply significant at the level of 0.01, 0.05 and 0.10, respectively; [c]Percentage of paddy yield changes due to a 1% increase in $X_i = 100^*(1.01^B - 1)$; and due to the value of D shifting from 0 to 1 by $100^*(e^B - 1)$; [d]Calculated based on Std. B
Software: SPSS 23.0; Variable selection: backward procedure

Fig. 5 Plot of regression standardized residual



2013). Similarly, for the other significant determinants, a 1% increase in the nitrogen amount, community LPV in panicle-forming stage, humus, field area, and exchangeable manganese were estimated to increase the yield by roughly 0.046, 0.065, 0.036, 0.014 and 0.014%, respectively. Meanwhile, a 1% decrease in the ratio of lime to magnesia and exchangeable potassium, ceteris paribus, would increase the yield by roughly 0.1 and 0.034%, respectively. Table 4 shows the yield changes due to a 1% increase in each X_i as well. For the dummy independent variable D_i, coefficient B implies yield changes by $e^{B}-1$ when D_i switches from 0 to 1, keeping other explanatory variables constant (Wooldridge 2013). Thus, for the variety of Akidawara, the coefficient of 0.153 denoted a roughly 15.3% higher yield, while the exact increase is 16.537%. Similarly, the variety of Milky queen, and well-drained direct sowing showed roughly 20.1%, and 23.6% lower yield on average, respectively, holding other factors constant (Table 4).

Within the continuous variables, an unstandardized coefficient B was affected by the units of measurement. We calculated the standardized coefficient, the absolute values of which show the relative importance of the explanatory variables. For example, according to the data in column Std. B in Table 4, panicle number in full-heading stage was shown as the most effective continuous factor to affect the yield of sorted brown rice. The variables in Table 4 were presented in the ascending rank of absolute values of Std. B, grouped in continuous and discrete variables.

3.2 *Discussion on Impact of the Continuous Determinants*

(1) In the full-heading stage, 40–50% of the stalks have finished sprouting panicles. This is an important stage to judge the growth for the whole year (Goto et al. 2000). Thereafter, the focus of cultivation management shifts from the growth of stem and leaves to panicle growth and grain filling. In this stage, more panicles

help to increase the yield directly according to the determined rice yield. This was shown in Fig. 6a, where the yield of sorted brown rice is plotted to rise upward with larger panicle numbers.

(2) Relatively earlier transplanting or sowing benefits high yielding. Generally, earlier transplanting or sowing is followed by a longer vegetation period to accumulate more nutrients and benefit the growth in the later stages. In Li et al. (2015a), we identified that the growth duration gets shortened when the transplanting or sowing time is delayed. For example, the paddy transplanted during April 11–20 grew for 109 days before heading, while those transplanted or sowed during June 21–30 grew only for 58.5 days on average. The shortened vegetative growth usually results in reduced panicles, spikelets, and poor ripening ratio (NARO 2011). Figure 6b verified the trend of a downward yield when transplanting or sowing time is delayed.

(3) Magnesia is the key ingredient of chlorophyll and, thus, indispensable for photosynthesis and for balancing the soil minerals. Nevertheless, its absorption efficiency is suppressed when the soil contains excessive lime. As shown in Fig. 6c, there was a positive correlation relationship, at the significance level of 0.01, between magnesia saturation and the yield of sorted brown rice.

(4) As an essential element for paddy growth, nitrogen exists mainly in the forms of protein, especially Rubisco, which accounts for 20–30% of the total nitrogen amount (CSSJ 2002, p. 126). Generally, adequate nitrogen helps to increase the yield, as shown in Fig. 6d, by enhancing photosynthesis. More than 90% of crop biomass is derived from photosynthesis, and rice has been found to have a photosynthesis rate that is 10 times that of some evergreen trees (Makino 2011). Therefore, increasing nitrogen appropriately positively relates to yield, with no lodging or other negative consequences.

(5) The panicle-forming stage is the young panicle grows to a length of 1–2 mm that is visible to the naked eye. This is an important stage in determining the optimum fertilizer amount and conducting panicle-length diagnosis. Further, the importance of preventing cold injury increases after this stage. To judge the nutrient content and decide the top-dressing amount, there is a quick way of reading the LPV, a higher grade of which indicates more nutrient content in the plant. Thus, this indicator positively related to yield, as plotted in Fig. 6e.

(6) As a kind of polymeric compound transformed from organic matter, humus composes an important source of carbon, hydrogen, oxygen, nitrogen, sulfur, phosphorus, and other nutrient elements (Makino 1998). Humus can significantly improve the soil's cation exchange capacity, hence contributing to store nutrient leached by rain or irrigation. On the other hand, humus can hold moisture up to 80–90% of its weight and strengthens the soil to withstand drought conditions. The biochemical structure enables humus to improve soil aeration and block toxic substances, excess nutrients, and excess acidity or alkalinity (Kono 1993). Thus, as shown in Fig. 6f, humus was positively correlated to the yield of sorted brown rice, significant at the 0.05 level.

(7) The inverse impact of exchangeable potassium, as shown in Fig. 6g, revealed the reality of the last few years—surplus potassium is accumulated in the paddy

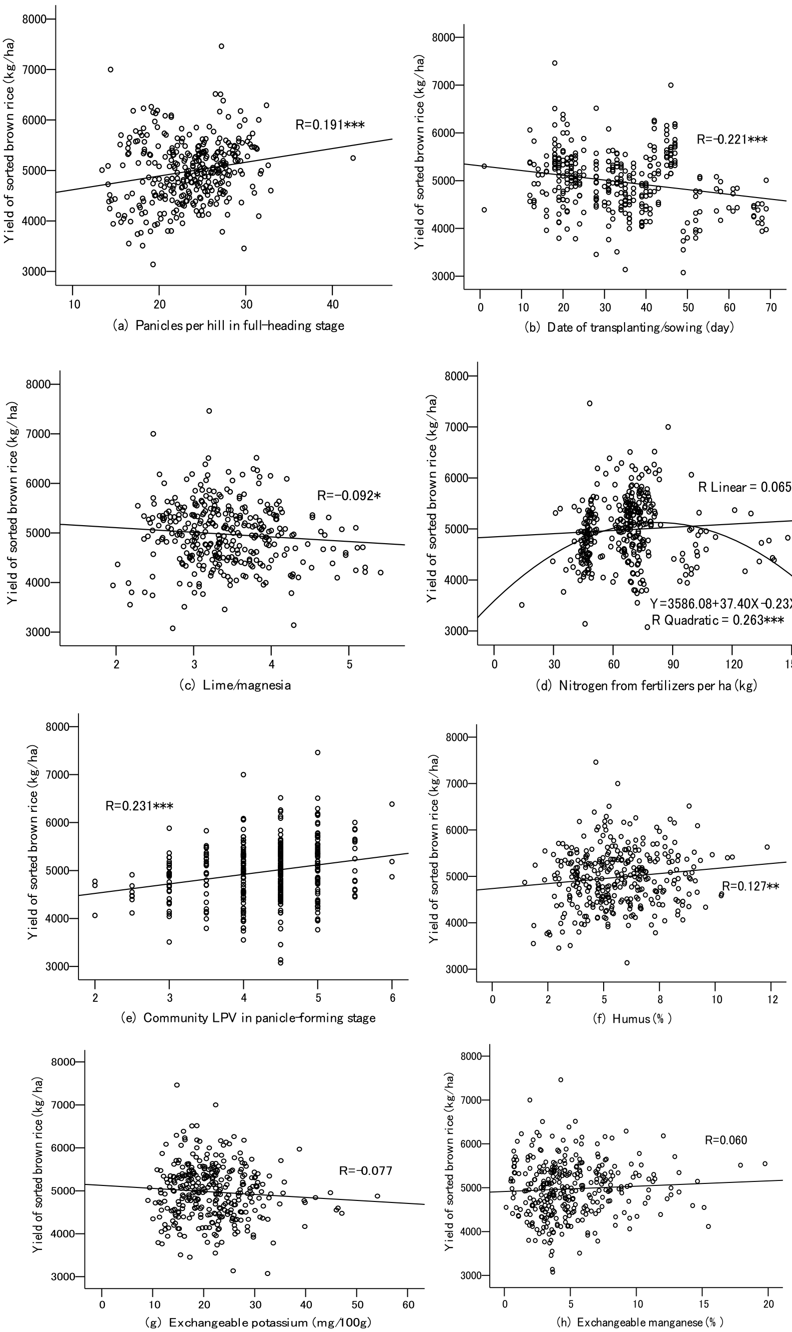
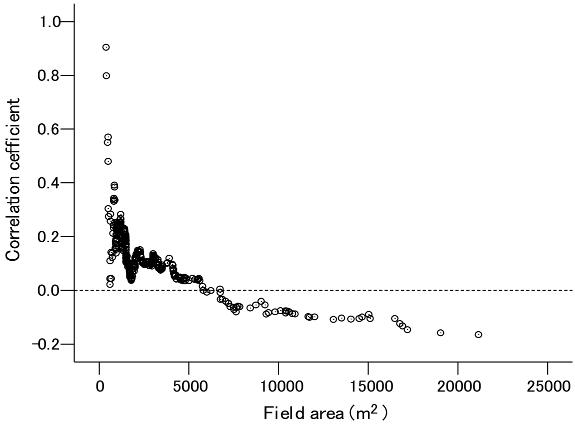


Fig. 6 Scatter plots of sorted brown rice yield and determinants. **a** Panicles per hill in full-heading stage. **b** Date of transplanting/sowing (day). **c** Lime/magnesia. **d** Nitrogen from fertilizers per ha (kg). **e** Community LPV in panicle-forming stage. **f** Humus (%). **g** Exchangeable potassium (mg/100g). **h** Exchangeable manganese (%)

Fig. 7 Correlation coefficients of field area and sorted brown rice yield



fields of Japan, due to an over-use of fertilizers (Watanabe et al. 2015). Within the sampled paddy fields, the average potassium saturation amounted to 2.6%, higher than the maximum threshold of 2.5% of the paddy fields in Ibaraki Prefecture (MAFF 2008).

(8) As an essential trace element for plant growth, manganese is involved in photosynthesis and the transformation of nitrogen, and it is active in the catalysis of many enzymes and redox processes. It can promote the synthesis of chlorophyll and the operation of carbohydrates. The deficiency of manganese in soil may lead to withered plants, dysplasia, and eventually, declined production. Thus, there was a positive relationship between the amount of exchangeable manganese and the yield of sorted brown rice, as shown in Fig. 6h.

Within this sample, 312 fields were less than 0.7 hectares in size, up to which positive correlation coefficients were observed for the yield of sorted brown rice and field area (Fig. 7). It can be interpreted that when fields are scaled less than 0.7 hectares, a larger area can usually increase yield through an enlarged sink size (i.e., spikelet number per unit land area). Meanwhile, the correlation coefficient of the field area and amount of nitrogen from fertilization was 0.46, significant at 0.01 level, indicating that a larger field facilitates application of fertilizer. Nevertheless, both factors indicated the existence of diminishing returns when inputs are increased over threshold values. As shown in Figs. 6d and 7, yield per hectare decreased in the fields more than 0.9 hectares in size, or when the nitrogen amount exceeds approximately 90 kg per hectare.

3.3 Discussion on the Impact of Discrete Determinants

As we have demonstrated in another study (Li et al. 2015a), rice variety was a significant factor that affects paddy yield in this sample. Akidawara is a new, lodging-resistant, and high-yielding variety and is suitable for cultivation in the Kanto Region. In this chapter, Akidawara yielded 7303 kg per hectare on average, the highest among the seven varieties observed. The average yield of the other six varieties was 6812 kg per hectare, 7.21% lower than that of Akidawara (Fig. 2). Further, Akidawara had, on average, the longest growth period of 80 days—from transplanting to heading—almost 10 days more than the other varieties. Thus, as analyzed above, it has an advantage of a prolonged vegetative growth with more panicles, spikelets, and increased ripening ratio, and so on. in contrast, Milky queen is a new rice variety bred in Koshihikari, with low amylose content in the endosperm. The Milky queen is not adapted to heavy chemical fertilizer use in paddy fields because it is susceptible to lodging after the heading stage and leaf- and panicle-blast diseases. In addition, Milky queen has low resistance to rice blast disease (Ise et al. 2001). Therefore, as shown in Fig. 2, the sorted brown rice yield of Milky queen was 3829 kg per hectare, the lowest among the seven varieties.

Direct sowing is one of the traditional cultivation regimes and it has significant savings in labor and energy inputs. However, due to unstable establishment, poor resistance to weed damage, and susceptibility to lodging, directly sowed rice yield is less than that of transplanted one, in general. In the well-drained direct sowing, its drawbacks are that sowing time is dependent on the weather, nutrient loss from cracked soil, and so on (CSSJ 2002, pp. 326–329). The survey data shows that the yield of paddy cultivated using well-drained direct sowing was the lowest, with the largest data dispersion denoted by CV, among the five cultivation regimes observed. In addition, it had the lowest number of panicles in the heading stage. Submerged direct sowing was used only to cultivate Akidawara, for which the average yield by submerged direct sowing was less than from the other cultivation regimes.

4 Conclusion

In the initial multivariate regression analysis, the candidate determinants included a variety of continuous variables of yield, field characteristics, transplanting time, nitrogen amount from fertilization, and growth data at different stages. In addition, three discrete variables were included for variety, cultivation regime, and soil type. The result of the multivariate regression analysis showed that, the panicle numbers in the heading stage and an earlier transplanting date are the most important determinants in increasing rice yield. The other significant determinants were: nitrogen amount, humus content, exchangeable manganese, and community LPV in the panicle-forming stage, ratio of lime to magnesia, and exchangeable potassium, all of which have a positive impact on the yield of sorted brown rice. Within the discrete determinants, the Akidawara and Milky queen were observed as the high-yield and low-yield varieties, respectively; while the well-drained direct sowing was shown as negatively affecting the yield of sorted brown rice. The regression coefficients indicated a positive impact of field area on yield, while the correlation coefficient and further analysis from the scatter plot show that extremely high values could lead to yield reduction.

We can use these empirical findings as a reference to increase yield in farm management. Nevertheless, paddy production in large-scale farms is a systematic procedure, subject to constraints of labor, funds, machinery, and so on. For instance, although earlier transplanting or sowing is shown to increase yield, it might be unrealistic or uneconomical to conduct transplanting or sowing in many fields simultaneously. Thus, optimal planning is necessary to conduct transplanting or sowing at different times while making full use of the limited machinery, labor, and funds (Chomei et al. 2015). Moreover, the amount of fertilizer and allocation of fields of different sizes must be optimized in future studies, considering the properties of different rice varieties. As analyzed above, the direct sowing was negatively related to a yield increase, but it promotes sustainable development. Hence, more rice varieties suitable for direct sowing should be bred and cultivated.

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Impact of Rice Variety and Cultivation Regime Through ANOVA

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This chapter identified the impact of rice variety and cultivation regime on paddy yield in the large-scale farms. The study objects were 351 fields in a farm corporation of over 113 hectares, locating in the Kanto Region, and the yield was measured by smart combine harvester The ANOVA result indicated that rice variety was a significant factor affecting yield; although the cultivation regime was not significant, it had a significant interaction with the effect of rice variety. According to the result of Duncan's new multiple range test (DNMRT), the rice varieties were divided into three groups. Further analyses using four factors and the ANOVA results showed that the time of transplanting or sowing, growth duration from transplanting or sowing stage to earring stage, total nitrogen amount, and field area were determining factors. Finally, the key points for higher paddy yield were summarized.

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1 Introduction

In recent decades, Japanese agriculture has been undergoing a recession. From 1985 to 2013, gross agriculture output decreased by 27% from 11.62 trillion JPY to 8.47 trillion JPY. Simultaneously, paddy output decreased by 53.51%, from 3.83 trillion JPY to 1.78 trillion JPY. Although it still has the largest share, output of paddy in agriculture has decreased from 32.93 to 21.03% (MAFF 2014). The decreasing paddy production has reduced agricultural growth to a large extent (Ohizumi, 2014).

After came back to power in end of 2012, the government led by the Liberal Democratic Party (LDP) of Japan issued the new policy of "proactive agriculture, forestry and fisheries", to increase the efficiency and competitiveness of these sectors in Japan. As to agriculture, it is essential to reduce the production costs and improve the yields, through the fiscal subsides to adopt efficient technologies, equipment, managerial models. Meanwhile, the keynote policy for paddy production is changing from acreage reduction adopted since early 1970s, to expand the exports actively and improve the international competitiveness. On the other hand, Japanese cuisine was designated to the UNESCO's intangible cultural heritage list on December 4, 2013. The government hopes to enhance global recognition and boost the exports of rice among other Japan's agricultural products.

Some scholars have studied the determinants of paddy yield in Japan, like Hirai et al. (2012), Tanaka et al. (2014). In the literature, rice variety and cultivation regime have been shown to be important determinants of paddy yield (Nishiura and Wada 2012; Muazu et al. 2014; Ju et al. 2015). Accordingly, this chapter identified the yield determinants from the perspective of rice variety and cultivation regimes. Unlike the previous studies that used experimental data, we used data of rice yield measured by smart combine harvester, and other data from 351 paddy fields of a large-scale farm corporation located in Ibaraki Prefecture of the Kanto Region.

2 Materials and Methods

2.1 Paddy Production in the 351 Fields

All the 351 fields are scattered compactly in a plain area of 2 sq. km. The paddy production is carried out with relatively fewer machineries utilizing just 2 officers, 11 full-time staff, and 5 temporary employees. The size of the fields ranges from 200 m^2 to 21148 m^2, with the average area of 3237.7 m^2. The major soil types are peat soil and gray lowland soil, accounting for 317 and 34 fields, and 91.97% and 8.03% of the total size, respectively.

Figure 1 presents the proportion in the total number of fields and total areas of fields surveyed, by rice variety. Within the seven varieties, Koshihikari had the largest share in both the number of fields and area cultivated, followed by Akitakomachi in terms of the number of fields cultivated, and Yumehitachi in terms of the area cultivated.

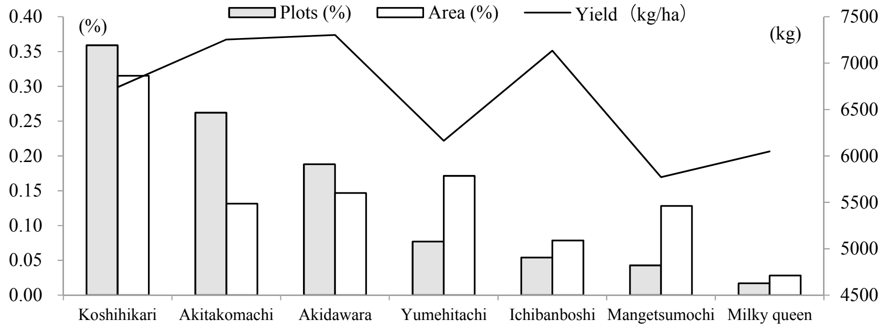

Fig. 1 Yield and proportion in total number of fields, and area among rice varieties

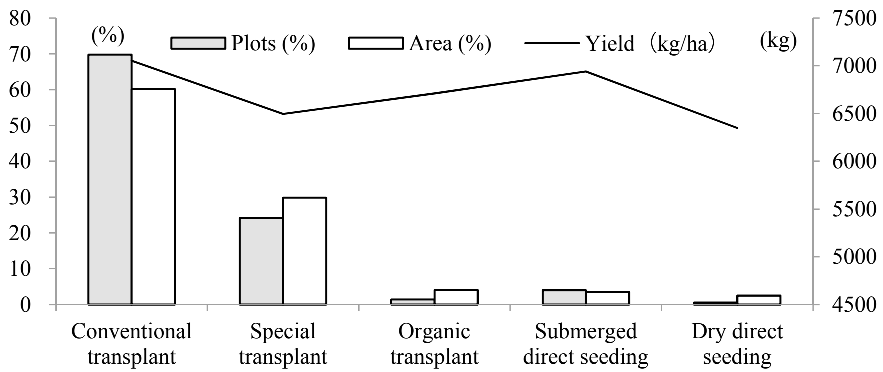

Fig. 2 Yield, proportion of total number of fields and area under different cultivation practices

Among the five cultivation regimes, the conventional transplant was most adopted, with almost 70% of the number of fields and 60% of area cultivated, followed by special transplant (Fig. 2).

2.2 *Statistical Analysis*

The effects of rice variety and cultivation practices on paddy yield were analyzed using two-way ANOVA. For the significant parameters, the means were compared using DNMRT, a post hoc multiple comparison method assuming equal error variance. For the rice varieties that utilize multiple cultivation practices, the effects of the latter were further estimated using one-way ANOVA. All the analyses were performed using SPSS 13.0 for Windows.

3 Results and Discussion

3.1 Result of ANOVA

As shown in Table 1, the model of two-way ANOVA was significant at the level of 0.01, and rice variety was found to be significant in affecting paddy yield at the same level. Cultivation regime was insignificant to yield, but it had a significant effect with rice variety and was found significant at the 5% level. Levene's test of equality of error variances ($p > 0.10$) indicated that, the null hypothesis was acceptable, and hence, there was no significant error variance of the dependent variable across the groups. The summary statistics of different rice varieties and cultivation regimes were shown in Table 2, including yield per hectare converted by 15% moisture, standard deviation, and the CV. The corresponding yield curves were shown in Figs. 1 and 2.

The equality of error variances was shown in Table 1 and the grouping information of yields based on DNMRT was summarized in Table 2. As to effect of rice variety, the average yields were divided into three subsets. The upper subset (A) included Akidawara (7303.14 kg per hectare), Akitakomachi (7253.93 kg per hectare), and Ichibanboshi (7134.20 kg per hectare) varieties; the moderate subset (B) consisted of Ichibanboshi (7134.20 kg per hectare) and Koshihikari (6740.11 kg per hectare) varieties; while the lower subset (C) comprised Yumehitachi (6162.95 kg per hectare), Milky queen (6050.08 kg per hectare), and Mangetsumochi (5771.73 kg per hectare) varieties. Except for the variety of Ichibanboshi, which came under both (A) and (B) subsets, the other subsets were different from each other in terms of average yield. In contrast, average yields cannot be divided into different subsets, from the perspective of cultivation regimes. Hence, it is not possible to identify yield variance in accordance with the result of ANOVA.

With respect to the significant interaction effect of rice variety and cultivation regime, one-way ANOVA was adopted to test the effect of multiple cultivation regimes used for some rice varieties. The result indicated that cultivation regime

Table 1 Result of the two-way ANOVA[a]

Source[b]	Sum of squares	df	Mean Square	F	Sig.
Variety	51965588.58	6	8660931.43	17.20***	0.000
Cultivation	2469156.73	4	617289.18	1.23	0.300
Variety × Cultivation regime	3373552.89	1	3373552.89	6.70**	0.010
$F_{\text{Total}} = 13.060^{***}$	$R^2 = 0.298$		Adjusted $R^2 = 0.275$		
Levene's equality test of error variances[a]		df1	df2	F	Sig.
		11	339	1.566	0.107

[a]Dependent variable in this chapter is yield per hectare converted by 15% moisture Software: SPSS 13.0
[b]Tests the null hypothesis that the error variance of the dependent variable is equal across groups
*** and **Denote significance at the 1 and 5% levels, respectively

Table 2 Paddy yield by variety and cultivation regimes

Rice variety and cultivation regime		N	Average yield (kg/ha)	Std. D. (kg/ha)	CV[a] (%)
Variety	Koshihikari	126	6740.11^{B}	674.89	10.01
	Akitakomachi	92	7253.93^{A}	839.80	11.58
	Akidawara	66	7303.14^{A}	686.28	9.40
	Yumehitachi	27	6162.95^{C}	591.29	9.59
	Ichibanboshi	19	7134.20$^{A, B}$	715.81	10.03
	Mangetsumochi	15	5771.73^{C}	751.05	13.01
	Milky queen	6	6050.08^{C}	318.45	5.26
Cultivation regime	Conventional transplant	245	7052.53^{D}	870.66	12.35
	Special transplant	85	6496.03^{D}	589.75	9.08
	Organic transplant	5	6711.14^{D}	310.07	4.62
	Submerged direct sowing	14	6940.27^{D}	761.47	10.97
	Dry direct sowing	2	6349.05^{D}	758.65	11.95
Variety × Cultivation regime	Koshihikari · Conventional transplant	56	6939.93***	738.41	10.64
	Koshihikari · Special transplant	65	6570.20***	592.19	9.01
	Koshihikari · Organic transplant	5	6711.14***	310.07	4.62
	Akitakomachi · Conventional transplant	92	7253.93	839.80	11.58
	Akidawara · Conventional transplant	52	7400.84**	637.65	8.62
	Akidawara · Submerged direct sowing	14	6940.27**	761.47	10.97
	Yumehitachi · Conventional transplant	11	5900.24	533.68	9.05
	Yumehitachi · Special transplant	14	6342.79	580.79	9.16

(continued)

Table 2 (continued)

Rice variety and cultivation regime		N	Average yield (kg/ha)	Std. D. (kg/ha)	CV[a] (%)
	Yumehitachi · Dry direct sowing	2	6349.05	758.65	11.95
	Ichibanboshi · Conventional transplant	19	7134.20	715.81	10.03
	Mangetsumochi · Conventional transplant	15	5771.73	751.05	13.01
	Milky queen · Special transplant	6	6050.08	318.45	5.26
Total	–	351	6904.42	833.32	12.07

[a]CV is the ratio of the standard deviation to mean, CV shows the dispersion of data
[A, B, C, D]Values followed by the same letter(s) within the same column are not significantly different at $P < 0.05$ according to DNMRT; [***]and [**]Denote significance at the 1 and 5% levels, respectively Software used: SPSS 13.0

Table 3 One-way ANOVA of cultivation regime for some varieties

Variety	Source	Sum of squares	df	Mean square	F	Sig.
Koshihikari	Between groups	4116673.67	2	2058336.84	4.793***	0.010
	Within groups	52817561.96	123	429411.07		
	Total	56934235.63	125			
Akidawara	Between groups	2339769.85	1	2339769.85	5.296**	0.025
	Within groups	28274331.97	64	441786.44		
	Total	30614101.82	65			
Yumehitachi	Between groups	1281241.80	2	640620.90	1.969	0.162
	Within groups	7808846.92	24	325368.62		
	Total	9090088.73	26			

Software: SPSS 13.0

was significant with the varieties of Koshihikari and Akidawara, at the significance level of 0.01 and 0.05, respectively, while it was insignificant with the variety of Yumehitachi (Table 3).

3.2 Discussion on the Effect of Variety

For further analysis on effect of the different varieties, we adopted four other factors: time of transplanting or sowing, growth duration from transplanting or sowing to earring, total nitrogen amount by fertilization, and field area. In our previous study (Li et al., 2015a), all these factors were demonstrated as significant determinants of paddy yield. To measure the effects of these factors, we divided the fields into three subsets same with those shown in Table 2. Results of ANOVA indicated that average values of all the four factors were significantly different across theses varieties and subsets (Table 4).

The transplanting dates ranged from April 14 to June 22. In most of the fields, paddy was transplanted simultaneously in May, accounting for the largest share in the total areas (Fig. 3). There was a clear trend that the growth duration got shortened when the transplanting season was relatively late. For instance, the paddy transplanted during April 11–20 can grow for 109 days before the earring stage, while those transplanted during April 11–20 can grow only for 58.5 days on average. For an easier analysis, we converted the time of transplanting or sowing to continuous numerals, with the earliest date of April 14 equal to 1 and the latest date of June 22 equal to 70. Ichibanboshi was transplanted earlier than the other varieties and its average growth duration amounted to more than 72 days. In contrast, Mangetsumochi was transplanted later than the other varieties and had the shortest growth duration of less than 60 days. Nitrogen is an essential element for paddy growth and its insufficiency could result in a yield decrease. In the sampled fields, total nitrogen amount was

Table 4 Yield determinants within varieties and subsets

Variety		Date of transplanting/sowing[a]	Growth duration (days)[b]	Nitrogen amount (kg/ha)[c]	Field area (m^2)
Akitakomachi		20.03	68.39	66.55	1625.33
Akidawara		41.26	79.55	74.05	2527.76
Ichibanboshi		13.37	72.53	76.93	4704.53
Koshihikari		34.22	72.27	52.12	2842.65
Yumehitachi		50.78	66.85	95.56	7211.41
Mangetsumochi		67.60	59.47	83.99	9709.40
Milky queen		49.50	67.17	62.94	5360.00
Subset (A)		27.23	72.99	70.46	2292.36
Subset (B)		31.49	72.30	55.37	3086.62
Subset (C)		55.88	64.58	87.53	7760.60
Total		33.66	71.58	66.09	3237.70
F value of one-way ANOVA	Variety[d]	244.611***[f]	52.097***	40.107***	30.052***
	Subset[e]	132.763***	31.730***	97.898***	83.265***

[a]Time of transplanting or sowing, with the earliest date of April 14 = 1, while the latest date of June 22 = 70; [b]Days from transplanting/sowing stage to earring stage; [c]Calculation based on the amount of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizer, according to the corresponding content of nitrogen; [d]Degree of freedom (df) of nitrogen amount is (6,342), the others are (6,344); [e]Ichibanboshi is excluded and the df of nitrogen amount is (2,327), while the others are (2,329); [f]***Denotes significance at the 1% level

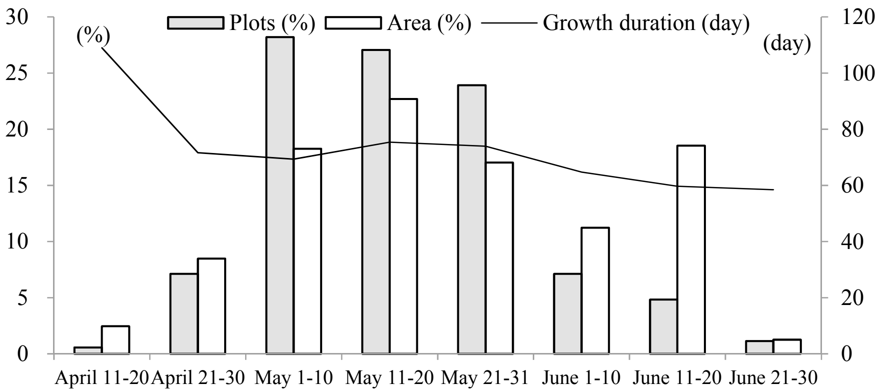

Fig. 3 Transplanting or sowing time and growth duration of 351 paddy fields of farm Y (Growth duration refers to the number of days from transplanting or sowing stage to earring stage)

calculated by the amount of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizer, multiplied with the corresponding percentage of nitrogen. Among the seven varieties, Yumehitachi received the largest nitrogen amount of 95.56 kg per hectare from fertilization, while Koshihikari received the least with 52.12 kg per hectare. As for the field area, the highest and lowest average values were for Akidawara and Mangetsumochi, respectively (Table 4).

Although readable by individual varieties, it is much easier to analyze the relationship between yield and the factors by subsets. The highest-yielding subset (A) had the earliest date of transplanting or sowing, the longest growth duration, and most compact fields, while the lowest-yielding subset (C) was transplanted or sown in the latest stage, had the shortest growth duration, and the broadest fields. As for nitrogen, subset (A) had a moderate amount, while the largest amount was applied to subset (C). The reasons can be summarized as follows. (1) An earlier transplanting or sowing time and a longer growth duration are propitious to vegetative accumulation, hence, there are more nutrients to increase the plant height and panicle numbers in the full-heading stage and increase yield in terms of higher spikelet numbers, higher percentage of ripened grains, and heavier grains. (2) Although nitrogen is indispensable, its excessive use can lead to a thinner cell wall of the plant and weakened disease resistance, resulting in yield reduction. (3) Within the 351 fields, there was a significant ($p < 0.01$) negative correlation coefficient of −0.160 between the yield and field area. This could indicate that a relatively compact field area favors the evenness of fertilizer spread and increase yield in general.

Table 5 presents the yield at different levels of the four factors across the three subsets, where the data roughly follows a normal distribution in general. In other words, the high yields were centered near the medium values of each factor. Namely, those transplanted or seeded in May, growing for 60–70 days, 40–100 kg of nitrogen per hectare, field size of 2000–8000 m^2. For most of the factors, subset (A) had higher yields than the other two subsets, including for those transplanted or seeded in May, growing for 70–79 days before earring stage, nitrogen amount of more than 40 kg per hectare, and fields scaled less than 6000 m^2, according to the classification used in this chapter. In addition, the relationships between the factors and yield across the subsets were shown at the factor levels (Table 4). For instances, subsets (B) and (C) had the highest yield when transplanted or seeded during May 1–10 and April 11–20, respectively. The significant correlation coefficients of the yield with some factors were generally in agreement with the findings demonstrated above, including the negative correlation with transplanting or sowing time of subset (B) and the positive correlation with field area in subsets (B) and (C).

Table 5 Yield of different levels for each factor

Factors and levels	Yield (kg/ha)			Factor and level	Yield (kg/ha)		
	Subset (A)	Subset (B)	Subset (C)		Subset (A)	Subset (B)	Subset (C)
Date of transplanting/sowing				Total nitrogen amount (kg/ha)			
April 11–20			6349.05	<40	6073.25	6244.61	4948.20
April 21–30	6441.73			40–60	7343.20	6751.04	6215.20
May 1–10	7310.60	7153.03		60–80	7230.86	6920.68	6061.18
May 11–20	6940.27	6770.67	4770.10	80–100	8080.20		6018.72
May 21–31	7449.08	6503.37		> = 100	7559.30	6745.70	6266.94
June 1–10	4940.50		6140.12	Correlation	0.091	0.160*	0.249*
June 11–20			6047.95	Field area (m^2)			
June 21–30			5407.50	<1000	7001.59	6131.15	5295.37
Correlation[a]	0.100	−0.290***	−0.081	1000–2000	7357.83	6552.92	5594.94
Growth duration (day)				2000–4000	7390.25	6891.34	5648.45
<60			5921.2833	4000–6000	7228.47	7016.62	6160.37
60–69	7281.24	7509.40	6058.4692	6000–8000	7049.05	7180.63	6169.30
70–79	7333.45	6733.96		8000–10000	4940.50	8380.10	6335.77
> = 80	6940.27		5822.7333	> = 10000		6988.46	6197.55
Correlation	−0.095	0.136	0.023	Correlation	−0.065	0.341***	0.256*

[a]Pearson's linear correlation calculated by SPSS 13.0; ***and *Denote significance at the 1 and 10% levels respectively

4 Conclusion

In Japan, the paddy production policy is transferring from acreage reduction to the expansion of exports with improved international competitiveness. The increased paddy yield is essential for improving exports and reducing the high production costs. Over the recent decades, agricultural corporations had a dramatic growth and they now represent the future of agricultural production in Japan.

Using yield data measured by smart combine harvester and other data from 351 paddy fields, this chapter analyzed the impact of rice variety and cultivation regime to paddy yield in a large-scale farm of over 113 hectares, located in the Kanto Region. The ANOVA result indicated that rice variety is a significant factor affecting paddy yield; the cultivation regime is found to be not significant, but it has a significant interactive effect with rice variety.

The rice varieties were divided into three subsets by adopting DNMRT. We also adopted four other factors: time of transplanting or sowing, growth duration from transplanting or sowing stage to earring stage, total nitrogen amount, and field area. Growth durations were found to be significantly shortened when the transplanting or sowing is later and vice versa. Further ANOVA across the three subsets showed that, a higher yield is possible with an earlier transplanting or sowing time, longer growth duration from transplanting or sowing stage to earring stage, moderate nitrogen amount, and a compact field area. Many of these conclusions were verified by further analyses, from different levels of the factors.

To sum up the key points for a higher paddy yield, it is essential to adopt the appropriate rice varieties in the first place. Moreover, a relatively earlier transplanting or sowing and longer growth duration are propitious to vegetative accumulation. A sufficient supply of nitrogen is important for paddy growth, while excessive application must be avoided. The fields should be of an appropriate size, to balance between scale economies (e.g., saving managerial costs and a larger sink size) and the even spread of fertilizer and pesticides.

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Identifying the Rice Yield Determinants Among Comprehensive Factors

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Paddy production in Japan is currently undergoing a transition, moving away from the former acreage reduction policies of the 1970s to improve the sector's efficiency and competitiveness. Meanwhile, agricultural production corporations and the adoption of ICT and GAP have been steadily increasing over last decades. This chapter aimed to identify the determinants of paddy yield measured by smart combine harvester within large-scale farms. The sample included 351 paddy fields from a farm corporation scaled over 113 hectares, located in the Kanto region of Japan. The candidate determinants included the continuous variables of field area and condition evaluation scores, transplanting or sowing time, and amount of nitrogen, as well as the stage-specific growth indicators for chlorophyll contain, number of panicles, plant height, and leaf plate value. Meanwhile, three discrete variables including variety, cultivation regime, and soil type were also adopted. Empirical analysis was conducted using a multivariate linear regression, with logarithmic transformations of the continuous

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variables. Within the continuous variables, transplanting or sowing time was identified as possessing the largest absolute standardized regression coefficient, and thus be the most important determinant. The negative coefficient indicated that earlier transplanting or sowing benefits vegetative growth, thus panicle number and plant height in heading stage, which were identified as positively significant together with field area, and amount of nitrogen. Within the discrete determinants, Akidawara was measured as a productive variety, while the well-drained and submerged direct sowing were identified as negatively affecting yield.

1 Introduction

As the staple crop in Japan, paddy accounted for the largest proportion of gross agriculture output in 2013 at 21.03% (MAFF 2014a). However, recently, paddy production has been decreasing and, consequently, overall agricultural growth has decreased (Ohizumi 2014). In 2014, paddy yielded 8.43 million metric tons, which was a decrease of 40.27% from 11.83 million metric tons in 1985. Within the same period, the planted area of paddy decreased by 45.58% from 2.29 million hectares to 1.57 million hectares. Since 2000, the average yield of paddy per hectare has been stagnant at approximately 5.30–5.40 metric tons. Especially during 2012–2014, paddy yield decreased from 5.40 to 5.36 metric tons per hectare (Komenet 2020), while the average paddy yield in the US amounted to 10.17 metric tons per hectare. Meanwhile, paddy production in Japan is faced with high costs examined by per weight unit. In 2013, the average production cost of paddy in Japan was 258 JPY per kilogram of brown rice (MAFF 2016), which was much higher than the average of merely about 35 JPY per kilogram of brown rice in the US (USDA 2014). Thus, according to the Japan Revitalization Strategy released in 2014, paddy production cost must be reduced by 40% over the next 10 years, as compared with the current national average value (PMJHC 2014).

Since recapturing control of the government at end of 2012, the government of liberal democratic party (LDP) has been pushing forward a series of measures under the program "Creating dynamism in agriculture, forestry and fisheries", to increase the efficiency and competitiveness of these sectors in Japan. Regarding agriculture, it is essential to reduce production costs and to improve yields through the fiscal subsides aimed at the adoption of efficient technologies, equipment, and managerial models. To increase paddy yield per unit of land area and, hence, reduce average production costs per kilogram, the government has declared that since 2018, the rice acreage reduction policy adopted in the early 1970s had been abolished, to expand production and exports for improved international competitiveness (Nikkei 2013).

Within the last decades, the number of agricultural production corporations has grown dramatically, from 2,740 in 1970, to 14,333 in 2014 (MAFF 2014b), and they have become important producers of paddy. The major reasons behind this boom include greater access to larger arable lands, stronger managerial ability, easier access to credit, diversified business development opportunities, better welfare, and, hence, ample human resource capabilities. Thus, more attention should be paid to agricultural corporations, which represent the current trend of agricultural development in Japan. Nevertheless, such large-scale farms usually own scattered paddy fields, with different scales, soil properties, altitudes, humidity, and exposure to the sun (JSAI 2014). At the same time, to address the problems related to agriculture, food, and the environment, the notion of GAP has spread throughout Japan. With respect to paddy production, GAP can improve an individual's work and consuming conditions, environmental protection (i.e., through the appropriate application of agro-chemicals and concerns for biodiversity), and food safety (i.e., food that is free from contamination and has balanced nutrition) (Li et al. 2014). Under these circumstances, to increase yield through reduced paddy production costs and according to GAP, ICT has been adopted and promoted to process the enormous amount of information available in sectors with innovative cultivation, production, and managerial technologies (JSAI 2014; Nanseki 2015).

In this chapter, we investigated paddy production and identify the yield determinants of large-scale farming in Japan, based on a case study of 351 paddy fields. There are prior studies on the determinants of paddy yield up to field-level on-farm data overseas include Abdullah and Ali (2014), Barrett et al. (2010), or using the experimental data sampled in Japan include Hirai et al. (2012). However, we found few similar studies sampling on-farm data of field-level in Japan. In the studies using samples from agricultural experiment institutions, the field areas are usually relatively small, rarely considering the costs and time, and the analyses are apt to be limited in cultivation test from the perspectives of agronomy and crop sciences. By contrast, the studies of "NoshoNavi1000" aimed to conduct empirical analysis obtaining practical results, using actual data collected in large-scale paddy farms with the consideration of costs and time. In addition, we adopted an explanatory variable, score of field evaluation, to reflect the field height, former crop, uneven soil fertility, illumination and herbicide application, water depth, leakage and inletting, all of which are difficult to be considered in experimental samples.

In this chapter, all the field-level data were sampled from a corporation farm locates in Ibaraki Prefecture, the Kanto Region of Japan. In this large-scale farm, yield data of each field was measured by smart combine harvester, besides which we collected other data with the cooperation of farm managers and fieldwork practitioners. It aimed to develop and demonstrate the smart paddy agriculture models implemented by the agricultural production corporations with the integration of ICT agro-machinery, field sensors, visualization farming, and skills transfer systems. Thereafter, it is indispensable to not only save the average fixed costs of rice production, but also provide clues to reduce the costs per kilogram directly, from less inputs respect to the significant determinants.

2 Materials and Methods

2.1 Yield Definition

In this chapter, paddy refers to the raw rice grain before threshing the hull, as illustrated in Fig. 7 in chapter "Smart Rice Farming, Managerial Model and Empirical Analysis". This definition is in accordance with the measurement of rice yield in most countries, e.g., the US, China, and Korea. According to the national standards of brown rice inspection in Japan (MAFF 2014c), the yield used in the following analyses was converted paddy with 15% moisture. At the same time, paddy weight and the percentage of moisture content applied were monitored directly by smart combine harvester equipped with a global navigation satellite system (GNSS) (Isemura et al. 2015). Accordingly, these measurements were more accurate than those of the estimated weight of brown rice by sampling. The calculations of the paddy yield for the 351 fields were shown in Table 1. Specifically, paddy yield was determined by

Table 1 Calculations of paddy yields of the 351 paddy fields

Field	Raw yield (kg)	Average moisture (%)	Total yield[a] (kg)	Field area (m^2)	Average yield[a] (kg/ha)
	(a)	(b)	(c) $= (a) \times [100-(b)]/85$	(d)	(e) $= 10{,}000 \times (c)/(d)$
No. 1	7894.10	20.80	7355.40	10389.00	7079.99
No. 2	7555.40	23.30	6817.50	10397.00	6557.18
…	…	…	…	…	…
No. 351	4126.30	20.10	3878.70	6000.00	6464.50
Min.	103.60	1.61	100.10	200.00	3484.44
Max.	13388.40	31.60	12871.60	21148.00	9945.93
Mean	2383.68	21.91	2189.89	3237.70	6904.42
Std.D.	2384.19	3.26	2191.54	3428.18	833.32
CV (%)	100.02	14.89	100.08	105.88	12.07

[a]Converted yield using a moisture content of 15%
Source Survey conducted by the authors in 2014

the following four factors: number of panicles, spikelet number per panicle, ratio of filled grains, and grain weight (CSSJ 2002).

2.2 Continuous Explanatory Variables

We constructed an indicator system of 25 continuous variables to outline paddy production and to present the candidate yield determinants of the sampled fields. As shown in Table 2, the continuous variables were divided into 3 types: (1) the basic attributes of the paddy fields showcased by area and the managers' general evaluation of planting conditions; (2) the general situation of growth management presented by date of transplanting or sowing and amount of nitrogen from fertilizer; and (3) detailed growth information, including the chlorophyll meter value of the SPAD, number of stems or panicles per hill, plant height, and individual and community LPV by the stage of panicle growth for the forming, heading, 10 days after full-heading, and maturity stages, as well as panicle length for the maturity stage only.

As denoted in Table 2, in addition to the field height, former crop, uneven soil fertility, illumination and herbicide application, field condition was evaluated by the water depth, water leakage, water inletting. These indicators were included considering that water is of essential importance to paddy planting. The overall score of field evaluation was the sum of these individual aspects, evaluated by the farm managers based on the referential criteria. For instance, a paddy field was scored 2–5 when the field-submerged water can be kept for less than 1 day, 1–2 days, 2–4 days, over 4 days; with a daily leakage of over 5 cm, 3–5 cm, 1–3 cm, less than 1 cm, respectively. Meanwhile, the condition of water inlet was scored 0–5 in terms of the time needed before field-submerged level, varying from over 48 h, 24–48 h, 12–24 h, 6–12 h, 3–6 h to less than 3 h. The date of transplanting or sowing was transformed by setting the earliest date of April 14 as 1, and the latest of June 22 as 70. Nitrogen was calculated based on the amounts of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizers, and the corresponding nitrogen contents.

2.3 Discrete Explanatory Variables

This chapter used variety and cultivation regime to analyze the determinants of paddy yield, which was like some prior studies, including Nishiura and Wada (2012), Muazu et al. (2014), and Ju et al. (2015). In addition, soil properties may affect growth and yield from the perspective of nutrition content, water drainage and conservation, and aeration (CSSJ 2002). Therefore, we investigated the soil types of the sampled paddy fields using the soil information navigation system of the national institute for agro-environmental sciences (NIAES 2015). We created a dummy variable named *soil type*, with the binary values of *gray lowland soil* and *peat soil*. A summary of the statistics of paddy yield by discrete variable are shown in Table 2.

Table 2 Summary of the explanatory variables

Continuous variable	Unit	N	Min.	Max.	Mean	Std.D.	CV (%)
Field area	(m^2)	351	200.00	21148.00	3237.70	3428.18	105.88
Score of field evaluation[a]	–	349	0.00	38.90	32.13	4.56	14.18
Date of transplanting/sowing[b]	(day)	351	1.00	70.00	33.66	13.98	41.55
Nitrogen from fertilizers per hectare[c]	(kg/ha)	349	14.00	148.83	66.09	20.02	30.29
SPAD in panicle-forming stage	–	351	26.30	63.30	36.06	4.26	11.82
Stems per hill in panicle-forming stage	(plant/hill)	351	13.80	34.60	24.34	4.18	17.15
Plant height in panicle-forming stage	(cm)	351	57.70	112.70	86.66	10.38	11.98
Individual LPV in panicle-forming stage	–	351	2.60	6.00	4.39	0.58	13.31
Community LPV in panicle-forming stage	–	351	2.00	6.00	4.29	0.73	17.05
SPAD in heading stage	–	347	24.60	50.70	35.60	4.17	11.72
Panicles per hill in heading stage	(plant/hill)	347	13.30	42.40	23.52	4.36	18.55
Plant height in heading stage	(cm)	347	79.50	117.60	102.61	6.71	6.54
Individual LPV in heading stage	–	347	2.60	6.20	4.47	0.67	14.98
Community LPV in heading stage	–	344	2.00	6.00	4.31	0.73	17.02
SPAD 10 days after full-heading	–	350	20.10	46.80	34.93	3.86	11.05
Panicles per hill 10 days after full-heading	(plant/hill)	350	12.60	33.30	23.23	3.92	16.89
Plant height 10 days after full-heading	(cm)	350	80.90	124.20	106.08	6.27	5.91

(continued)

Table 2 (continued)

Continuous variable	Unit	N	Min.	Max.	Mean	Std.D.	CV (%)
Individual LPV 10 days after full-heading	–	350	2.00	6.00	4.05	0.75	18.42
Community LPV 10 days after full-heading	–	349	2.00	6.00	4.02	0.74	18.40
SPAD in maturity stage	–	350	12.80	42.30	31.31	4.71	15.04
Individual LPV in maturity stage	–	350	1.00	6.40	3.18	0.79	24.79
Community LPV in maturity stage	–	350	1.00	6.00	3.13	0.82	26.22
Panicles per hill in maturity stage	(plant/hill)	350	12.80	33.50	23.12	3.86	16.72
Panicle length in maturity stage	(cm)	349	16.90	23.80	19.99	1.23	6.14
Plant height in maturity stage	(cm)	350	65.60	99.30	83.95	5.87	7.00
Dummy variable		N	Yield (kg/ha)				
			Min.	Max.	Mean	Std.D.	CV (%)
Variety	Koshihikari (V_1)	126	4778.10	8544.40	6740.11	674.89	10.01
	Akitakomachi (V_2)	92	5286.40	9945.90	7253.93	839.80	11.58
	Akidawara (V_3)	66	4940.50	9141.80	7303.14	686.28	9.40
	Yumehitachi (V_4)	27	4770.10	7023.60	6162.95	591.29	9.59
	Ichibanboshi (V_5)	19	6120.20	8866.90	7134.20	715.81	10.03
	Mangetsumochi (V_6)	15	3484.40	6848.70	5771.73	751.05	13.01
	Milky queen (V_7)	6	5578.80	6412.00	6050.08	318.45	5.26
Cultivation regime	Conventional transplant	245	3484.40	9945.90	7052.53	870.66	8.75

(continued)

Table 2 (continued)

Continuous variable	Unit	N	Min.	Max.	Mean	Std.D.	CV (%)
	Special transplant[d]	85	4770.10	8380.10	6496.03	589.75	7.04
	Organic transplant[e]	5	6441.10	7080.00	6711.14	310.07	4.38
	Submerged direct sowing[f]	14	6126.50	9085.70	6940.27	761.47	8.38
	Well-drained direct sowing[g]	2	5812.60	6885.50	6349.05	758.65	11.02
Soil type	Gray lowland soil	34	5524.70	8393.30	7068.72	700.05	8.34
	Peat soil	317	3484.40	9945.90	6886.79	845.43	8.50

[a]Evaluation items include variables concerning height difference, water depth, water leakage, former crop, water inletting, uneven soil fertility, illumination, and herbicide application; [b]The earliest date of April 14 = 1 and the latest date of June 22 = 70; [c]Calculation based on the amounts of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizers, and the corresponding nitrogen contents. [d]Paddy cultivated by seedlings with a 50% reduction in the amount of nitrogen contained in the fertilizers and pesticides according to national guidelines; [e]Paddy cultivated by seedlings and improved soil fertility by organic fertilizers, rather than chemical fertilizers and pesticides; [f]Direct sowing on flooded paddy field; [g]Direct sowing on well-drained paddy field
Source Survey conducted by the authors in 2014

2.4 Statistical Analysis

The impact of the explanatory variables on paddy yield was analyzed using a multivariate regression. Similar with Barrett et al. (2010), values of the yield and the continuous variables were taken natural logarithmic transformations, to make easier interpretation of the regression coefficients in terms of elasticity (Gujarati 2015). All analyses were performed using SPSS 13.0 for Windows.

3 Results and Discussion

3.1 Relationship Between Yield and the Determinants

In the initial multivariate regression model, the independent variables included all continuous and discrete variables shown in Table 2. For each discrete variable, a dummy variable was formulated taking the value of 1 or 0 to indicate the presence or absence, respectively, of the categorical effect. However, as some of these variables may be redundant, leading to higher occurrence of multicollinearity and inefficient coefficient estimators with over-large variances (Gujarati 2015). Thus, we refined the

Table 3 Results of the log-linear multivariate regression estimation

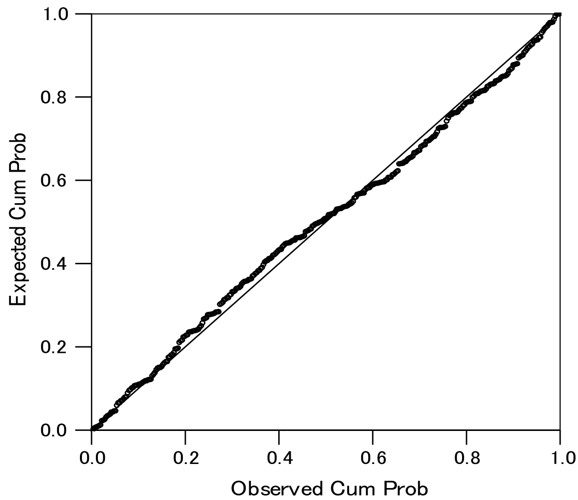
Independent variable	B[a]	ΔY%[b]	Std. B	t	VIF
(Constant)	5.657			12.792	
Date of transplanting (X_1)	−0.153***	−0.152	−0.620	−7.049	4.846
Number of ears in heading stage (X_2)	0.224***	0.223	0.355	5.921	2.244
Plant height in heading stage (X_3)	0.552***	0.551	0.304	5.243	2.109
Field area (X_4)	0.026***	0.026	0.171	3.641	1.387
Nitrogen from fertilizers per hectare (X_5)	0.052***	0.052	0.128	2.747	1.354
Akidawara (D_1)	0.200***	22.175	0.646	12.124	1.775
Well-drained direct sowing (D_2)	−0.591***	−44.605	−0.370	−6.029	2.353
Submerged direct sowing (D_3)	−0.146***	−13.584	−0.238	−5.006	1.409
Valid $N = 345$; $F = 36.201^{***}$; Adjusted $R^2 = 0.450$; LM test: $0.118 \times 336 = 39.648 < \chi^2$ (0.01, 38) = 61.162					

[a]***implies significant at the 1% level; [b]Percentage of paddy yield changes due to a 1% increase of X_i by = $100^*(1.01^{B} - 1)$; and due to value of D_i shifting from 0 to 1 by $100^*(e^{B} - 1)$
Variable selection: backward; Software: SPSS 13.0

regressors by adopting the *Backward* method of SPSS. According to the estimation result, five continuous and three discrete variables were included in the final model (Table 3). The value of the adjusted R^2 denoted that 45% of the variation in the dependent variable, for the sample of 345 valid paddy fields, can be explained by eight significant independent variables. The significant values of the F-test and t-statistics showed that both the model and each independent variable can help identify the variation. The VIFs of all dependent variables were less than 10; hence, we eliminated the probability of collinearity. In the standardized residual plot of the regression, as shown in Fig. 1, the expected cumulative probability increases as the observed cumulative probability increases. This indicates that heteroskedasticity does not exist in the final model (Carter et al. 2012). In addition, the Lagrange multiplier (LM) test indicated that there is no significant bias generated due to the variable refinement, with a significant level of 0.01 (Gujarati 2015).

In Table 3, Column "B" contains the unstandardized estimated regression coefficients. For each continuous variable (X_i), the coefficient is the elasticity of yield with respect to X_i. With respect to X_1, the negative coefficient indicated that earlier transplanting or sowing can increase paddy yield. For a certain date, a 1% decrease of the transformed value can increase yield by 0.153%, holding other variables fixed. For a more exact calculation, the estimated yield increased by $1.01^{0.153} - 1 = 0.152\%$ (Wooldridge 2013). Similarly, for the other significant determinants, a 1% increase in the number of panicles in the heading stage, plant height in the heading stage, field area, and amount of nitrogen was estimated to increase yield by roughly 0.224, 0.552, 0.026, and 0.052%, respectively. Table 3 shows the percentage change in paddy yield due to a 1% increase of each X_i. For the dummy independent variable (D_i), the estimated coefficient implies yield changes by $e^{B} - 1$ when D_i shifts from 0 to 1, keeping other explanatory variables constant (Wooldridge 2013). Thus, for Akidawara, the

Fig. 1 Plot of standardized residuals



coefficient of 0.2 denoted a 22.14% higher paddy yield, while well-drained direct sowing and submerged direct sowing present a paddy yield of 44.62 and 13.58% less than the average value, respectively, holding other factors constant (Table 3).

Of the continuous variables, the unstandardized coefficient (B) is affected by the unit of measurement. Hence, we calculated the standardized coefficient, the absolute values of which show the relative importance of the explanatory variables. For example, according to the data in Column "Std. B" in Table 3, transplanting or sowing was measured as the most effective continuous factor affecting paddy yield.

3.2 Impact of the Continuous Determinants

(1) We find that earlier transplanting or sowing leads to higher yields. Generally, earlier transplanting or sowing is followed by a longer vegetation period that allows the paddy to accumulate more nutrients and improve growth in later stages. Another study (Li et al. 2015) found that the duration of growth is shortened with later transplanting or sowing. As cited in former chapter, paddy transplanted during April 11–20 can grow for 109 days before heading, while those transplanted or sowed during June 21–30 can grow only for 58.5 days on average. A shortened period of vegetative growth usually results in a reduced number of panicles and spikelet and a poor ripening ratio (NAFRO 2011).

(2) The heading stage refers to the stage when 40–50% of the stalks have finished sprouting panicles. This is an important stage in which to judge the growth and other properties of the variety for the whole year (Goto et al. 2000). Thereafter, the focuses of cultivation management shift from stem and leaf growth, to panicle growth and grain filling. According to the determinants of paddy yield

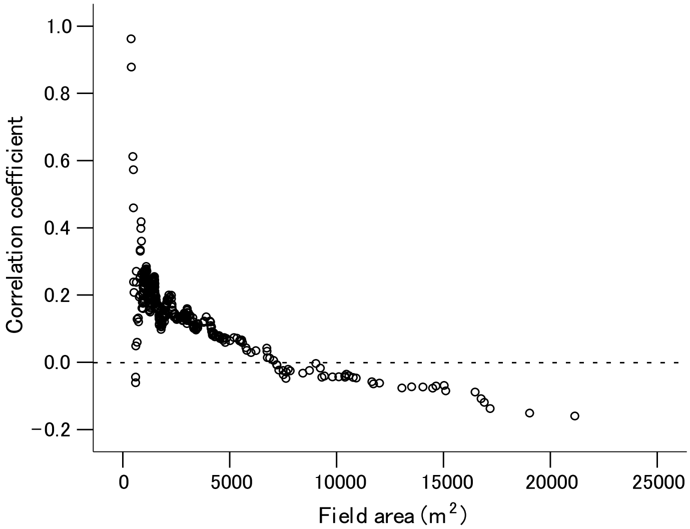


Fig. 2 Correlation coefficient of field area and paddy yield

as defined above, more panicles in this stage directly increase yield. Additionally, a higher plant height can increase yield through longer panicles and, hence, more spikelet per panicle.

(3) Within this sample, positive correlation coefficients were observed between yield and field area for the 312 of the 351 fields comprised of less than 0.7 hectares (Fig. 2). This suggested that with fields scaled less than approximately 0.7 hectares, a larger field area can usually increase yield through an enlarged sink size. Analyzing this result from the perspective of farm management, an appropriately enlarged field area can achieve economies of scale. Specifically, economies of scale include the advantages of savings in fixed costs per unit of yield and reduced variable costs, such as moving the combine harvesters among fields and water and agro-chemicals wasted due to longer ditches and ridges.

(4) As an essential element for paddy growth, nitrogen exists mainly in the form of a protein, particularly rubisco, which accounts for 20–30% of the total amount of nitrogen used in paddy cultivation (CSSJ 2002). Generally, nitrogen increases paddy yield by enhancing photosynthesis. More than 90% of crop biomass is derived from photosynthesis, and rice has been found to possess a high photosynthesis rate, which is 10 times that of some evergreen trees (Makino 2011). Therefore, we found that an increased amount of nitrogen positively relates to paddy yield, when kept at an appropriate level that does not lead to lodging or other negative consequences.

3.3 Impact of the Discrete Determinants

As measured in our earlier study (Li et al. 2015), variety significantly affected the paddy yield of this sample. Akidawara, being a new, lodging-resistant, high-yielding variety, is suitable for cultivation in the Kanto Region. In this chapter, Akidawara yielded 7,303.14 kilograms per hectare on average, possessing the highest yield among the seven varieties. The average yield of the other six varieties was 6,812.08 kilograms per hectare, which was 7.21% lower than that of Akidawara (Table 2). Meanwhile, Akidawara had the longest growth period of 79.55 days from transplanting to heading, which was almost 10 days longer than the average growth period of the other varieties. Thus, according to the analysis above, Akidawara has an advantage because of its prolonged vegetative growth, which leads to more panicles, spikelets, and an increased ripening ratio.

Direct sowing is a conventional cultivation regime that is outstanding in reducing labor and energy. However, due to the general flaws of spatially unbalanced seeding establishment, poor resistance to weed damage, and the occurrence of lodging, directly sowed paddy yields are lower than transplanted paddy yields in most cases. With respect to the well-drained direct sowing, we found problems related to sowing time due to weather and nutrient loss from cracked soil (CSSJ 2002). Reviewing the results of the survey data shown in Table 2, the yield of the paddy cultivated using the well-drained direct sowing was the lowest, showcased the largest data dispersion denoted by the CVs among the five cultivation regimes. In addition, this method reported the smallest number of panicles in heading stage. With respect to submerged direct sowing, this method was only used to cultivate Akidawara; the average yield of submerged direct sowing was less than that of the other cultivation regimes. Plant heights in the heading stage were the lowest in both direct sowing methods, with the similar values of 94.25 and 94.02 for well-drained and submerged direct sowing, respectively.

4 Conclusion

In the initial multivariate regression analysis, the candidate determinants included a variety of continuous variables for yield, field characteristics, transplant time, amount of nitrogen from fertilizer, and growth by stage. In addition, three discrete variables were included to present rice variety, cultivation regime, and soil type. The results of the multivariate regression analysis showed that an earlier transplanting date was the most important determinant of increased paddy yield. Other significant determinants included number of panicles and plant height in the heading stage, field area, and amount of nitrogen, all of which have a positive impact on paddy yield. Of the discrete determinants, Akidawara was measured as the most productive variety, while the direct sowing methods of both well-drained and submerged paddy fields were identified as negatively affecting yield. At the same time, as denoted by the adjusted

R^2, this model did not explained more than half of the yield variation. Hence, it may be necessary to adopt more explanatory variables to conduct further measurements of yield determinants. As paddy yield is affected by the circumstances of planting, we will collect the relevant data, starting with data on meteorology and soil analysis. The meteorological indicators will include temperature, amount of solar radiation, precipitation, water level, and temperature. The soil analysis will present the contents and saturation of the major chemical compositions, such as pH, CEC, and the elements of nitrogen, potassium, phosphorus, calcium, magnesium, silicon, iron, zinc, and copper, among others; humus to reduce fertilizer scorch, conserve water, and maintain permeability; and other substances that assist in the decomposition of organic matter and protect against insects and disease. We adopted more variables in following chapters and hope to improve our empirical estimations.

These empirical findings were referential for farm managers, in terms of the solutions recommended to increase paddy yield, while reduce the production costs per weight unit simultaneously. Nevertheless, paddy production within large-scale farms is a systematic procedure, subject to the constraints of labor, funds, and machinery. For instance, although earlier transplanting or sowing has been shown to increase yield, it may be unrealistic or uneconomical to transplant or sow on many fields simultaneously. Thus, optimal planning is necessary to conduct transplanting or sowing during different times and to make full use of the limited machinery, labor, and funds (Chomei et al. 2015). Meanwhile, fertilizer amount and field allocation need to be optimized in further studies, considering the properties of the different varieties. As analyzed above, the adoption of direct sowing negatively relates to yield increasing; however, the attributes of this method were in line with the sustainable ideas of GAP. Hence, additional rice varieties suitable for direct sowing should be bred and adopted.

In this chapter, we conducted cross-sectional analysis on the yield determinants of individual paddy fields. In the following chapters, we incorporated more variables and data to support further studies, say, analyzing the plot fixed effects through establishing panel-data sets. In particular, as irrigation management of different growth stages is of great importance in further measurement of yield determinants, we were monitoring the soil humidity, water temperature and water level since the following year of 2015, data of which were included and weighed through the adoption of PCA. Furthermore, using the database of the four agricultural production corporations in this research project, we analyzed the farm fixed effects, relationship between farm size and productivity, to improve the yield determinant specification and production efficiency.

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Path Analysis on the Interacting Determinants and Paddy Yield

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This chapter measured the interacting effects of paddy yield determinants using path analysis. The data was sampled in 2014, from 301 paddy fields planted with Koshihikari, from two large-scale farms in Japan. The result indicated that there are significant interactions among the determinants, which affect the total yield in the form of indirect effects. Solar radiation and temperature had the most effect; and the former affected the latter significantly. Farm difference was another important factor in explaining yield variation among paddy fields, through indirect effects. In addition, we examined the interaction with paddy yield and the determinants, using a two-year sample of 117 paddy fields planted Koshihikari, from a farm in the Kanto Region. This chapter expanded the sample by including the ratio of full-grain rice

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in sorted brown rice to identify the interacting determinants of paddy yield, grain quality, and their determinants.

1 Introduction

Paddy production in Japan is transiting from acreage reduction to improvement in efficiency and competitiveness, by decreasing production costs. In 2014, the yield of sorted brown rice was 8.43 million metric tons, a decreased of 40% from 11.83 million metric tons in 1985 (MAFF 2016). In 2013, the average production cost of sorted rice in Japan was 258 JPY per kilogram (E-Stat 2015), much higher than that of the US, at 35 JPY per kilogram on average (USDA 2014). Higher yield and quality are essential for improving rice productivity and market competitiveness. Koshihikari is the most widely planted rice variety in Japan and is exceedingly popular for its aesthetic appearance and palatability. It accounts for around 37% of the total area under rice cultivation (Komenet 2020). We measured the interacting effects of paddy yield determinants, based on the data from 301 paddy fields of two farms growing Koshihikari.

2 Materials and Methods

2.1 Data of the Two Farms

The data was collected in 2014 from two farms—23 hectares and 36 hectares in size—located in the Hokuriku and Kanto Regions, respectively. With relatively limited farmlands of 40 hectares in total, farm B adopted an intensive input strategy (e.g., more nitrogen fertilizer). In contrast, the paddy fields in farm Y were extensive in space distribution, with much larger farmlands of 125 hectares and higher soil capacity.

The yield was measured by paddy with 15% moisture. As shown in Table 1, the determinants included: (1) dummy variable of farm (0 = farm Y, 1 = farm B); the continuous variables of (2) field area, (3) nitrogen fertilizer amount; (4) solar radiation and (5) temperature 20 days since full-heading; (6) panicles per hill and (7) plant height in heading stage; and (8) land capability measured using the principal component of 21 soil property indices (Table 2). As a structural equation modeling (SEM) technique, path analysis was performed using IBM Amos 23.0, to measure the direct effects among the determinants.

Rice yield was weighed by paddy with 15% moisture content, and the ratio of full-grain rice was measured using grain analyzer RGQ120A, a product of Satake Co., Ltd. The entire farm was scaled at 125 hectares, while the sampled 117 fields were 34 hectares in total acreage. The average yield per hectare in 2014 and 2015

Table 1 Summary of the yield and determinants in 126 paddy fields

Variable	Farm Y			Farm B			Difference (B-Y)[d]
	N	Mean	CV (%)	N	Mean	CV (%)	
Paddy yield (ka/ha)	126	6740.11	10.01	170	7351.88	11.53	611.76***
Field area (m^2)	126	2842.65	85.57	175	1312.67	72.77	−1529.98***
Nitrogen fertilizer amount (kg/ha)[a]	126	52.12	29.98	175	101.81	15.76	49.70***
Average solar radiation (MJ/m2)[b]	126	20.99	5.31	175	13.73	3.16	−7.25***
Average temperature (°C)[b]	126	27.05	0.77	175	25.87	0.85	−1.17***
Panicles per hill in heading stage	126	24.24	12.96	175	23.22	12.14	−1.02***
Plant length in heading stage (cm)	126	105.69	4.91	175	114.83	5.92	9.14***
Land capacity[c]	126	1.02	59.49	170	−0.75	−48.27	−1.77***

[a]Calculation based on the amount and corresponding nitrogen content of manure, compound chemical, ammonium sulfate, and urea fertilizer
[b]Data of 20 days since full-heading
[c]Measured using the principal component of 21 soil property indices
[d]Difference of the mean values in farm B and farm Y
Note *** and ** denotes significance at the 0.01 and 0.05 levels, respectively, and same hereafter

were 6705 kilograms and 6155 kilograms, respectively. Simultaneously, the ratio of full-grain rice reduced from 67 to 62%, with a larger coefficient of variance of 19.78% in 2015, compared to 8.40% in 2014. Path analysis was performed to measure the direct, indirect, and total effects.

2.2 Data of One Farm in Two Years

Similarly, summary statistics of rice yield, quality, and determinants in 117 fields were shown in Table 3. The two-year data were provided for comparison, in terms of the minimum, maximum and average values, standardized deviation, coefficient of variance (CV), and differences of the annual means.

Table 2 Component matrix of soil properties

Soil property		Component					
		1	2	3	4	5	6
Exchangeable magnesia		**0.950**	−0.005	0.171	0.086	−0.042	−0.137
Exchangeable lime		**0.928**	0.288	0.043	−0.025	−0.060	0.139
CEC		**0.882**	0.407	−0.077	−0.067	0.024	−0.073
Phosphate absorption coefficient		**0.845**	0.335	0.054	−0.044	0.103	−0.012
Available silicic acid		**0.817**	0.047	0.187	0.228	0.078	0.044
pH		**0.805**	−0.089	−0.006	0.129	−0.305	0.233
Magnesia/potassium		**0.801**	−0.403	0.208	−0.210	0.160	−0.016
EC (ms/cm)		**0.773**	0.293	0.054	−0.036	0.125	−0.040
Free iron oxide		**0.740**	0.271	0.199	0.185	0.287	−0.182
Humus		**0.717**	0.467	−0.335	−0.170	−0.120	0.003
Potassium saturation		**−0.715**	0.253	0.118	0.510	−0.213	−0.144
Magnesia saturation		**0.641**	−0.567	0.358	0.245	−0.182	−0.099
Effective phosphoric acid		**−0.582**	0.117	0.393	0.297	−0.043	0.209
Lime/magnesia		−0.502	0.531	−0.192	−0.237	0.154	0.505
Lime saturation		0.502	−0.250	0.349	0.105	−0.238	0.644
Nitrate nitrogen		0.320	−0.243	−0.481	0.208	−0.026	0.066
Soluble copper		−0.295	−0.040	0.731	−0.050	0.387	−0.101
Soluble zinc		−0.274	0.286	0.511	−0.051	0.069	0.239
Exchangeable potassium		−0.176	0.714	0.213	0.460	−0.318	−0.166
Ammonium nitrogen		−0.168	0.203	0.456	−0.634	−0.076	−0.115
Exchangeable manganese		0.037	−0.007	−0.211	0.473	0.738	0.178
Extracted sums of squared loadings	Eigenvalue	8.961	2.350	2.051	1.552	1.222	1.023
	%	42.674	11.189	9.767	7.391	5.820	4.871
	Cumulative %	42.674	53.863	63.629	71.021	76.841	81.712

[a]Extraction method used: PCA
[b]Six components were extracted when the eigenvalues are not less than 1, and component 1 is used to illustrate the land capability in this chapter
[c]Variables are sorted according to the absolute loadings without rotation, high values of which are in boldface
Software IBM SPSS 23.0

Table 3 Summary of rice yield, quality, and the determinants of 117 fields in 2014–2015

2014	Min	Max	Mean	Std. D	CV (%)	Differ
Yield[a] (kg/ha)	4778.34	8544.16	6705.01	676.63	10.09	0.00
Ratio of full-grain rice[b] (%)	47.10	80.85	66.95	5.62	8.40	0.00
Nitrogen fertilizer[c] (kg/ha)	14.00	106.91	51.86	15.88	30.63	0.00
Temperature[d] (°C)	26.73	27.49	27.04	0.21	0.77	0.00
Solar radiation[d] (MJ/m^2)	19.73	22.91	20.95	1.12	5.33	0.00
Panicles per hill[e]	17.00	29.50	23.36	2.72	11.62	0.00
Culm length[e] (cm)	77.10	99.30	87.41	4.43	5.07	0.00
Base saturation (%)	60.86	136.45	82.08	10.55	12.86	0.00
Inorganic nitrogen (mg/100 g)	1.05	3.99	2.13	0.64	30.15	0.00
Field area (m^2)	200.00	14037.00	2859.94	2490.78	87.09	0.00
Farming condition score[f]	26.80	37.85	32.72	2.31	7.06	0.00
2015	Min	Max	Mean	Std. D	CV (%)	Differ
Yield[a] (kg/ha)	3976.41	8298.88	6155.00	642.65	10.44	−550.01
Ratio of full-grain rice[b] (%)	34.40	83.50	61.87	12.23	19.78	−5.08
Nitrogen fertilizer[c)] (kg/ha)	37.50	200.00	76.42	36.06	47.18	24.56
Temperature[d] (°C)	24.02	27.56	26.78	0.56	2.11	−0.27
Solar radiation[d] (MJ/m^2)	15.65	21.15	19.19	0.90	4.68	−1.75
Panicles per hill[e]	12.80	29.50	21.09	2.58	12.23	−2.27
Culm length[e] (cm)	74.00	100.00	87.17	4.44	5.10	−0.24
Base saturation (%)	50.39	90.20	73.50	7.52	10.23	−8.58
Inorganic nitrogen (mg/100 g)	0.38	3.21	1.19	0.42	34.92	−0.94
Field area (m^2)	200.00	14037.00	2859.94	2490.78	87.09	0.00
Farming condition score[f]	26.80	37.85	32.72	2.31	7.06	0.00

[a]Converted by 15% moisture content
[b]sorted brown rice after removing the cracked, broken, dead, and immature rice grains
[c]calculation based on the amount and corresponding nitrogen content of manure, compound chemical, ammonium sulfate, and urea fertilizer
[d]average values of 20 days since full-heading
[e]data at the mature stage
[f]managers' appraisal on height difference, water depth, water leakage, former crop, amount of water inlet, fertility unevenness, illumination, and herbicide application

3 Results

3.1 Results of the Two Farms

In the path diagram (Fig. 1), logarithms of continuous variables were used to include more linear relationships. The numbers over the single arrowhead lines are the standardized path coefficients. They designate the direct effects of the original variables

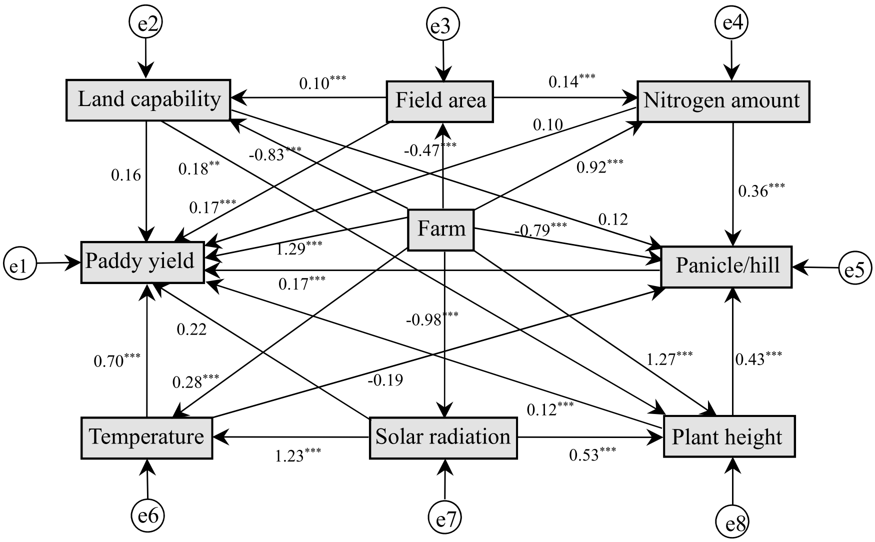


Fig. 1 Path diagram of paddy yield determinants (RMSEA = 0.049, CFI = 0.997, N = 301, df = 12, Chi-square = 20.482 [P = 0.059]. *Note* Standardized estimates using logarithmic continuous values)

on the targeted variables and allow a direct comparison among variables. For instance, the standardized path coefficient from the culm height was 0.17. It is higher than the panicles per hill, 0.12, and thus the former affects paddy yield more than the latter, *ceteris paribus*. Each circled e-*i* (*i* values 1–8) represents a residual—unmeasured causes of the endogenous variable. The model fit indices RMSEA = 0.049 and CFI = 0.997 showed that the model had a high goodness of fit (Kline 2011).

Table 4 summarizes the interacting effects of the variables. The direct effects are the path coefficients in Fig. 1; the indirect effects include all the other concerned path coefficients; while the total effects aggregate both. For instance, the total effect of plant height (0.19) was the sum of the direct effect (0.12) and the indirect effect via panicles per hill (0.43×0.17). The paddy yield was determined mainly by solar radiation, temperature, farm, land capacity, sorted considering the magnitude of the total effect.

Farm had the largest direct effect, followed by temperature, solar radiation, and so forth. Meanwhile, solar radiation had the largest indirect effect, through higher temperature and plant height, and hence more panicles per hill. Meanwhile, paddy yield was influenced by field area via nitrogen amount and land capability—by nitrogen amount via panicles per hill; by land capability via plant height and panicles per hill; and then by plant height via panicles per hill. In terms of the total effects, paddy yield was determined by solar radiation and temperature first, followed by farm, land capability, field area, plant height, panicles per hill, and nitrogen amount (Fig. 2).

Table 4 Effect analysis between the determinants

Variable[a]	Farm	Field area	Nitrogen amount[b]	Land capability[c]	Solar radiation[d]	Temperature[d]	Panicles per hill[e]	Plant height[e]
Direct								
Field area	−0.47	—	—	—	—	—	—	—
Nitrogen amount[b]	0.92	0.14	—	—	—	—	—	—
Land capability[c]	−0.83	0.10	—	—	—	—	—	—
Solar radiation[d]	−0.98	—	—	—	—	—	—	—
Temperature[d]	0.28	—	—	—	1.23	—	—	—
Panicles per hill[e]	−0.79	—	0.36	0.12	—	−0.19	—	0.43
Plant height[e]	1.27	—	—	0.18	0.53	—	—	—
Paddy yield	1.29	0.17	0.10	0.16	0.22	0.70	0.17	0.12
Indirect								
Field area	—	—	—	—	—	—	—	—
Nitrogen amount[b]	−0.06	—	—	—	—	—	—	—
Land capability[c]	−0.05	—	—	—	—	—	—	—
Solar radiation[d]	—	—	—	—	—	—	—	—
Temperature[d]	−1.21	—	—	—	—	—	—	—
Panicles per hill[e]	0.63	0.07	—	0.08	−0.01	—	—	—
Plant height[e]	−0.68	0.02	—	—	—	—	—	—
Paddy yield	−0.96	0.04	0.06	0.06	0.92	−0.03	—	0.07
Total								
Field area	−0.47	—	—	—	—	—	—	—
Nitrogen amount[b]	0.86	0.14	—	—	—	—	—	—
Land capability[c]	−0.88	0.10	—	—	—	—	—	—
Solar radiation[d]	−0.98	—	—	—	—	—	—	—
Temperature[d]	−0.94	—	—	—	1.23	—	—	—
Panicles per hill[e]	−0.16	0.07	0.36	0.19	−0.01	−0.19	—	0.43
Plant height[e]	0.59	0.02	—	0.18	0.53	—	—	—

(continued)

Table 4 (continued)

Variable[a]	Farm	Field area	Nitrogen amount[b]	Land capability[c]	Solar radiation[d]	Temperature[d]	Panicles per hill[e]	Plant height[e]
Paddy yield	0.33	0.21	0.16	0.22	1.14	0.67	0.17	0.19

[a]Logarithmic value of the continuous values
[b]Nitrogen by fertilization
[c]Principal component of 21 soil property indices
[d]Average value of 20 days since the full heading
[e]Data of the heading stage
Software IBM Amos 23.0

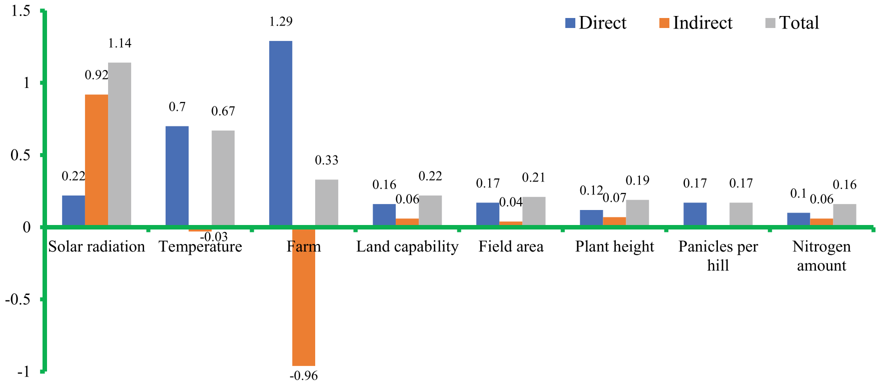


Fig. 2 Effects on the yield by path analysis

3.2 Result of One Farm in Two Years

Figure 3 shows the variables and path diagram, where logarithms of continuous variables with a hectare base were used to include more linear relationships. The numbers over single arrowhead lines are the standardized path coefficients, designating direct effects of the origin to the target. Each circled e-*i* (*i* values 1–10) represents a residual; the numbers over two arrowhead lines are correlation coefficients. The fit statistics (i.e., RMSEA < 0.1) showed that this model fitted the data well (Kline 2011).

Table 5 summarizes the total effect aggregating the direct effect (i.e., the path coefficients shown in Fig. 3) and the indirect effects (i.e., all the other path coefficients via other variables). For instance, the total effect of culm length (0.30) to paddy yield was the sum of the direct effect (0.23) and indirect effect via panicles per hill (0.41 × 0.19).

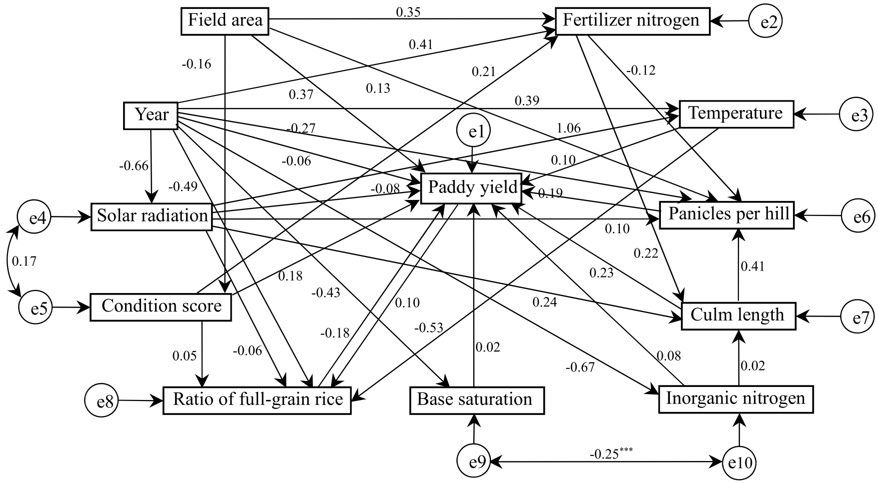


Fig. 3 Path diagram of paddy yield, quality, and determinants (N = 117, df = 32, RMSEA = 0.095, CFI = 0.938 [Year = 0 for 2014, Year = 1 for 2015]. ***, ** and * implies significance at the 0.01, 0.05, and 0.10 levels, respectively. *Software* IBM Amos 23.0)

4 Discussion

4.1 *Effect of Farm Difference*

Like the comparison shown in Table 1, all the determinants were significantly different between farms and in terms of the path coefficients (Fig. 1). The variation in the difference and direct effect for all the determinants were shown in Fig. 4, except for temperature. This revealed that temperature is strongly affected by solar radiation, indicated by the path coefficient of 1.23 from solar radiation to temperature. Thus, temperature tends to be higher in farm B, excluding the effect via solar radiation.

4.2 *Solar Radiation and Temperature*

As shown in Fig. 5a, significant linear relationship was found between the two variables in the sampled 301 fields. The high determination coefficient, $R^2 = 0.934$, was significant at the 0.01 level, demonstrating the high path coefficient from solar radiation to temperature. Farm Y was higher than farm B on both indices.

Table 5 Total effect between the variables

Variable	Year	Field area	Condition score[a]	Nitrogen fertilizer	Inorganic nitrogen	Base saturation	Solar radiation[b]	Temperature[b]	Culm length	Panicles per hill	RFG[c]	Paddy yield
Condition score[a]	—	−0.16	—	—	—	—	—	—	—	—	—	—
Nitrogen fertilizer	0.41	0.31	0.21	—	—	—	—	—	—	—	—	—
Inorganic nitrogen	−0.67	—	—	—	—	—	—	—	—	—	—	—
Base saturation	−0.43	—	—	—	—	—	—	—	—	—	—	—
Solar radiation[b]	−0.66	—	—	—	—	—	—	—	—	—	—	—
Temperature[b]	−0.30	—	—	—	—	—	1.06	—	—	—	—	—
Culm length	−0.08	0.07	0.05	0.22	0.02	—	0.24	—	—	—	—	—
Panicles per hill	−0.42	0.12	−0.01	−0.03	0.01	—	0.20	—	0.41	—	—	—
RFG[c]	−0.30	0.03	0.07	—	0.01	—	−0.60	−0.51	0.03	0.02	—	0.10
Paddy yield[d]	−0.15	0.38	0.18	0.05	0.09	0.02	0.22	0.19	0.30	0.19	−0.18	—

[a]Managers' appraisal on height difference, water depth, water leakage, former crop, amount of water inlet, fertility unevenness, illumination, and herbicide application
[b]Average data within 20 days since full-heading
[c]Ratio of full grains
[d]Converted by 15% moisture content
Software IBM Amos 23.0

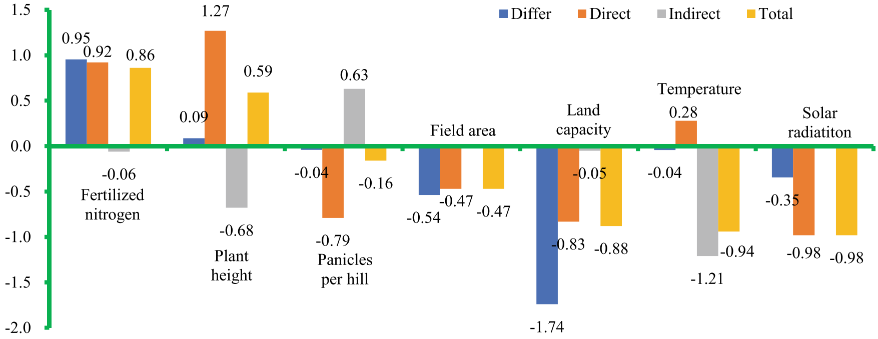


Fig. 4 Standardized difference (the standardized difference divided by the corresponding value of farm Y) and effects of the determinants

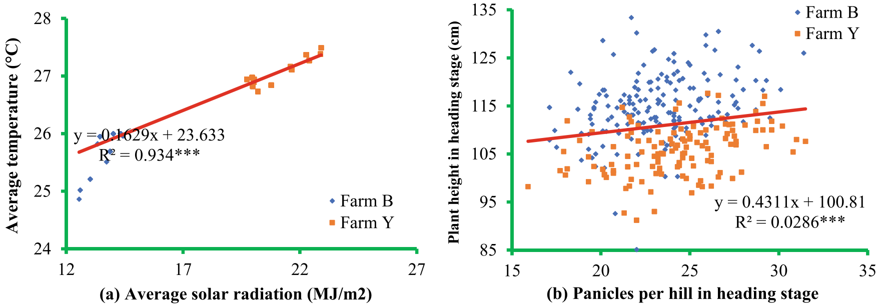


Fig. 5 Interaction effects between the determinants. **a** Average solar radiation (MJ/m^2). **b** Panicles per hill in heading stage

4.3 Panicles Per Hill and Plant Height

There was a significant linear relationship between the two variables (Fig. 5b). Both were significantly and positively correlated with paddy yield (Fig. 6a, b). Plant height in farm B was greater than in farm Y. In addition, according to the total effects in Table 4, these two growth indices were affected by land capability, solar radiation, and field area.

As the most significant growth indices, both culm length and panicle number per hill were positively related to rice yield. In addition, there was a significant positive relationship between them (Fig. 7).

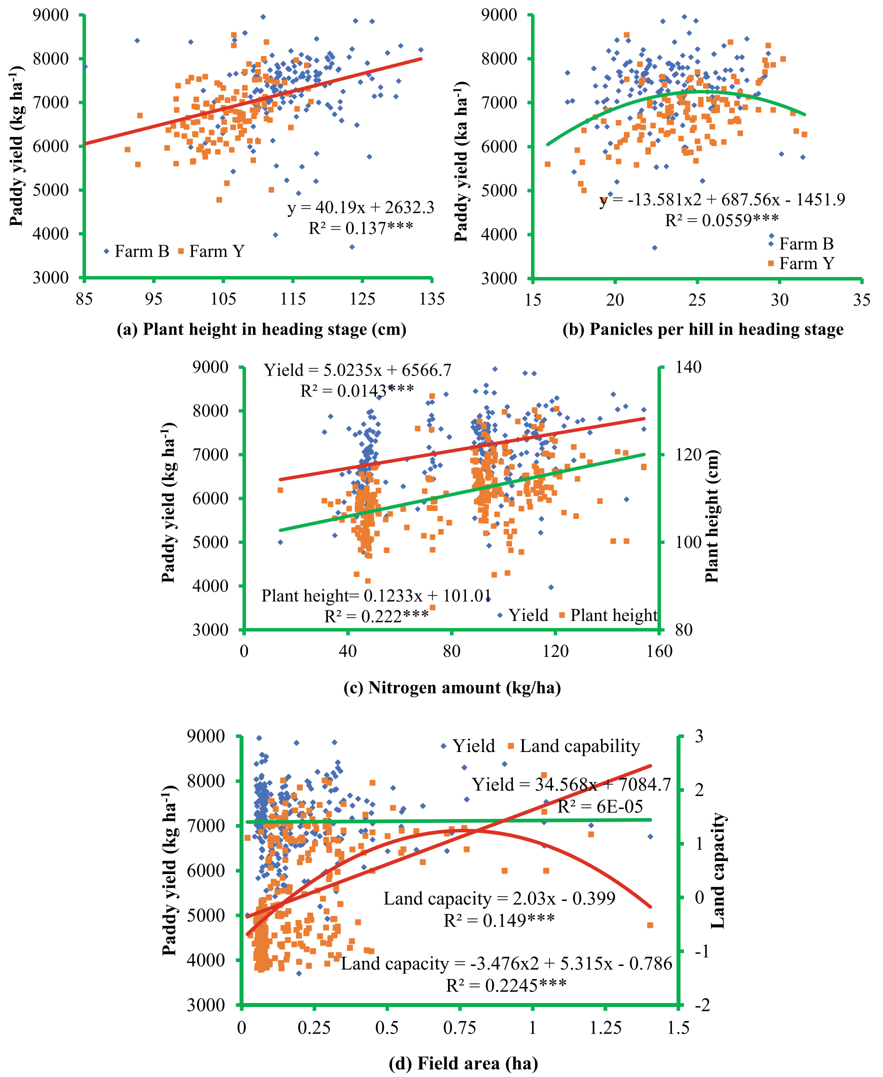
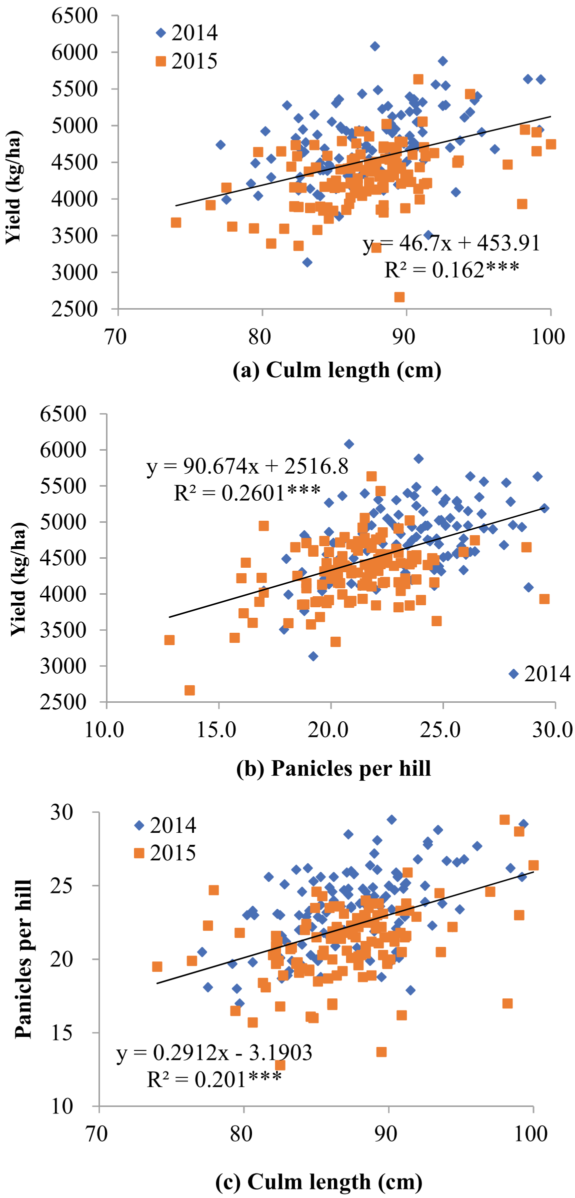


Fig. 6 Paddy yield and the determinants. **a** Plant height in heading stage (cm). **b** Panicles per hill in heading stage. **c** Nitrogen amount (kg/ha). **d** Field area (ha)

4.4 The Other Determinants

The amount of nitrogen fertilizer was positively related with yield via panicle number. Meanwhile, there was a quadratic relationship with yield, showing that yield peaks at roughly 95 kilograms per hectare (Fig. 6c). Field area was positively related with yield via nitrogen fertilizer, land capability, panicle number, and plant height. The

Fig. 7 Field area farming condition and rice yield in 117 fields of farm Y. **a** Culm length (cm). **b** Panicles per hill. c Culm length (cm) (*Source* Li et al. 2016)



quadratic relationships indicated that, land capability peaks when paddy fields are scaled at roughly 0.76 hectares (Fig. 6d).

5 Conclusion

With high goodness of fit, the path analysis models identified the interactions between the significant determinants of paddy yield. Paddy yield was determined mainly by field conditions including, solar radiation, temperature, and land capacity. In accordance with the corresponding managerial strategies, farm B had a higher yield than farm Y on average, judging from the effect of the dummy variable.

The mutual causality of paddy yield and grain quality was illustrated through a bidirectional path. This revealed that an increase in yield relates to higher grain quality, while emphasizing on higher grain quality tends to result in a lower yield. The time trend, *year*, induced significant reduction in both quality and yield after controlling the implicit changes. This was in accordance with the fact that among all the other variables, only nitrogen fertilizer per hectare increased from 52 kilograms to 76 kilograms in the two years. In contrast, field area and planting condition score were shown as affecting both yield and grain quality positively and significantly. Culm length significantly affects panicles per hill, both are important growth indices in determining paddy yield and quality. Solar radiation significantly affected temperature. Solar radiation and temperature exerted positive effects on paddy yield, and they are negatively related to grain quality. The amount of nitrogen fertilizer affected paddy yield mainly through a longer culm. Inorganic nitrogen, the sum of ammonium and nitrate nitrogen, affected both quality and yield, through a longer culm and more panicles per hill. Base saturation, sum of the saturation of potassium, lime, and magnesia, were shown to have a positive effect on paddy yield.

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Impact of Soil Fertility in 92 Paddy Fields of Kanto Region

Dongpo Li, Teruaki Nanseki, Yosuke Chomei, and Shuichi Yokota

This chapter aimed to measure the determinants of rice yield, from the perspectives of fertilizer nitrogen and soil chemical properties. The data were sampled in 2014 and 2015, comprising 92 peat soil paddy fields, from a large-scale farm located in the Kanto Region of Japan. The rice variety was Koshihikari, which is most widely planted in Japan. The yield was measured by paddy with 15% moisture. The 12 soil chemical properties included pH, cation exchange capacity, content of pyridine base elements, phosphoric and silicic acids. The results indicated that fertilizer nitrogen affected the yield significantly, with a significant sustained effect to the subsequent year. In addition to silicic acid, magnesia positively affected the yield, in forms of its exchangeable content, saturation, ratios to potassium and lime; phosphoric acid affected the yield negatively. We measured soil chemical properties by the synthesized soil quality index and PCA. Positive effects were identified on the overall scores of both approaches, while the former performs better in explaining the rice yield. In soil quality index, the individual standardized soil properties and margins for improvement were indicated for each paddy field. Finally, multivariate regression on the principal components identified the most significant properties.

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1 Introduction

Soil is critical to crop growth in providing the growth locale and indispensable nutrients, and any degradation of soil quality may result in the decreased productivity, quality and thus profitability (Juhos et al. 2016; Li et al. 2012; Liu et al. 2014; Obade and Lal 2016). Soil properties can be measured from mainly the physical, chemical, and biological aspects (DFPJA 2011). The chemical properties typically relate more directly to the sustainability of agro-ecosystem, in addition to the variability of crop yield (Bouma 2002; Obade and Lal 2016; Qi et al. 2009). Meanwhile, comparing with the other aspects, the chemical properties are more feasibly to be improved, through proper fertilization and other farm managerial activities (Gray and Morant 2003). Thus, in narrow sense, the soil fertility refers to the chemical properties, drawing wide attentions from different aspects. Many researchers analyzed the relationship between soil chemical prosperities and rice yield. Juhos et al. (2016) constructed a soil quality index using three principal components derived from more than ten basic indicators, to evaluate the chemical and physical properties of soil and the impact on yields of maize, winter wheat and sunflower, sampled in 225 hectares farmland from east Hungary. Liu et al. (2014) analyzed the rice yield and the effect of eight soil chemical properties sampled in 13 provincial regions of south China, individually and synthetically using a soil quality index, based on PCA model adopted from Qi et al. (2009).

In Japan, rice (*Oryza sativa L.*) is the most important staple crop, and by 2015, it accounted for the largest proportion of 17% in gross agriculture output (MAFF 2016a). Japan is striving to improve the rice productivity and global competitiveness. By 2016, the total planted area of rice is estimated to be 1.57 million hectares, decreased roughly one third in the past three decades. At the same time, the aggregate production decreased by nearly 30% (MAFF 2017). Therefore, the accurate measurement of soil fertility and its yield effect is essential to promote the rice production in Japan. Some scholars have studied concerning the soil chemical properties of the paddy fields in Japan. In the estimation of the total CH_4 emission from rice paddies, Katayanagi et al. (2016) analyzed the soil chemical properties of 986 plots sampled across the country, through the individual indicators of pH (H_2O) and total carbon. Matsumoto et al. (2016) estimated the effects of iron materials applied in an experimental field at Shimane University, Matsue city of Shimane Prefecture, and the soil chemical properties were presented by the content of available arsenic and phosphorus, acid ammonium oxalate extractable iron and aluminum. To measure the effect of fermented bark as a soil amendment in the experimental site of Gunma Prefecture, Japan, Mori et al. (2016) measured the soil chemical properties using pH, CEC, oxidation-reduction potential, the content of heavy metals including cadmium, copper, and zinc. Judging from the literature, it is necessary to quantify the soil chemical properties through the adoption of synthesized indices, and the on-farm data sampled from individual paddy fields can provide more practical enlightenments.

We fulfilled the following targets in the rest sections: presented the status of fertilizer nitrogen and soil chemical properties in the sampled paddy fields; revealed effect of the fertilizer nitrogen to the rice yield; measured impact of the soil chemical properties to rice yield, through the construction of soil quality index and standardized soil properties; identified the most significant properties using PCA and multivariate regression; and summarized the empirical findings and countermeasures to improve rice yield.

2 Materials and Methods

2.1 Sample and Data

The data were sampled in 2014 and 2015, comprising 92 peat soil paddy fields, from a large-scale farm located in the Kanto Region of Japan. The rice variety was Koshihikari, which enjoys highly appreciated taste and appearance at home and abroad. By 2015, it accounted for the largest share of 36% (Komenet 2020) in the domestic rice planting area, with its strong cold resistance and stable yield (Goto et al. 2000). The rice yield was measured by the grain weight of paddy with 15% moisture. The weight and moisture content of the raw paddy were monitored by combine harvesters equipped with advanced information technologies.

Fertilizer nitrogen was calculated using the amounts of chicken manure, chemical fertilizer, ammonium sulphate, urea fertilizers, and the corresponding nitrogen contents. Based on the local technical guidance (MAFF 2016b), we presented the soil chemical properties by 12 indicators, including the (1) pH specifying acidity (<7) or basicity (>7) of the soil; (2) CEC, number of negative ions, e.g., the loam and humus. It shows the capability of holding the positive ions, such as the ammonium $NH4+$, $Ca2+$, $Mg2+$ and $K+$, and hence soil fertility, capacity to protect the groundwater from cation contamination (DFPJA 2011; Mori et al. 2016); (3) phosphoric acid, essential to ensure the grain quality, while superfluous content may bring about premature and decreased yield (Fujiwara et al. 1996); (4) silicic acids, indispensable for rice growth in preventing the soften stems and leaves, decayed roots; and (5) the contents and ratios of the pyridine base elements, including the potassium, lime and magnesia.

2.2 Analysis Framework

Firstly, we analyzed the effect of fertilizer nitrogen through regressions with the rice yield over the two years. We analyzed the synthesized effect of the soil chemical properties, by constructing the SQI (soil quality index). Using the standardized SQI of each paddy field, we identified the relative margins to improve the soil properties.

Furthermore, we conducted the PCA on the 12 soil chemical properties. We extracted five principal components of the total variance and analyzed their effects on rice yield. Finally, we identified the most significant properties using the multivariate regression on the principal components. The regression and PCA were performed using IBM SPSS 23.0 for windows.

3 Results and Discussion

3.1 *Effect of the Fertilizer Nitrogen*

Amount of the fertilizer nitrogen affected the yield significantly and positively, according to the aggregate estimation over the two years (Fig. 1a). In 2015, the linearity relationship between fertilizer nitrogen and rice yield was significant, while it was insignificant in 2014. It thus indicated that the fertilization was improved to increasing the rice yield over all the sampled paddy fields. Meanwhile, as illustrated by the scatting points, amounts of the fertilizer nitrogen of 2015 were larger than those of 2014. In fact, the average amounts per hectare were 50 kilograms and 69 kilograms in 2014 and 2015, respectively. As a result, a quadratic relationship was estimated to be significant in 2015, indicating that diminishing returns to scale held, when the fertilizer nitrogen transcended roughly 105 kilograms per hectare.

As analyzed in, we hypothesized that it may take some time for the fertilizer nitrogen to enrich the soil and thus plant growth. Hence, we identified the significant and positive effect of the amount of fertilizer nitrogen of 2014 on the rice yield of 2015. On average, one-kilogram increase of fertilizer nitrogen in 2014 resulted in 12.8 kilograms of paddy yielded per hectare in 2015. It was higher than the effect of the fertilizer nitrogen in 2015, which was merely 8.3 kilograms as shown in Fig. 1b. The results hereby confirmed the existence of the sustained effect of fertilizer nitrogen, and it is necessary to investigate the amount of nitrogen residuals in the soil before fertilization (Fujiwara et al. 1996).

3.2 *Effect of the Individual Soil Properties*

In Japan, the soil tends to be acid, due to the rich precipitation that washing away the alkaline components of calcium and magnesium (Fujiwara et al. 1996). CEC of the sampled fields was slightly lower than the local criterion, indicating that the soil fertility needed to be improved. The negative correlation to rice yield may indicated that in Japan, phosphoric acid is easier to be fixed by the rich volcano ash soil, and supplied through the overused organic fertilizers (DFPJA 2011). Silicic acid increases the yield and a positive correlation was observed in Table 1. Within the pyridine base elements, significant and positive effects were observed in magnesia,

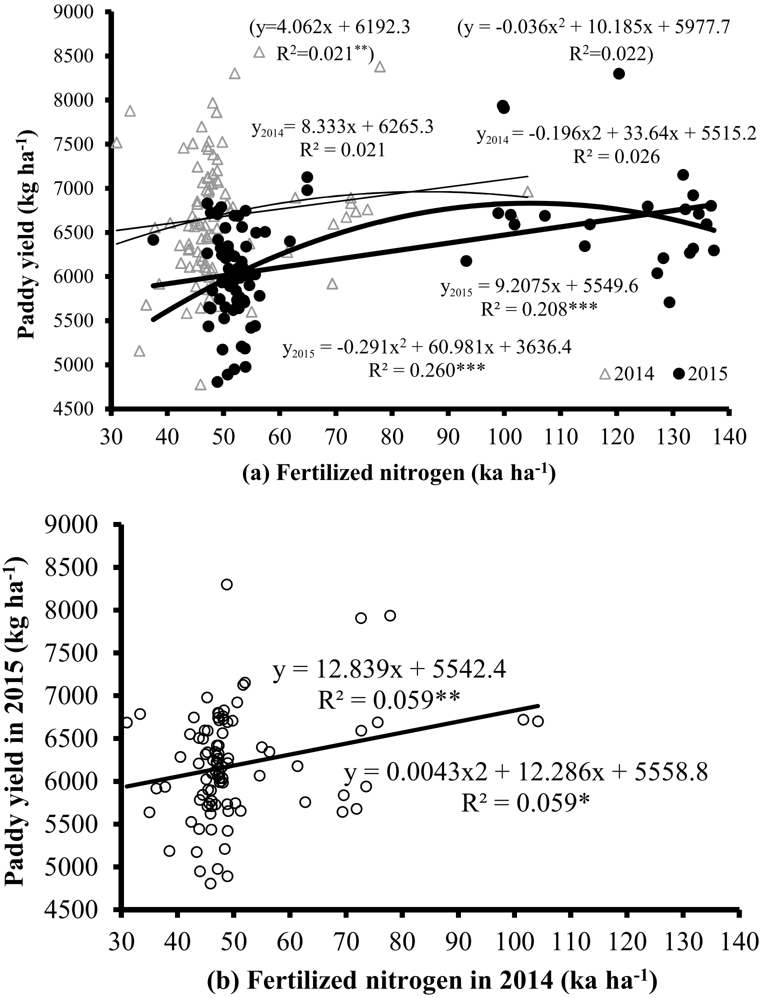

Fig. 1 Fertilizer nitrogen and rice yield (a) within 2014–2015 and (b) from 2014 to 2015. **a** Fertilized nitrogen (ka ha^{-1}). **b** Fertilized nitrogen in 2014 (ka ha^{-1}) (*Note* ***, ** and * indicate significant at 1, 5 and 10%, respectively)

from the perspectives of its exchangeable content, saturation, ratios to potassium and lime (Table 1).

Table 1 Rice yield, fertilizer nitrogen and soil chemical properties of 92 peat soil paddy fields in 2014–2015. Each property is evaluated based on the average and ideal values

Variable	N[a]	Min	Max	Mean	CV[b] (%)	Optimum[c]	Score[d]	R[e]
Paddy with 15% moisture (kg/ha)	184	4778.10	8544.40	6434.38	10.86	—	—	1.000
Fertilizer nitrogen (FN, kg/ha)	184	30.96	137.30	59.61	42.27	—	—	0.150**
pH	184	5.66	6.50	6.16	2.93	6	1.03	−0.072
CEC (meq/100 g)	184	5.69	31.00	18.61	30.25	27	0.69	0.015
Effective phosphoric acid (mg/100 g)	184	1.04	31.10	9.61	54.99	10–30	0.96	−0.289***
Effective silicic acid (mg/100 g)	184	6.70	56.27	20.75	55.93	30–40	0.69	0.414***
Exchangeable potassium (mg/100 g)	184	8.43	34.92	19.14	29.04	25–30	0.77	0.055
Exchangeable lime (mg/100 g)	184	93.73	472.50	303.71	28.71	300–350	1.00	0.033
Exchangeable magnesia (mg/100 g)	184	18.31	115.57	58.43	31.80	35–40	1.46	0.291***
Potassium saturation (%)	184	0.86	6.16	2.31	31.58	2.0–2.5	1.00	0.013
Lime saturation (%)	184	34.02	96.80	58.82	12.23	40–45	1.31	0.015
Magnesia saturation (%)	184	8.57	36.29	16.04	26.14	6–7	2.29	0.317***
Lime/magnesia	184	2.19	6.84	3.85	22.30	5.4–7.1	0.71	−0.347***
Magnesia/potassium	184	2.75	18.12	7.52	37.78	2.7–3.8	1.98	0.209***

[a] 92 paddy fields in two years
[b] Coefficient of variance
[c] MAFF (2016b)
[d] Equals to 1 when the mean falls into the optimal range, or dividing the mean by the corresponding nearer bound, lower or upper, of the optimal range
[e] Correlation coefficient with the yield of paddy with 15% moisture in 2014–2015, while *** and ** * indicate significant at 1 and 5%, respectively
Data source Survey by the authors conducted in 2014–2015

3.3 Soil Quality Index

Referring to the Hungarian soil quality index adopted by Juhos et al. (2016) and using the 12 chemical properties analyzed above, we constructed an SQI for each paddy field *i* as:

$$SQI_i = \sum_{j=1}^{12} SSP_i \times w_j$$

$$SSP_i = \sum_{j=1}^{12} \frac{SP_{ij} - \min(SP_j)}{\max(SP_j) - \min(SP_j)},\ w_j = \frac{R_j}{\sum_{j=1}^{12} |R_j|}\ (i = 1, 2, \ldots, n), \quad (1)$$

where SSP means the standardized soil property; w_i is the weight of soil property j (SP_j); $|R_j|$ is the absolute value of correlation coefficient of SP_j with the paddy yield, as indicated in Table 1; n is the number of paddy fields.

Due to the normalization using the extreme values, the values of both SSP and SQI ranged from 0 to 1. A significant correlation was observed between SQI and the rice yield (Fig. 2). The determination coefficient (R^2) indicates that 24% of the yield was explained by the soil quality defined in Eq. (1). This result thus supported that good soil chemical property is essential to increase the rice yield (Liu et al. 2014). In addition, comparison of the SQIs showcased the difference of soil quality among the sampled paddy fields. In this chapter, the two-year average SQI was 0.536,

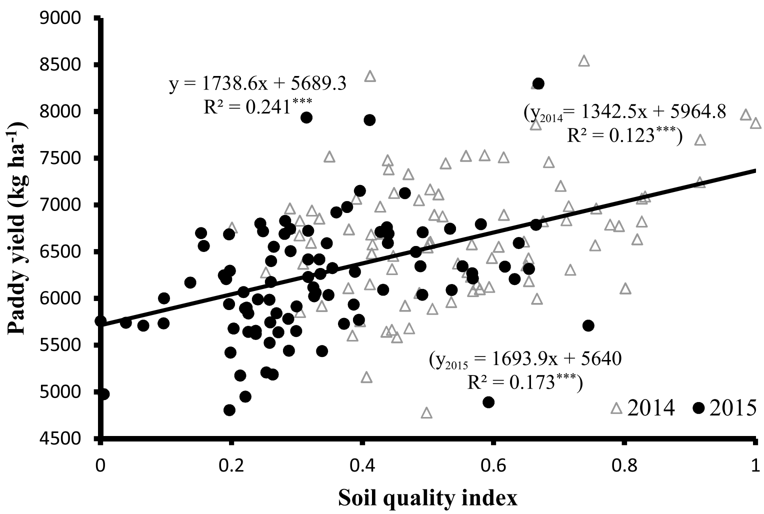

Fig. 2 Regression analysis between the rice yield and the SQI in 2014–2015 (*Note* *** indicates significant at 1%)

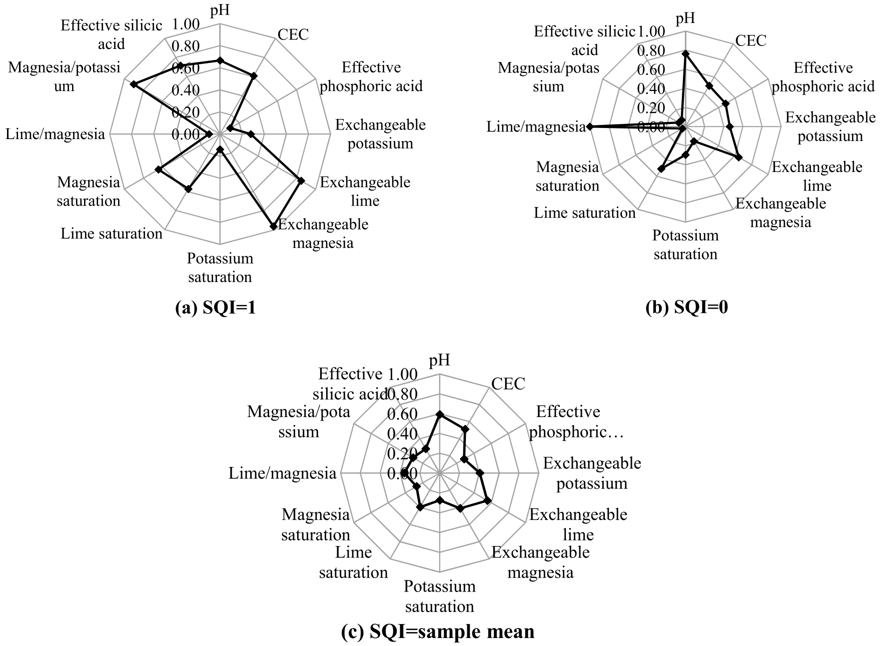

Fig. 3 Relative soil quality of paddy fields with different SSP. **a** SQI=1. **b** SQI=0. **c** SQI=sample mean (*Note* *** indicates significant at 1%)

higher than that of 0.323 in 2015. It may contribute to the reduced average rice yield per hectare, from 6683 kilograms to 6186 kilograms, within the two years. However, with respect to its correlation with rice yield, the determination coefficient R^2 in 2015 was higher than that of 2014, thus indicating the soil quality was more important to explain the rice yield in 2015 (Fig. 2).

Using the indicator specific SSPs of each paddy field, we identified the relative soil quality from different aspects, which were referential for soil quality improvement through optimal fertilization, etc. In the paddy fields with SQIs valued as 1 and 0, the highest SSPs was observed in the exchangeable magnesia (Fig. 3a) and the ratio of lime to magnesia (Fig. 3b), respectively; while the SSPs were much balanced in the paddy fields with the average SQI of the sample (Fig. 3c). Similar radar charts were available for all the other paddy fields.

3.4 Principal Component Analysis (PCA)

To reduce and synthesize the soil quality indicators, the PCA has been used in many studies (Qi et al. 2009; Liu et al. 2014; Juhos et al. 2016). In this chapter, we conducted the PCA on 12 soil chemical properties with varimax rotation. Using the criteria of eigenvalues greater than 1, we extracted five principal components, explaining 91.34% of the total variance. The KMO (Kaiser-Meyer-Olkin) measurement (0.610) of sample adequacy and Bartlett's test of sphericity (significant at 0.01) indicated the PCA was appropriate (Hutcheson and Sofroniou 1999).

Principal component 1 (PC_1) was identified as CEC and content of exchangeable pyridine base elements, due to the high loadings of the concerning items. The PC1 accounts for 27.07% of the total variance. Similarly, the other PCs were labelled as magnesia (PC_2), potassium (PC_3), pH and lime (PC_4), phosphoric and silicic acids (PC_5), respectively, considering their high loadings of the relating properties. Accordingly, the variance explained by these PCs decrease from 19.82 to 12.65% (Table 2). Weighting the five principal components using the corresponding percentage of variance explained, we synthetic principal component and regress it with the paddy yield. As shown in Fig. 4a, the determination coefficient ($R^2 = 0.092$) was significant but less than that of the regression taking SQI as the independent (Fig. 2). Same results hold comparing the models of the either year. Thus, the SQI performed better as indicators to explicate the increased rice yield.

To explore the possible reasons, we conducted the analysis of principal component regression (Juhos et al. 2016; Obade and Lal 2016), using the stepwise method to select the variable. The result indicated that only PC_2 and PC_5 were significant (Table 3). Accordingly, as illustrated in Fig. 4b, the determination coefficients

Table 2 Rotated component matrix of the five principal components on the soil quality indicators

Soil quality indicator	PC_1	PC_2	PC_3	PC_4	PC_5
pH	0.103	0.192	0.177	**0.784**	−0.112
CEC (meq/100 g)	**0.952**	−0.152	−0.036	−0.206	−0.104
Effective phosphoric acid (mg/100 g)	0.136	−0.096	0.05	0.053	**−0.901**
Effective silicic acid (mg/100 g)	0.235	0.282	0.161	0.309	**0.713**
Exchangeable potassium (mg/100 g)	**0.567**	−0.062	**0.805**	0.032	0.057
Exchangeable lime (mg/100 g)	**0.959**	−0.175	−0.064	0.159	0.011
Exchangeable magnesia (mg/100 g)	**0.799**	**0.527**	−0.127	0.143	0.148
Potassium saturation (%)	−0.506	0.097	**0.795**	0.186	0.105
Lime saturation (%)	−0.08	−0.014	−0.081	**0.905**	0.24
Magnesia saturation (%)	−0.134	**0.819**	−0.119	0.445	0.229
Lime/magnesia	0.125	**−0.971**	0.037	0.046	−0.133
Magnesia/potassium	0.282	**0.543**	**−0.755**	0.085	0.102
Explained variance after rotation (%)	27.069	19.821	16.275	15.526	12.653
Cumulated %	27.069	46.890	63.166	78.692	91.344

KMO measurement of sample adequacy: 0.610; Bartlett's test of sphericity: Chi-Square (66) = 3019.791^{***}

Rotation method Varimax with Kaiser normalization converged in 6 iterations; bolded factor loadings are considered as high

Software IBM SPSS 23.0 for windows

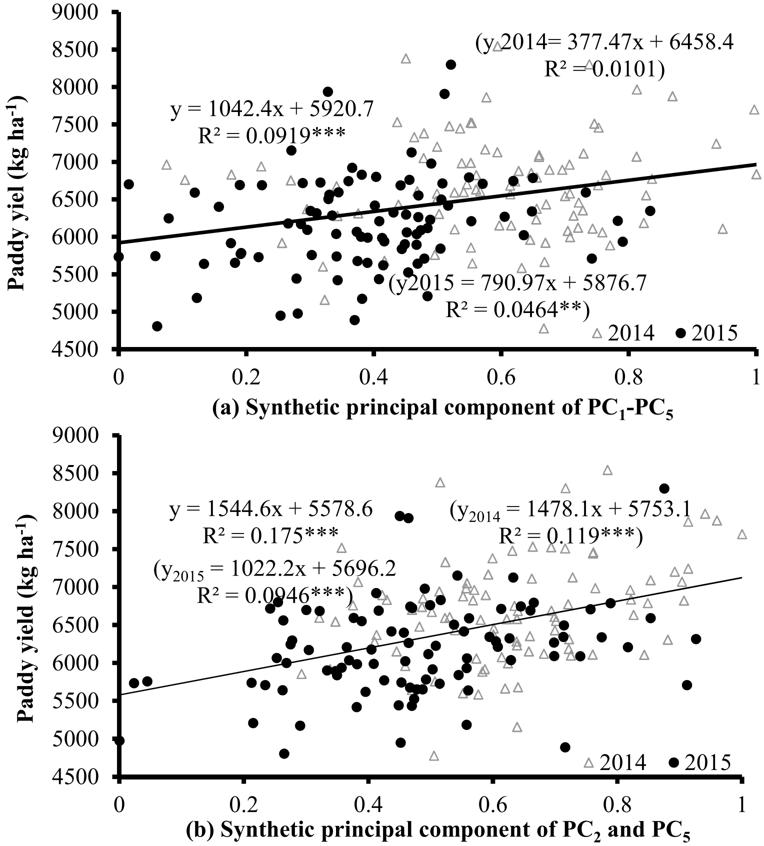

Fig. 4 Synthetic sore of five principal components and rice yield in 2014–2015. **a** Synthetic principal component of PC_1–PC_5. **b** Synthetic principal component of PC_2 and PC_5 (*Note* *** and ** indicate significant at 1 and 5%, respectively)

Table 3 Result of multivariate regression on the five principal components

Independent	Unstandardized coefficient		Standardized coefficient	t	Sig	Collinearity statistics	
	B	Std. E	Beta			Tolerance	VIF
PC_2	227.622	45.383	0.326	5.016	0.000	1.000	1.000
PC_5	252.772	45.383	0.362	5.570	0.000	1.000	1.000
(Constant)	6434.376	45.259	0.362	142.167	0.000	1.000	1.000
$N = 184$, $R = 0.487$, $R^2 = 0.237$, Adj. $R^2 = 0.228$, $F\ (2, 181) = 28.089^{***}$							

Dependent variable Yield of paddy with 15% moisture (kg/ha); independent selecting method: stepwise out of PC_1 through PC_5

*** indicates significant at 1%

Software IBM SPSS 23.0 for windows

increased, when regressing on the synthesized principal component of PC_2 and PC_5. Thus, integrating with the respective high loadings, the significant properties included those concerning magnesia, phosphoric and silicic acids.

4 Conclusion

Amount of fertilizer nitrogen affected the yield significantly and positively over the two years, while diminishing returns to scale held, when the fertilizer nitrogen was roughly 105 kilograms per hectare. In addition, the existence of the sustained effect of fertilizer nitrogen was confirmed. Thus, the effects on the subsequent years need to be investigated in planning the proper fertilization.

Based on the 12 chemical properties, the constructed SQIs were observed as significantly related to the rice yield, in the sampled paddy fields. The higher determination coefficient R^2 in 2015 indicated the soil quality was more important to explain the rice yield than that in 2014. Using the SSP of each paddy field, we identified the relative soil quality on different properties, and thus be referential for soil quality through improved fertilization. Comparison on the paddy fields of highest and lowest SSP showcased that magnesia was an essential soil indicator. Similarly, the following PCA and stepwise multivariate regression indicated that, the most significant soil properties included concerning magnesia, phosphoric and silicic acids. The SQIs and SSPs constructed in this chapter provided important indices to monitor both the overall and individual soil property of the paddy fields. To improve the rice yield, SQIs and SSPs should be included in the panel database of rice yield and soil prosperities. Thereby in future studies, the analyze framework can be adapted for multiple farms of different regions and soil types, incorporating much more soil properties.

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Impact of Soil Fertility in 93 Paddy Fields of Hokuriku Region

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To contend with decreasing gross amounts and soaring costs, viable rice production in Japan requires high yield levels. This chapter assessed the effects of nitrogen fertilizer and soil chemical properties on rice yield. Data were collected from 93 paddy fields at a farm larger than 30 hectares in Hokuriku Region, Japan. Koshihikari, the most widely planted rice variety in Japan, was cultivated in the sampled fields. Soil chemical properties were quantified using 12 variables, namely pH, cation exchange capacity, phosphoric acid content, silicic acid content, content, and saturation of the three exchangeable bases, and the equivalent ratios of calcium to magnesium and magnesium to potassium. Three principal components (PCs) were extracted explaining 76% of the total variation and comprised mainly the magnesium (PC_1), potassium (PC_2), and acidity-basicity (PC_3) variables. The multivariate regression

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model retained significant determinants, with the standardized principal components (SPCs) and the time trend explaining 66.6% of the total variation. The results showed that higher squared values of SPC_1 positively related to rice yield, while SPC_2 and SPC_3 increased rice yield up to a threshold, at which point increases plateaued. These findings were then confirmed through correlation analyses between each soil chemical property and both the PCs and rice yield. The effect of nitrogen fertilizer was insignificant, due to low variation among the paddy fields in which the special cultivation regime was adopted. Further investigations were conducted into countermeasures to improve soil chemical properties, especially those highly related to SPC_2 and SPC_3.

1 Introduction

Rice (Oryza sativa L.) is the most important food crop in Japan. However, rice farmers currently contend with decreases in gross production and high input costs. By 2017, the production of sorted brown rice was 7.82×10^6 t, 33.9% lower than the 11.83×10^6 t produced in 1985 (MAFF 2018a). In 2016, the average production cost of sorted rice was 243.1 JPY per kilogram, 27% lower than that in 1988 (MAFF 2018b). The costs typically decreased as farming scale increased. In 2016, the average production cost of sorted rice in large farms over 15 hectares was 181.7 JPY per kilogram. In our research consortium, in farms with 30 hectares and over 100 hectares of land, the cost per kilogram decreased further to 155 JPY and 150 JPY, respectively (Nanseki et al. 2016). Nevertheless, there are limits to the reduction in production costs that can be achieved by simply increasing the scale. Thus, rice production was analyzed from the perspective of increasing the yield of individual fields in a large-scale farm. The target rice variety is Koshihikari, which accounted for 35.6% of the total domestic planting area in 2017 (Komenet 2020) and is the most widely planted rice variety in Japan.

Among the soil properties, chemical properties are more causally related to crop yield and the sustainability of agro-ecosystems (Yanai et al. 2001; DFPJA 2011). Through proper fertilization and other farm management practices, chemical properties can also be more easily improved as a whole, compared with physical and biological soil properties (Bouma 2002; Gray and Morant 2013; Qi et al. 2009). Rice yield depends more on soil fertility than does the yield of many other crops. Accurate measurement of soil chemical properties and their effects on rice yield are particularly important in Japan, where many nutrients are deposited in dammed rivers (DFPJA 2011). This has been the topic of some studies, although many of these primarily used data from a limited number of paddy fields or from the perspective of only few properties. Yanai et al. (2001) evaluated the relationship between rice yield and spatial variability of soil chemical properties. The data was obtained from a 0.5 hectares paddy field located at the experimental farm of Kyoto University locates in Takatsuki, Osaka Prefecture, Japan. The soil chemical properties included pH, EC, total C; total, mineralizable, and inorganic N; available P; exchangeable Ca, Mg, K, Na, and C/N ratio. Yoshida et al. (2016) modeled the effects of N application on growth, yield, and plant properties associated with the occurrence of chalky grains of rice, using 80 samples from a field experiment conducted at Shiga Prefecture Agricultural Technology Promotion Center in 2010. Khem et al. (2018) investigated the effects of different application methods of fertilizer and manure on soil chemical properties (i.e., total and available N, total P, exchangeable content, and saturation of K) and yield in whole crop rice cultivation, among 10 fields cultivated by five different farmers in the Itoshima, Fukuoka Prefecture, Japan. In Li et al. (2017a, 2018b), the effects of soil chemical properties and nitrogen fertilizer on rice yield were measured using principal components analysis and multivariate regression, using two-year data from 92 and 116 paddy fields in two large-scale farms in Kanto and Kinki Regions, Japan. Studies that include empirical analyses based on large numbers of paddy fields sampled from large-scale farms have more practically applicable findings than those do not incorporate these elements. Further analyses on more large-scale farms could include more scenarios in terms of soil type, cultivation regime, and land subdivision.

The study objective was to measure the effects of nitrogen fertilizer and soil chemical properties on rice yield in a farm over 30 hectares in area located in Hokuriku Region, Japan, through PCA and multivariate regression. Additionally, this chapter aimed to summarize the empirical findings and proposed countermeasures to improve rice yield (Li et al. 2019).

2 Materials and Methods

Data were recorded in 2014 and 2015 from 93 paddy fields on a large-scale farm located in Ishikawa Prefecture, Hokuriku Region, Japan. The soil type was fine-grained gray lowland soil, No. F3z1t1 of the Japanese national soil inventory (NARO 2019). Being an alluvial plain with an altitude of 40 m above sea level on the coast of the Japan Sea, this granary region benefits from the mild climate, with an average annual air temperature, precipitation, and insolation duration of 14.6 °C, 2398.9 mm, and 1680.8 h, respectively (JMA 2010). At this farm, the daily average air temperature and solar radiation of 20 days since rice-heading in 2015 were recorded as 26.19 °C and 20.37 MJ m^{-2}, respectively (Li et al. 2017b). The rice variety was Koshihikari, the taste and appearance of which make it desirable to consumers both in Japan and abroad. As mentioned above, this variety accounts for the largest proportion of the area planted for domestic rice, due mainly to its strong cold resistance and stable yield. Rice yield was measured as the grain weight of the paddy with 15% moisture content. The regime of special cultivation was adopted in the agronomic management of all the 93 paddy fields. In this cultivation regime, the amounts of pesticides and chemical fertilizers were suppressed to 50% or less of those used in conventional cultivation, according to the guidelines on specially cultivated agricultural products formulated by the MAFF.

The weight and moisture content of the raw paddy were monitored using combine harvesters equipped with a matchbox-sized sensor positioned at the input slot of the grain tank, and a global navigation satellite system (GNSS) conveyed data to the cloud server shared by companies, institutes, and farms. Nitrogen fertilizer was calculated based on the amounts of manure, chemical fertilizer, ammonium sulfate, and urea fertilizers applied and their corresponding nitrogen content. Soil chemical properties were measured using 12 indicators. The pH specifies the acidity (<7) or basicity (>7). Being the total amount of anions within clay and humus, CEC was used to showcase soil fertility, i.e., the capacity of soil to hold positively charged ions, such as NH_4^+, Ca^{2+}, Mg^{2+}, and K^+, which protect the groundwater from cation contamination. Phosphoric acid is essential to ensure grain quality, while excessive amounts can lead to premature or low yield. Silicic acid is indispensable for rice growth as it prevents the softening of stems and leaves, and root decay. The exchangeable bases include the exchangeable cations that can easily be absorbed by the crop, i.e., exchangeable calcium that is indispensable for root growth, magnesium necessary for photosynthesis, and potassium essential for anthesis and seed-setting (DFPJA 2011; Li et al. 2018b). Exchangeable content was transformed to milligram equivalents via division by the corresponding quotients of atomic weight and charge number. The quotients for exchangeable calcium, magnesium, and potassium were 28.04, 20.15, and 47.10, respectively. Using the milligram equivalents, saturation was the percentage of exchangeable calcium, magnesium, and potassium in the CEC. The ratios among them were also calculated.

A summary of these variables in the studied paddy fields is shown in Table 1. The smallest and largest variations occurred in pH and effective phosphoric acid,

Table 1 Rice yield, nitrogen fertilizer, and soil chemical properties recorded in 2014–2015 from a farm located in Hokuriku Region, Japan

Variable	Min.	Max.	Mean	S.D.	CV (%)
Paddy with 15% moisture (kg/ha)	4880.00	8588.20	6593.12	976.56	14.81
Fertilizer nitrogen (kg/ha)	70.86	154.05	109.15	14.45	13.23
pH	5.29	6.34	5.80	0.21	3.66
CEC (meq/100 g)	7.86	17.95	10.90	1.41	12.90
Effective phosphoric acid (mg/100 g)	11.05	171.19	33.60	21.32	63.46
Effective silicic acid (mg/100 g)	5.29	53.46	14.35	7.03	49.02
Exchangeable potassium (mg/100 g)	9.37	44.45	20.22	6.37	31.49
Exchangeable calcium (mg/100 g)	99.79	237.90	157.60	25.58	16.23
Exchangeable magnesium (mg/100 g)	16.85	49.91	27.53	7.10	25.79
Potassium saturation (%)	1.53	9.76	3.97	1.52	38.18
Calcium saturation (%)	27.25	69.12	51.87	7.65	14.74
Magnesium saturation (%)	6.43	22.05	12.68	3.40	26.86
Calcium/magnesium (equivalent ratio)	2.55	6.63	4.26	0.78	18.37
Magnesium/potassium (equivalent ratio)	1.58	9.53	3.54	1.34	37.92

N = 186 (93 × 2 years); CV: coefficient of variation = S.D./mean
Data source Survey by the authors conducted in 2014–2015 (Li et al. 2018a)

with CVs of 3.66 and 63.46%, respectively. Data of the grain yields and nitrogen fertilizer were collected and recorded by the farm staff, with the support of machinery, information technology companies, and local agricultural promotion agencies. Soil chemical properties were analyzed by a company that specializes in the analysis of soil, compost, and plant samples. We took all the 93 out of 219 paddy fields with the rice variety Koshihikari and fine-grained gray lowland soil type. On each paddy field, a soil sample of 500–1000 g was designed to be collected and dried from center and four corners, with the depth of 10–20 cm.

The empirical methodology used to mine the determinants of rice yield can be summaries as follow. Effect of nitrogen fertilizer on rice yield was analyzed over two years through regression analysis. We estimated the relationships between rice yield and the other factors mainly by using PCA and multivariate regression. These empirical analyses were accomplished using the statistical software package SPSS 23 for Windows, IBM corp.

3 Results and Discussion

3.1 Effects of Nitrogen Fertilizer

Each year, nitrogen fertilizer was seen to positively affect rice yield, but no statistical significance was observed (Fig. 1). It can be inferred that at this farm, the regime of special cultivation has been introduced (Nanseki et al. 2016), and low variation

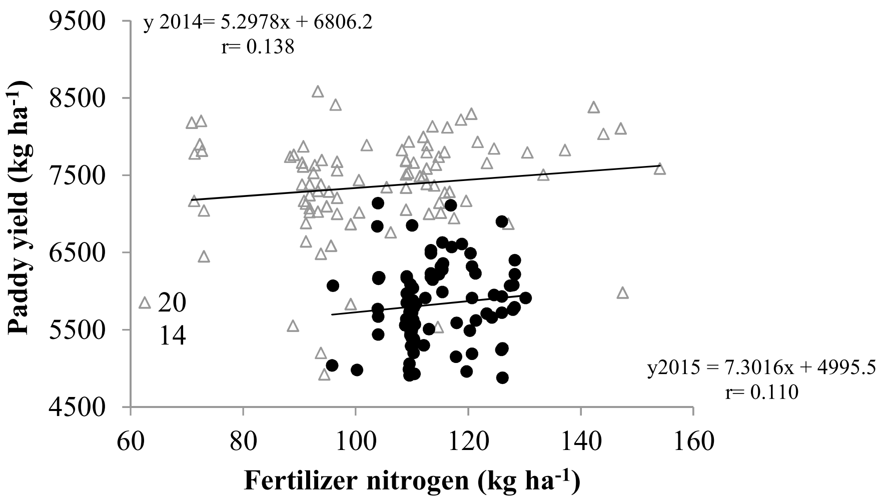

Fig. 1 Nitrogen fertilizer and rice yield of paddies with 15% moisture content, measured in 2014–2015 from a farm located in Hokuriku Region, Japan

exists in the amount of fertilizer applied among paddy fields. As shown in Table 1, the CV of nitrogen fertilizer was 13.23%, smaller than that of rice yield and most soil properties.

3.2 Principal Component Analysis (PCA)

We conducted the PCA on the 12 soil chemical properties with varimax rotation to identify high loadings and simplify the interpretation of the principal components (PCs). The scree plot (Fig. 2) illustrates that when there are more than three principal components, the initial eigenvalues are less than one with slight changes. Thus, similar to the method reported by Juhos et al. (2016), three PCs explaining 76% of the total variation were extracted using a cutoff of the initial eigenvalues over one, with each almost equally accounting for more than 25% of the variation (Table 2). Sample adequacy was confirmed based on a KMO measurement (0.628) larger than 0.5. Bartlett's test of sphericity was significant at 0.01 (Table 2), indicating that the adoption of PCA was appropriate. To equalize the range and data variability, each value (V) of the PCs was standardized by recalculating them as SPCs using the following formula: (V-min V)/(max V-min V). The loadings highlighted the correlation coefficients of each chemical soil property, and the highest loading of the PCs on each chemical property are in bold (Table 2). Figure 3 illustrates correlations between the SPCs and the soil chemical properties with high loadings.

According to the loadings in bold and the plus or minus signs on soil chemical properties shown in Table 2 and Fig. 3, further interpretation of the main properties included in the PCs is available as follows: (1) PC_1 represents magnesium content, which positively relates to the concentration of exchangeable magnesium, magnesium saturation, and ratio of exchangeable calcium to magnesium. (2) PC_2 represents potassium content, and its higher value indicates a greater proportion of exchangeable concentration and saturation forms of potassium, and a smaller ratio

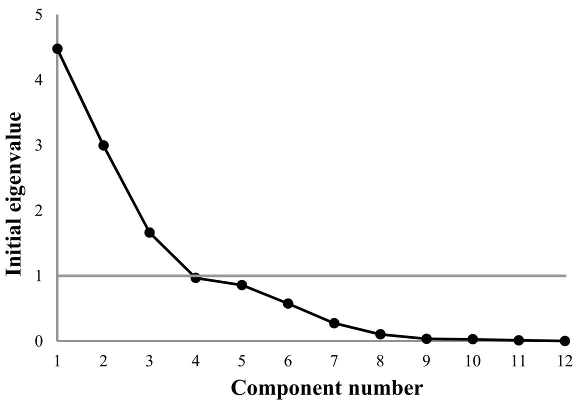

Fig. 2 Scree plot of the principal component numbers and the initial eigenvalues, recorded in 2014–2015 from a farm located in Hokuriku Region, Japan

Table 2 Rotated component matrix from 12 soil chemical properties recorded in 2014–2015 from a farm located in Hokuriku Region, Japan

Soil chemical property	Principal component and loading		
	PC_1	PC_2	PC_3
pH	0.559	−0.101	**0.595**
CEC (meq/100 g)	−0.398	**−0.569**	0.376
Effective phosphoric acid (mg/100 g)	−0.020	0.430	**0.515**
Effective silicic acid (mg/100 g)	0.103	0.177	**0.537**
Exchangeable potassium mg/100 g)	0.087	**0.886**	0.271
Exchangeable calcium (mg/100 g)	0.058	−0.268	**0.936**
Exchangeable magnesium (mg/100 g)	**0.754**	−0.120	0.578
Potassium saturation (%)	0.194	**0.952**	0.109
Calcium saturation (%)	0.386	0.187	**0.705**
Magnesium saturation (%)	**0.904**	0.151	0.367
Calcium/magnesium (equivalent ratio)	**−0.906**	−0.091	0.066
Magnesium/potassium (equivalent ratio)	0.449	**−0.805**	0.155
Rotated eigenvalue	3.088	3.042	3.005
Explained variance (%)	25.73	25.35	25.050
Cumulated %	25.73	51.08	76.130

Kaiser-Meyer-Olkin (KMO) measurement of sample adequacy: 0.628; Bartlett's test of sphericity: Chi-Square (66) = 3296.186***
Rotation method Varimax with Kaiser normalization converged in 11 iterations, and for each property the highest loadings among the principal components are bolded
Software IBM SPSS 23.0 for windows

of magnesium to potassium. CEC is determined by soil properties such as the clay mineral and humus content, and it is difficult to improve (DFPJA 2011). Although high loading was observed with PC_2, CEC can be interpreted more as a control variable due to the fact that saturation of the exchangeable bases was calculated by the ratio of their milligram equivalent (meq) to CEC (DFPJA 2011). Thus, lower CEC relates to higher potassium saturation. (3) PC_3 represents acidity and basicity, as the high loadings, i.e., the significant and positive correlations, occur with pH, effective phosphoric acid, effective silicic acid, exchangeable content, and saturation of exchangeable calcium. Exchangeable calcium was included because soil in Japan tends to be acidic, as shown by pH values lower than 7, and calcareous materials are often used to reduce soil acidity when the pH value is low (DFPJA 2011).

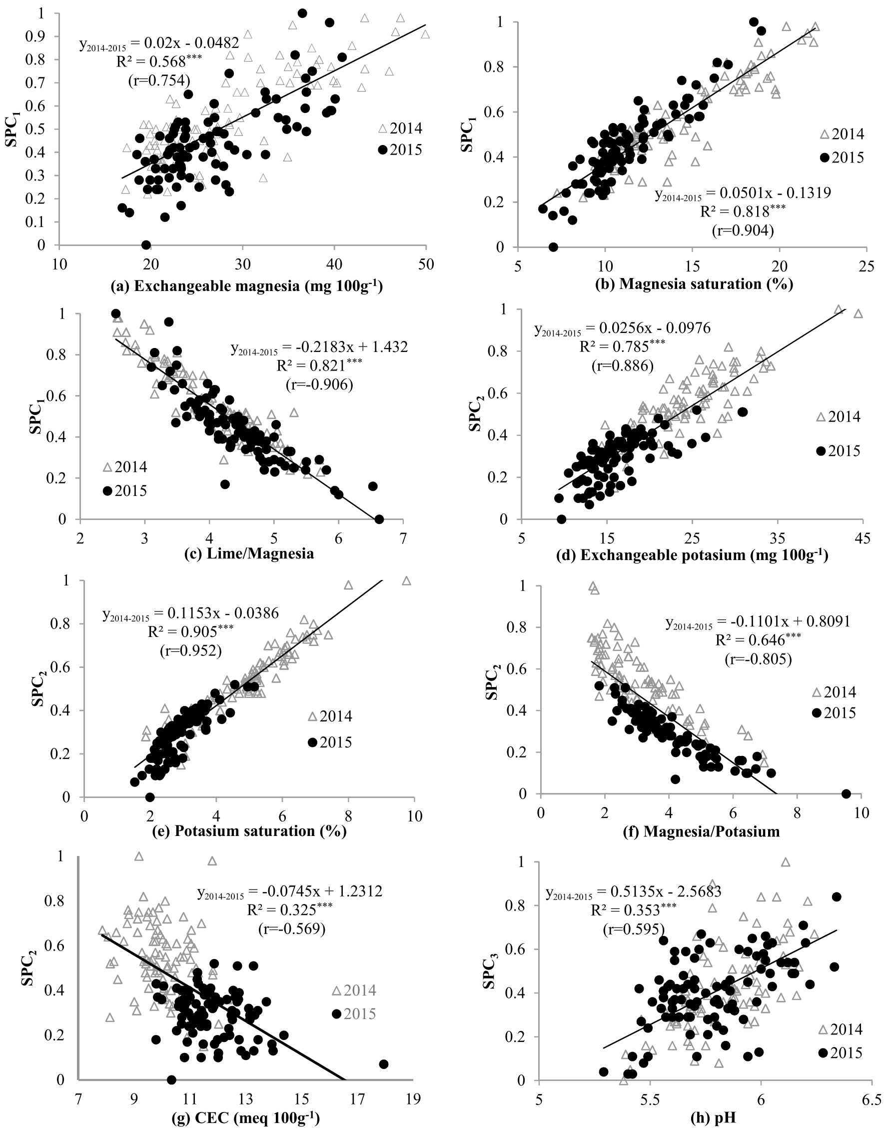

Fig. 3 Soil chemical properties and standardized principal components (SPCs), recorded in 2014–2015 from a farm located in Hokuriku Region, Japan. **a** Exchangeable magnesia (mg 100 g^{-1}). **b** Magnesia saturation (%). **c** Lime/Magnesia. **d** Exchangeable potasium (mg 100 g^{-1}). **e** Potasium saturation (%). **f** Magnesia/Potasium. **g** CEC (meq 100 g^{-1}). **h** pH. **i** Exchangeable lime (mg 100 g^{-1}). **j** Lime saturation (%). **l** Effective silicic acid (mg 100 g^{-1}) (*** indicates significance at 1%)

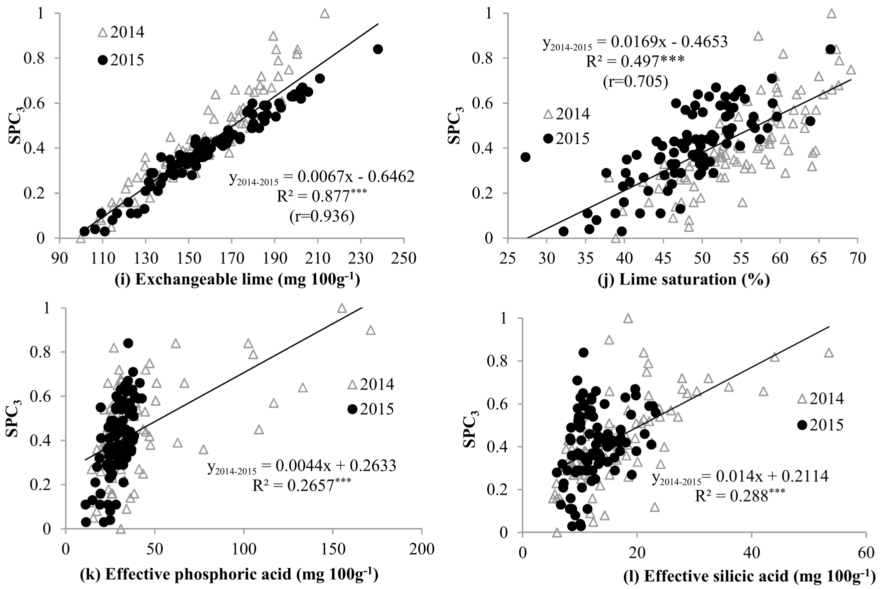

Fig. 3 (continued)

3.3 Multivariate Regression Analysis

Stepwise procedure was performed in SPSS to select the significant determinants of rice yield out of the time trend (year), nitrogen fertilizer, and the three PCs of soil chemical properties. We included the quadratic terms of the principal components, considering the possible optimum values, as identified in Yanai et al. (2001), and in our previous studies (Li et al. 2017a, 2018b). Results of the most appropriate model are shown in Table 3. To remove the offsets in the regressors with values in linear and squared forms arising owing to the presence of positive and negative values of the original PCs, the standardized values transformed as mentioned above were used. The adjusted R^2 indicates that the model explained 66.6% of the variation in the dependent variable, i.e., grain yield pf paddy with 15% moisture. F-test and T-test values verified the overall and individual significance of the estimated coefficients. Like the analysis shown in Fig. 1, nitrogen fertilizer was not included as a significant variable, and the other factors also remained the same.

In Table 3, the unstandardized coefficients indicate the estimated changes to grain yield at 15% moisture content with respect to one-unit change for each regressor, *ceteris paribus*. The standardized coefficients indicate partial effects when values of all the variables are standardized to normally distributed data, with zero mean and unit variation. According to the result above, the regression equation of the grain yield (Y) and the determinants can be presented as:

$$Y = -1522.79\text{Year} + 3294.69\text{SPC}_2 + 2119.79\text{SPC}_3 + 461.13\text{SPC}_1^2$$

Table 3 Results of principal component regression analysis, using data recorded in 2014–2015 from a farm over located in Hokuriku Region, Japan

Variable	Unstd. B	Std. E	Std. B	t	Sig.
Year	−1522.79	130.36	-0.78^{***}	−11.68	0.000
SPC_2	3294.69	988.37	0.62^{***}	3.33	0.001
SPC_3	2119.79	836.46	0.40^{**}	2.53	0.012
SPC_1^2	461.13	222.76	0.10^{**}	2.07	0.040
SPC_2^2	−3789.42	975.33	-0.68^{***}	−3.89	0.000
SPC_3^2	−2367.98	917.61	-0.41^{**}	−2.58	0.011
(Constant)	6242.04	393.42		15.87	0.000
$N = 186$ (93 × 2 years), Adj. $R^2 = 0.666$, $F(6, 179) = 62.593^{***}$					

Dependent variable Yield of paddy with 15% moisture (kg/ha). Independent variables selecting method: stepwise out of year (1 = 2015, 0 = 2014), level and squared fertilizer nitrogen, level and squared PC_1 through PC_3, *** and **indicate significance at 1 and 5%, respectively
Software IBM SPSS 23.0 for windows

$$- 3789.42SPC_2^2 - 2367.98SPC_3^2 + 6242.04 \quad (1)$$

The inclusion of *year*, a dummy variable for time trends, indicates that significant difference existed between the yields of the two years, as illustrated in Fig. 1. According to the value of the unstandardized coefficient, when the value of year changes from 0 to 1, the rice yield decreases by 1522.79 kilograms, keeping the other regressors constant. In 2014 (year = 0) and 2015 (year = 1), average grain yields of paddy with 15% moisture were 7360 kilograms per hectare and 5419 kilograms per hectare, respectively. The difference of 1941 kilograms per hectare, higher than that estimated by the regression model, indicates the reduction in yield over the two years, with no other regressors controlled as constants.

On the other hand, when the effect of time, i.e., the *year* was controlled, higher squared SPC_1 values increased the yield, while SPC_2 and SPC_3 positively affected yield up to a threshold, over which the average yield decreased. Through simple calculus on Eq. (1), the partial effect of each SPC can be easily calculated as follows:

$$\begin{aligned}
&\partial(Y)/\partial(SPC_1) = 2 \times 461.13SPC_1\\
&\partial(Y)/\partial(SPC_2) = 3294.69 - 2 \times 3789.42SPC_2\\
&\partial(Y)\partial(SPC_3) = 2119.79 - 2 \times 2367.98SPC_3 \qquad (2)
\end{aligned}$$

Using one-variable calculus to solve $\partial(Y)/\partial(SPC_i) = 0$, it could be determined that the thresholds of rice yield occurred when SPC_2 and SPC_3 equaled 0.435 and 0.448, respectively.

3.4 Relationship Between the PCs and Rice Yield

Based on the results of principal component regression analysis, Fig. 4 illustrates the relationships between the standardized principal components (SPCs) and yield

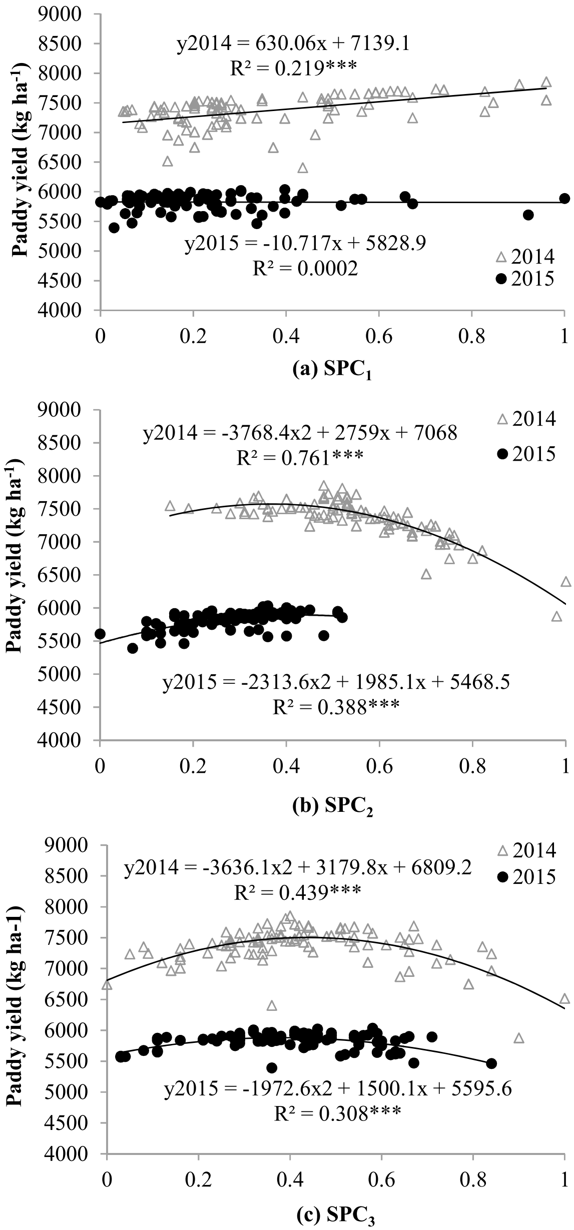

Fig. 4 Standardized principal components (SPCs) and yield of paddy with 15% moisture, recorded in 2014–2015 from a farm located in Hokuriku Region, Japan. **a** SPC_1. **b** SPC_2. **c** SPC_3 (*** indicates significance at 1%)

of paddy with 15% moisture. Considering the significant effect of the time trend, year-specific regressions were estimated for each SPC. The quadratic SPC_1, mainly representing magnesium content, exerted significant and positive effects on rice yield in 2014, while no significant effect was identified in 2015 (Fig. 4a). With respect to SPC_2, which principally represented potassium content, the quadratic relationships with rice yield are significant. In both 2014 and 2015, the thresholds SPC_2 values which generated the highest rice yield were 0.366 and 0.428, respectively (Fig. 4b). In terms of SPC_3, which mainly represented the acidity and basicity, significant quadratic relationships with rice yield were measured in both years. In the two years, the highest rice yield occurred at SPC_3 values of 0.437 and 0.380, respectively (Fig. 4c).

Often, a single value is desired to describe the relationship between the dependent variable and each explanatory variable. However, this becomes tricky in the model presented in Eq. (1), where the quadratic terms lead to changes in the partial effects of the explanatory variables depending upon their values. To tackle this problem, a popular countermeasure is to calculate the APE (average partial effect), also known as average marginal effect (AME), through plugging the sample average values of the partial effect of each explanatory variable (Wooldridge 2016) into the equation. In this chapter, the sample average values of SPC_1, SPC_2, and SPC_3 were 0.502, 0.419, and 0.412, respectively. Hence, after plugging these values into Eq. (2), their APEs are 463.421, 117.072, and 169.521, respectively. This indicated that on average, the size of the partial effect of PC_1 in terms of improving the rice yield was higher than that for the other two PCs. This result is in line with Eq. (1), i.e., with respect to rice yield, the squared PC_1 exerted a linear or straight effect, while significantly quadratic or devious effects were measured from PC_2 and PC_3.

3.5 Effects of Individual Soil Chemical Properties

The PCA analysis provided different options to improve rice yield through adjusting soil chemical properties. However, quadratic relationships were identified on the effects of PC_2 and PC_3, and each of the soil chemical properties may vary in certain characteristics, such as the estimated threshold and optimal maximum content, depending on interactions or antagonisms with other properties. Thus, it is necessary to discuss the relationships between the individual soil chemical properties and rice yield. To calculate the precise and stable relationships between the variables and yield, regression lines relating rice yield to each of the soil chemical properties were estimated, taking data from the two years as a whole sample.

(1) Magnesium content: A higher value contributed to higher rice yield. As shown in Figs. 5a through 5c, a significantly linear effect on rice yield was confirmed in the scope of the recorded data. The slope parameters indicated changes in grain yield at 15% moisture content, in kilograms per hectare, when magnesium content increases by one unit. Thus, the parameters verified the positive relationship between magnesium content and rice yield in this sample. Similar findings were reported by

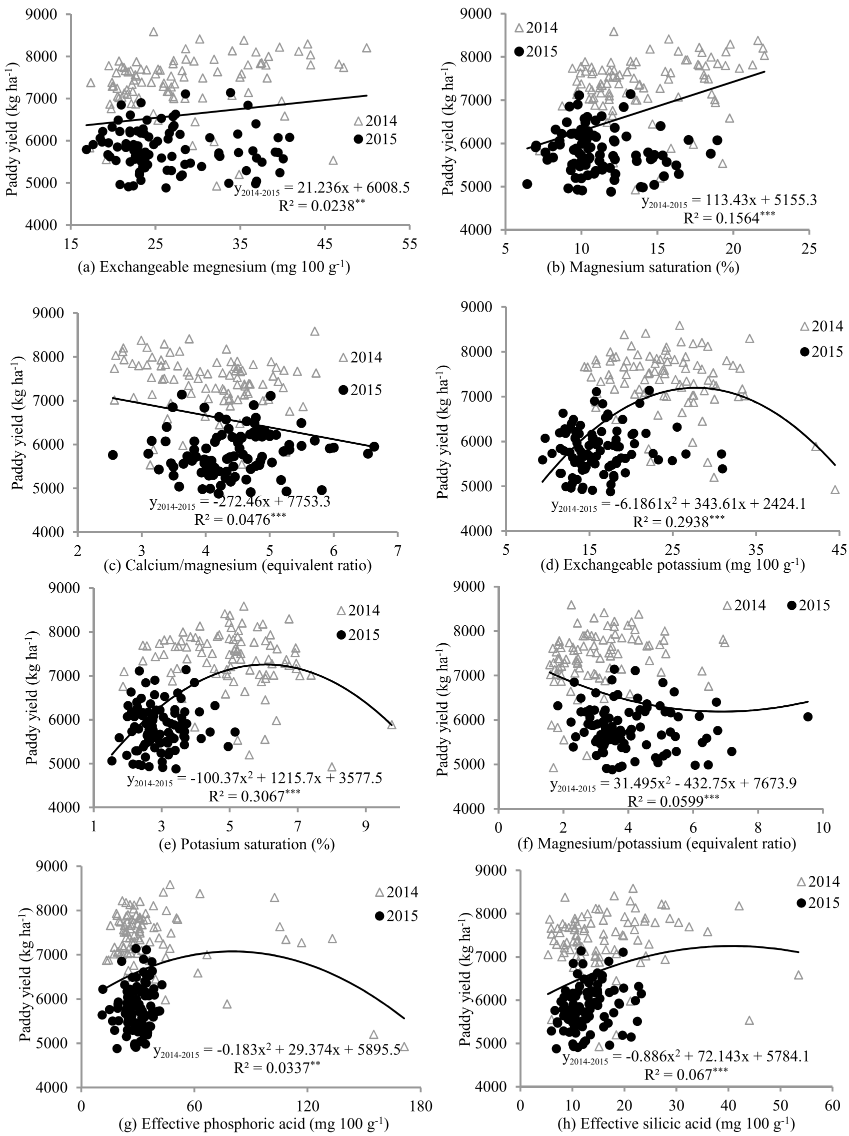

Fig. 5 Soil chemical properties and yield of paddy with 15% moisture, recorded in 2014–2015 from a farm located in Hokuriku Region, Japan. **a** Exchangeable megnesium (mg 100 g^{-1}). **b** Magnesium saturation (%). **c** Calcium/magnesium (equivalent ratio). **d** Exchangeable potassium (mg 100 g^{-1}). **e** Potasium saturation (%). **f** Magnesium/potassium (equivalent ratio). **g** Effective phosphoric acid (mg 100 g^{-1}). **h** Effective silicic acid (mg 100 g^{-1}). **i** Exchangeable calcium (mg 100 g^{-1}). **j** Calcium saturation (%). **k** pH. **l** CEC (meq 100 g^{-1}) (*** and ** indicate significance at 1 and 5%, respectively. No significant regression was fit for Figure-*i* and Figure-*k*)

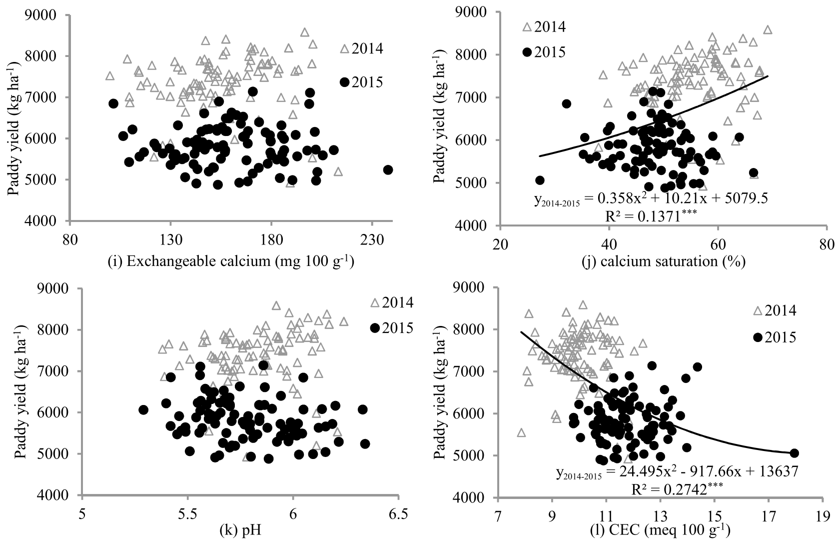

Fig. 5 (continued)

Li et al. (2016), in which exchangeable magnesium and the ratio of exchangeable calcium to magnesium were found to be significant determinants of rice yield, in a sample of 351 paddy fields in a corporate farm located in Kanto Region, Japan.

(2) Potassium content: It exerted significant quadratic effects on rice yield. According to the regression equations shown in Figs. 5d through 5e, rice yield increases at first and then begins to decrease. The thresholds of exchangeable potassium and potassium saturation were 27.77 mg per gram and 6.06%, respectively. In contrast, the decreasing rice yield begins to increase when the ratio of magnesium to potassium surpasses the turning point of 6.87, as shown in Fig. 5f. These findings confirmed that potassium (K) is an essential nutrient for rice growth. Liu et al. (2009) demonstrated that rice requires potassium more than nitrogen (N) and phosphorus (P). Seth et al. (2018) measured the critical levels of K, using paddy soil sampled from West Bengal, India.

(3) Phosphoric and silicic acid: These exerted significant quadratic effects to rice yield. Figures 5g and 5h illustrate that the content of effective phosphoric and silicic acids quadratically affects rice yield, and the maxima per 100 grams were 80.26 mg and 40.71 mg, respectively, over which the rice yield decreases. Phosphoric acid is essential to ensure grain quality, while excessive amounts may lead to premature or low yield (Fujiwara et al. 1996; Li et al. 2018b). Silicic acid accounts for roughly 20% of the rice yield, due to the high silicon accumulation ability of rice (DFPJA 2011; Fujiwara et al. 1996). Deficiency may result in declining growth and delayed heading, leading to worse grain-filling, softened stems and leaves, and an increased risk of pest damage and lodging. Excessive content may change soil pH, cause alkalization disorder, or decrease yield (Fujiwara et al. 1996). In the present study, 66.1% of the

effective silicic acid values were lower than the 15 mg per 100 g minimum optimal threshold provided by soil fertility promotion guidelines (DFPJA 2011; MAFF 2008). Silicic acid content can be improved through the application of silica fertilizers, for example calcium silicate. However, the amount of fertilizer to be applied should depend on the target amount of silicic acid, soil depth, and local soil characteristics.

(4) Exchangeable calcium: It was positively related to rice yield. Although no significant effect of was identified, as illustrated in Fig. 5i, exchangeable calcium saturation exerts a significant quadratic effect. However, the estimated threshold of 14.26% was beyond the range measured in this chapter; hence, its increase was observed to increase rice yield (Fig. 5j). In addition to exchangeable calcium, saturation of magnesium and potassium had higher R^2 values with respect to rice yield than their changeable content. This constitutes a reason for the local guidelines on soil fertility promotion to present the improvement target values of exchangeable bases as saturations and equivalent ratios between exchangeable calcium, magnesium, and potassium (DFPJA 2011).

(5) pH: The direct effect of pH on rice yield was insignificant. A significant effect was not found for pH (Fig. 5k), partly due to little variation in this variable among the paddy fields (the CV value in Table 1). In Japan, paddy field soil tends to be acidic due to little natural calcium and magnesium (DFPJA 2011), as shown by the distribution of pH from 5.29 to 6.34 in this chapter. According to soil fertility promotion guidelines, optimal pH values are 6.0–6.5 (DFPJA 2011; MAFF 2008), while in this chapter 79.6% of the pH values were lower than 6. pH can be increased via the application of calcareous fertilizers, including calcium carbonate (CaCO3), calcium oxide (CaO), and calcium hydroxide (Ca(OH)2). Higher saturation of the exchangeable bases can also increase the pH. In this chapter, the correlation coefficient between pH and base saturation was 0.645, significant at 0.01.

(6) CEC: It is negatively related to rice yield. Figure 5l shows the significant quadratic relationship between rice yield and CEC. The turning point of 18.73 milliequivalents per 100 grams was beyond the range measured in this chapter, and hence, like a report by Li et al. (2018b), more CEC related to lower yield. CEC is the total amount of clay and humus anions, more of which means an increased capacity to hold positive ions of ammonium nitrogen, potassium, calcium, and magnesium. Although high CEC values indicate soil fertility, they also relate to lower saturation of nitrogen and exchangeable bases, which are important determinants of rice yield (DFPJA 2011). In this chapter, the Pearson correlation coefficients between CEC and the saturations of potassium, exchangeable calcium, and magnesium were −0.51, −0.31, and −0.32, respectively, all of which were significant at the 0.01 level. The strong correlation between potassium and CEC likely contributed to potassium and CEC being included in the same principal component (PC_2). Although CEC is difficult to adjust and was interpreted as a control variable, it is an important indicator of soil fertility improvement and fertilization. For instance, the amount of fertilizer should be reduced, or the fertilizer changed to a slow-release fertilizer in paddy fields where CEC values were lower than the optimal range. For the gray lowland soil observed in this chapter, the optimal range was 15–20 milliequivalents per 100 grams, beyond which the nutrients will be oversupplied to the soil (DFPJA 2011).

4 Conclusion

We provided a study estimating the effects of nitrogen fertilizer and soil properties on rice yield. The amount of nitrogen fertilizer was not identified as a significant determinant, due to the adoption of special cultivation regime that reducing at least 50% amounts of pesticides and chemical fertilizers than conventional cultivation. It related to the low variation among paddy fields, and hence insignificant effect to the yield. The three principal components extracted from 12 soil chemical properties represented magnesium, potassium, and acidity-basicity, and explained 76% of the total variation. The regression model included rice yield, significant standardized principal components, and the time trend of the two years, and explained 66.6% of the dependent variable variation. The negative coefficient of year indicated a lower yield in 2015 than that in 2014, though the difference was reduced owing to the assumptions regarding maintaining the other regressors constant. Higher values of squared SPC_1 increased the yield, while SPC_2 and SPC_3 increased yield up to a threshold, after which yield decreased. The size of APEs confirmed that PC_1 affected the rice yield with a significant linear effect, and this effect was greater than that of PC_2 and PC_3, which exerted quadratic effects. The direct correlation analyses between the effects of individual soil chemical properties and both the principal components and rice yield confirmed these results, alongside concrete approaches to adjust the chemical properties. In this chapter, increased magnesium, in terms of its exchangeable content, saturation, and ratios to potassium and exchangeable calcium, contributed higher yield. In terms of variables contributing greatly to SPC_2 and $SPC_{3,}$ appropriate CEC content, potassium, and phosphoric and silicic acids content are of great importance to increase and maintain high grain yields.

Thus, the PCA produced general measurements of the effects of the soil chemical properties and an approach to increase rice yield in the sampled paddy fields. Soil fertility can be adjusted through increasing the magnesium in terms of its exchangeable content, saturation, and ratio to exchangeable calcium. It is also essential to maintain appropriate levels of potassium and acidity while also considering the interactions and ratios of the individual properties.

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Impact of Soil Fertility in 116 Paddy Fields of Kinki Region

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Japan is in urgent need of reducing its rice production costs through increasing yield, which is highly dependent on soil fertility. This chapter investigated the determinants of rice yield, from the perspective of nitrogen fertilizer and soil chemical properties. The data were collected in 2014 and 2015, from 116 paddy fields, on a large-scale farm located in the Kinki Region. The rice included Koshihikari and other seven varieties, cultivated using conventional, special, and organic methods. The nine soil chemical properties were: pH value, cation exchange capacity, ammonium nitrogen, effective phosphoric and silicic acid, saturation of base elements, exchangeable potassium, lime, and magnesia. Multiple regression analysis indicated that positive effects were found for silicic acid, exchangeable potassium, and ammonium nitrogen; while phosphoric acid affects yield negatively, while controlling rice variety, cultivation regime, and field area. Finally, countermeasures are put forward to improve soil fertility and rice yield.

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1 Introduction

Soil chemical properties are critical for growth, yield, quality, and market competitiveness of crops and their degradation results in decreased soil fertility, nutrients, and productivity (Juhos et al. 2016; Liu et al. 2014; Obade and Lal 2016). With respect to a sustainable agroecosystem, soil chemical properties can be improved through fertilization, cropping adjustment, and other farm managerial practices (Li et al. 2017a; Bouma 2002). Therefore, many researchers have studied the variability and impact of soil chemical properties on rice yield. Juhos et al. (2016) explored the yield determinants of crops by constructing a soil quality index (SQI) from more than ten chemical and physical indicators, on a farmland of 225 hectares in east Hungary. Obade and Lal (2016) tested four methods in constructing an SQI and identified the properties determining soil quality and crop yield, in the private fields of Ohio, the US.

In Japan, although rice still has the largest contribution in gross agriculture output, its share (Oryza sativa L.) has decreased from 27.8% in 1990 to 18.0% in 2016 (MAFF 2017a). Under the acreage reduction policy, the total planted area of rice decreased by 24% in the past two decades (MAFF 2017b). Compared with other crops, rice yield is determined more by soil fertility. For higher rice production, a precise measurement of soil properties and their impact on yield is needed in Japan, where most of the soil nutrients are drained by rain, or deposited in dams (DFPJA 2011). A large part of literature has focused on the soil chemical properties of paddy fields in Japan. Katayanagi et al. (2016) analyzed them in a nationwide sample of 986 plots, adopting the individual indicators of pH (H_2O) value and total carbon. To estimate the effect of soil chemical properties, Matsumoto et al. (2016) included the amount of available arsenic, phosphorus and acid ammonium oxalate, extractable iron, and aluminum. In addition to cadmium, copper, and zinc, Mori et al. (2016) represented the soil chemical properties by pH value, CEC, and oxidation-reduction potential. Li et al. (2017a) assessed the determinacy of soil chemical properties on rice yield, using on-farm data of individual paddy fields.

This chapter investigated the soil chemical properties and their determinacy on rice yield, using on-farm data of individual paddy fields, controlling for rice varieties, cultivation regimes, and field area.

2 Materials and Methods

2.1 Sample and Data

We collected the data of 116 paddy fields in 2014 and 2015, from a farm scaled over 170 hectares in Kinki Region. Rice yield is measured using paddy with 15% moisture. The paddy weight and moisture content were monitored using a combine harvester, through a matchbox-sized sensor fitted in the input slot of the grain tank.

The data was then conveyed by GNSS, via a cloud server connecting farms, institutes, and companies. The soil chemical properties, represented by nine indicators, were sampled and analyzed by a professional company (TAC 2018).

2.2 Analysis Framework

The significant soil chemical properties were identified using multivariate regression. We estimated the effects of the properties on rice yield by incorporating the natural features of the soil and rice production in Japan. The analyses were conducted using SPSS 23.0 for Windows, IBM Corp.

3 Results and Discussion

3.1 Rice Yield Analysis

In the two years, average yield decreased from 6347 kilograms to 5730 kilograms per hectare, with a smaller coefficient of variance. Over the same period, 85 paddy fields were planted with the same varieties, while 31 fields changed the rice varieties. Of the different rice varieties, Nakateshinsenbon had the highest average yield of 6652 kilograms per hectare with the least variance. The second highest yield was of Koshihikari, which accounted for the largest share (36.2% in 2016) of planted area in Japan (Komenet 2020), has an aesthetic appearance and good taste, strong cold resistance, and stable yield (Goto et al. 2000). Of all the methods, the conventional and special cultivation regimes yielded 6355 kilograms and 5910 kilograms per hectare, respectively, which were much higher than that of organic cultivation, 4734 kilograms per hectare on average (Table 1).

3.2 Soil Chemical Properties

As shown in Table 2, the paddy fields were scaled from 634 m^2 to 13562 m^2, with an average value of 4965 m^2. The pH value indicates soil acidity (<7) or basicity (>7). CEC shows soil fertility in the capacity to hold the positive ions of ammonium, calcium, magnesium, and potassium, for protecting groundwater from cation contamination (DFPJA 2011; Mori et al. 2016). Ammonium nitrogen, referring to the nitrogen directly absorbed by the rice plant, is essential for major plant components, such as proteins, nucleic acids, chlorophyll. It promotes growth by vigorously activating cell division, nutrient absorption, and anabolism (DFPJA 2011). Effective phosphoric acid refers to those that can be absorbed by the crops directly. Although

Table 1 Rice yield specified by variety and cultivation regime in 2014–2015

Specification	N	Paddy with 15% moisture (kg/ha)				CV[a] (%)
		Mini	Maxi	Mean	Std. D	
Total in two years	232	4040.60	8452.40	6038.63	1016.92	16.84
Year: 2014	116	4040.60	8452.40	6347.26	1129.74	17.80
2015	116	4070.00	8220.00	5730.00	780.23	13.62
Two-year variety: different	170	4040.60	8452.40	6057.80	1009.74	16.67
same	62	4230.00	7933.70	5986.07	1042.87	17.42
Variety: Koshihikari	9	4862.10	7483.30	6402.18	859.34	13.42
Milky queen	28	4090.00	7449.10	5663.57	745.52	13.16
Kinuhikari	9	4581.00	8452.40	6269.33	1529.22	24.39
Nipponbare	11	4134.90	7564.50	6259.53	1110.70	17.74
Nakateshinsenbon	29	5280.00	8298.30	6651.69	857.27	12.89
Yumeoumi	24	4040.60	8358.80	6189.56	1201.38	19.41
Nikomaru	30	4340.00	7999.90	5999.68	1052.49	17.54
Himenomoti	92	4070.00	7933.70	5848.31	937.95	16.04
Conventional cultivation	83	4040.60	8358.80	6355.10	1064.85	16.76
Special cultivation[b]	143	4070.00	8452.40	5909.69	934.54	15.81
Organic cultivation[c]	6	4090.00	5190.00	4733.80	442.29	9.34

[a]Coefficient of variance. [b]Nitrogen content is reduced by 50% in compost and chemical fertilizers and chemical pesticides according to the national guidelines. [c]soil fertility is improved by compost fertilizers, not by chemical fertilizers and chemical pesticides

essential for ensuring grain quality, its excessive content could lead to premature or low yield (Fujiwara et al. 1996). Silicic acid is indispensable for rice growth in reducing softened stems and leaves, and decayed roots (DFPJA 2011; Fujiwara et al. 1996). Of the exchangeable content of the base elements, lime is important for root growth, magnesia is necessary for photosynthesis, while potassium is crucial for anthesis and seed-setting (DFPJA 2011).

The correlation analysis indicated the significant properties—ammonium nitrogen, effective silicic acid, and exchangeable potassium affect yield positively, while effective phosphoric acid and CEC affect yield negatively (Table 2).

3.3 *Significant Rice Yield Determinants*

In the multivariate regression analysis, the values of yield, soil properties, and field area were taken as the natural logarithmic transformations to capture linearity and interpret the regression coefficients in terms of elasticity. Dummy variables were included to control the effect of year (1 = 2015, 0 = 2014), rice varieties (1 = each, 0 = others), their changes in the two years (1 = same, 0 = different), and

Table 2 Field area and soil chemical properties of 116 paddy fields in 2014–2015

Variable	N	Min	Max	Mean	Std.D	CV[a] (%)	R[b]
Filed area (m^2)	232	634.00	13562.00	4964.91	2863.40	57.67	−0.105
pH	232	4.98	6.63	5.97	0.29	4.83	−0.102
CEC (meq/100 g)	232	5.89	18.21	10.67	1.92	18.04	−0.128*
Ammonium nitrogen (mg/100 g)	232	0.10	2.25	0.51	0.42	81.98	0.135**
Effective phosphoric acid (mg/100 g)	232	3.10	26.51	11.60	4.32	37.27	−0.254***
Effective silicic acid (mg/100 g)	232	6.38	69.13	16.14	10.14	62.82	0.147**
Saturation of base elements (%)	232	52.63	123.23	79.70	11.21	14.06	0.037
Exchangeable potassium (mg/100 g)	232	3.21	23.09	10.43	3.34	32.03	0.182***
Exchangeable lime (mg/100 g)	232	101.01	297.49	193.50	37.14	19.19	−0.108
Exchangeable magnesia (mg/100 g)	232	3.80	50.73	26.18	7.18	27.41	−0.009

[a]Coefficient of variance
[b]Pearson's correlation coefficient with yield of paddy with 15% moisture; ***, **, * indicate significance at 1, 5, and 10% levels, respectively

cultivation regimes (1 = each, 0 = others). Using backward procedure, the significant independent variables were selected. The result indicates that each regressor (t-test) and the entire model (F-test) are significant. All the VIFs are less than 10, indicating zero multicollinearity. The adjusted R^2 indicated that 24.4% of the yield variations are explained. White test eliminates the presence of heteroskedasticity and the bias of excluding variables that could affect the regressors significantly (Table 3).

Among the soil chemical properties, effective silicic acid, exchangeable potassium, and ammonium nitrogen affected yield positively, significant at 0.05 level and effective phosphoric acid and exchangeable lime affected the yield positively, significant at the 0.01 and 0.10 levels, respectively. With respect to the control variables, field area and organic cultivation related negatively to yield, while Nakateshinsenbon had a higher yield than the other varieties. These findings are in accordance with the correlation analyses. The estimated multiple coefficients indicated the change in yield with respect to each regressor, holding other variables fixed. For the continuous regressors, a coefficient indicates the elasticity, for example, a 1% increase in ammonium nitrogen increased yield by 0.034%, while a 1% increase in effective phosphoric acid decreases yield by 0.099%. For the dummy regressors, the average yield of Nakateshinsenbon was 16.6% higher than of the other varieties, and organic cultivation yielded 19.8% less than the other methods, *ceteris paribus* (Table 3).

Table 3 Result of multivariate regression on the significant rice yield determinants

Independent variable[a]	Unit	Unstandardized coefficient		t	Sig.	Collinearity statistics	
		B[b]	Std. E			Tolerance	VIF
Ln (Effective silicic acid)	mg/100 g	0.060**	0.024	2.482	0.014	0.678	1.476
Ln (Exchangeable potassium)	mg/100 g	0.068**	0.031	2.178	0.030	0.870	1.149
Ln (Ammonium nitrogen)	mg/100 g	0.034**	0.017	2.050	0.042	0.606	1.650
Ln (Effective phosphoric acid)	mg/100 g	−0.099***	0.026	−3.816	0.000	0.866	1.155
Ln (Exchangeable lime)	mg/100 g	−0.102*	0.057	−1.806	0.072	0.781	1.280
Ln (Filed area)	m^2	−0.030**	0.015	−2.092	0.038	0.912	1.097
Nakateshinsenbon	Dummy	0.166***	0.031	5.315	0.000	0.869	1.151
Organic cultivation	Dummy	−0.198***	0.063	−3.167	0.002	0.938	1.066
(Constant)	—	7.115***	0.315	22.588	0.000	—	—

N = 232, R = 0.519, R^2 = 0.270, Adj. R^2 = 0.244, F (8, 223) = 10.294*** (p = 0.000); White test: 0.228 × 232 = 52.896 < $\chi^2(8)$ = 20.090

[a]Selected using backward procedure, and the excluded variables include year, two-year same/different varieties, rice varieties except for Nakateshinsenbon, conventional and special cultivation regime, ln(pH), ln(CEC), ln(exchangeable magnesia), and ln(saturation of base elements). Dependent variable: ln(yield of paddy with 15% moisture per hectare)
[b]***, **, * significant correlation at 1, 5, and 10% levels, respectively

3.4 Further Discussion

To confirm and supplement the result of the multivariate regression, Fig. 1 illustrates the soil properties identified as statistically significant at the 0.05 level in Table 3.

1. Silicic acid accounts for 10–15% of dry straw and 2–3% of paddy grain due to the high silicon accumulation ability of rice (DFPJA 2011; Fujiwara et al. 1996). Its deficiency results in declining growth, delayed heading, poor grain-filling, softened stems and leaves, and increased risks of pest damage and lodging. Although it is unlikely to occur, excessive silicic acid could cause changes in soil pH, alkalization disorder, and decreased yield (Fujiwara et al. 1996). Compared with the national minimum criterion of 15 mg per 100 grams (DFPJA 2011), a higher content of silicic acid can also increase rice yield. However, a significant quadratic relation is found as well, indicating an optimal amount of 39.8 mg per 100 grams.
2. In Japan, potassium and other base elements are drained by the ample rainfall (DFPJA 2011). For soils rich in humus, like surface gray lowland soil, the optimal

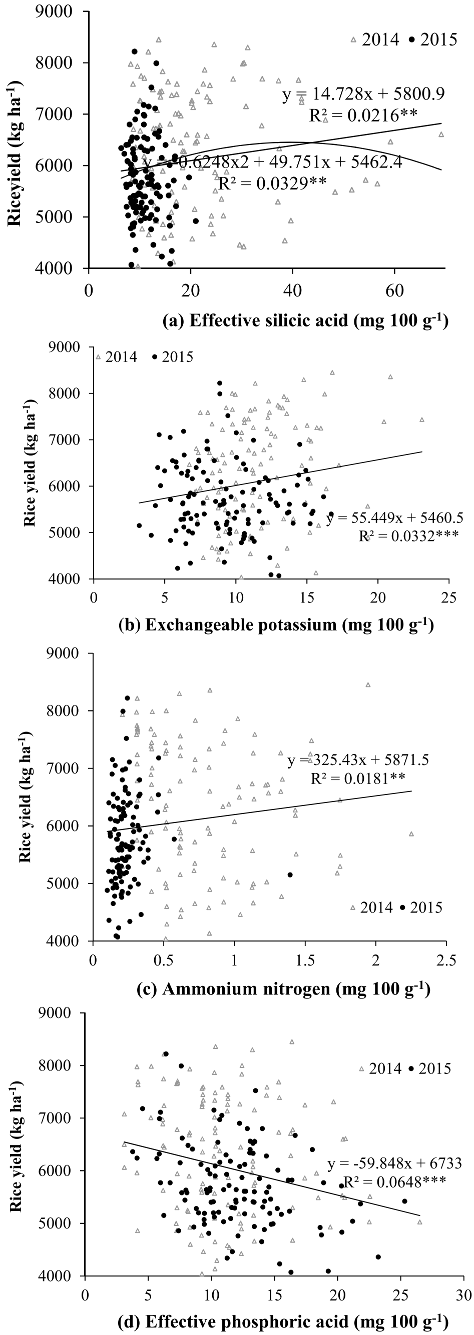

Fig. 1 Relationship of rice yield and the significant soil chemical properties.
a Effective silicic acid (mg 100 g^{-1}). **b** Exchangeable potassium (mg 100 g^{-1}).
c Ammonium nitrogen (mg 100 g^{-1}). **d** Effective phosphoric acid (mg 100 g^{-1}) ($N = 232$, ***and ** indicate significant correlation at 1 and 5% levels, respectively)

range of exchangeable potassium was 20–30 mg per 100 grams. It was higher when CEC was lower than 30 milliequivalents per 100 grams (DFPJA 2011). In the sampled fields, average exchangeable potassium was 10.43 milligrams per 100 grams, with a maximum CEC of 18.21 milliequivalents per 100 grams; thus, its increase undermined the rice yield.

3. Rice growth relies heavily on nitrogen, 60% of which is supplied by the soil (DFPJA 2011; Fujiwara et al. 1996). Ammonium nitrogen, directly absorbable by crops, is essential for a high rice yield. Here, its highest content was merely 2.25 milligrams per 100 grams, much lower than the optimal range of 10–20 milligrams per 100 grams (Fujiwara et al. 1996). Therefore, an increase in its content benefited higher rice yield.
4. In Japan, the soil of the paddy fields is usually acidic, as shown by the average pH value of 5.97 in this sample, because of drained calcium and magnesium. In an acidic soil, more iron and aluminum are dissolved, and phosphoric acid is easily fixed and less applicable to crops. Moreover, phosphoric acid can be easily over-supplied, through organic fertilizer and compost, as indicated by the negative correlation with rice yield here. Excess phosphoric acid shows up as brown streaks on the leaf blade and whitened leaf tips (DFPJA 2011), which cannot be easily observed.

In practice, there are significant correlations between some chemical properties (Table 4). Thus, it is important to consider and adjust them collectively through, say, soil improvement and an appropriate fertilization rate determined by professional agencies, in different paddy fields (DFPJA 2011).

As Nakateshinsenbon is a high-yielding and lodging-resistant variety, it is widely planted in the Kinki Region of Japan. Although a zero application of pesticides and chemical fertilizers reduces agricultural pollution, organic cultivation has a lower yield due to increased pest damages and insufficient fertility. Over-scaled paddy fields may undermine rice yield, in terms of unbalanced fertilization; hence soil fertility and irrigation management are important factors. The quadratic relation indicated an optimal scale of 0.38 hectares in this sample.

Table 4 Correlations between the soil properties significant to rice yield

Variable	Effective silicic acid	Exchangeable potassium	Ammonium nitrogen	Effective phosphoric acid
Effective silicic acid	1.000	—	—	—
Exchangeable potassium	0.117	1.000	—	—
Ammonium nitrogen	0.306^{***}	0.206^{***}	1.000	—
Effective phosphoric acid	0.170^{***}	−0.111	0.146^{**}	1.000

N = 232, *** and ** indicate significant correlation at 1 and 5% levels, respectively

4 Conclusion and Suggestion

This chapter provided a case study of estimating the soil properties and their impact on rice yield. Based on nine soil chemical properties and control variables, the regression model explained 24.4% of yield variation. The significant chemical properties were generally in accordance with the direct correlation analysis. Positive and significant impacts were identified for silicic acid, exchangeable potassium, and ammonium nitrogen, while phosphoric acid affects rice yield negatively, *ceteris paribus*. These empirical findings were in accordance with the soil properties, and rice production in Japan. In addition, yield was significantly affected by rice variety and cultivation regime, while smaller paddy fields tend to have a higher yield.

Accordingly, soil fertility can be improved to increase rice yield in the sampled paddy fields. Soil silicic acid can be supplemented through the application of silicate-calcium and other siliceous fertilizers. Potassium can be directly supplemented by chloride or sulfate potassium that do not contain other base elements or by sulfate potassium magnesia and silicate potassium, considering a balance with other base elements. Ammonium nitrogen can be increased through enhanced nitrogen mineralization, which can be promoted by accelerated microbial activity caused by irrigating of the dry soil after spring-plowing, irrigation after the application of silicate-calcium fertilizers, and when ground temperature rises over 30 °C. To decrease the phosphoric acid content, say, over 30 milligrams per 100 grams, fertilizer-free farming should be adopted.

In future studies, this model should be extended to accommodate more soil types and rice varieties. For precise analyses on soil chemical properties and soil fertility improvement, regular soil testing and local technical guidance are necessary as well. Proper selection of rice variety and cultivation regime is especially important for increasing rice yield.

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Production Efficiency and Irrigation of 110 Paddy Fields in Kanto Region

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Irrigation is increasingly important for rice productivity to maintain soil temperature and fertility with the presence of global warming. Meanwhile, rice production in Japan is in urgent need to reduce the costs through improving the efficiency and market competitiveness. This chapter aimed to measure effect of water depth and water temperature on rice yield of individual paddy fields and improve the practice of irrigation management for them. In first stage, we measured the production efficiency of rice yield through the adoption of DEA. The results indicated that enlarged scale of the paddy fields increases the efficiency, and rice quality can be improved more than quantity. Moreover, the most inefficiently used inputs included the amount of fertilizer nitrogen and the soil capacity, which was a compound measurement of 21 soil chemical properties. In the second stage, after comparing the 20 paddy fields with highest and lowest technical efficiency, an observation showed that the rice yield is much more affected by water temperature than by water depth. The data of all the variables used in this chapter was sampled in 2015, and comprised of 110 paddy fields of Koshihikari, one of the most popular Japanese rice varieties, from a large-scale farm located in Kanto Region of Japan. In the analysis, the outputs included yields

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of raw paddy, paddy with 15% moisture, unsorted brown rice, sorted brown rice, milled rice, and full-grain rice. The inputs included the field area, air temperature, solar radiation, fertilizer nitrogen, soil capacity, and farming conditions.

1 Introduction

In Japan, the production of rice (Oryza sativa L.) needs to improve the efficiency and competitiveness, confronting the decreases in gross production and high costs of the inputs, and challenges in the TPP era (Nanseki et al. 2016). In 2014, the production of sorted brown rice was 8.43×10^6 t, 40% lower than the 1985 production of 11.83×10^6 t. The average production cost of sorted brown rice in Japan was 256.9 JPY per kilogram (MAFF 2016). The cost typically decreases when the farming scale increases. In farms scaled to over 15 hectares, the average production cost of sorted brown rice was 193 JPY per kilogram. In our research consortium, the cost per kilogram decreased further to 155 JPY and 150 JPY, for the farms scaled to 30 hectares and over 100 hectares, respectively (Nanseki et al. 2016). Nevertheless, it is difficult to further reduce the production cost by merely increasing scale without technological innovation and, hence, higher production efficiency. Thus, we analyzed rice production from the perspective of technical efficiency, using field-level data from a large-scale farm. To isolate the bias arising from the differences in rice variety, we concentrated the study on Koshihikari. As one of the most popular rice varieties in Japan, Koshihikari accounts for approximately 36% of the total domestic planting area (Komenet 2020).

Prior studies on the determinants of rice yield using overseas field-level on-farm data include Abdullah and Ali (2014), Barrett et al. (2010), and Kozak et al. (2007). Studies using the experimental data sampled in Japan include Hirai et al. (2012). In the prior study, we analyzed the determinants of Koshihikari, using the data from a large-scale farm in the Kanto Region of Japan (Li et al. 2016). However, we found few similar studies, sampling field-level on-farm data in Japan. In this chapter, we continued our previous study of Li et al. (2018) by analyzing the determinants of the yield of rice, with the adoption of DEA in the first stage. The effect of irrigation management on rice yield was analyzed in the second stage. Irrigation management is the control and movement of water resources to minimize damage to life and property and to maximize efficient beneficial use. Irrigation systems make the most efficient use of limited water resources for agriculture (NRCS 2017).

Since the pioneering work of Farrell (1957), studies devoted to the estimation of efficiency have mainly embraced two approaches: the parametric function symbolized by the stochastic frontier production (SFP, Aigner et al. 1977) and the nonparametric approach of DEA (Charnes et al. 1978). SFP requires specification of the function between the inputs and outputs. In contrast, DEA is advantageous in including multiple inputs and outputs simultaneously, even with different units. Moreover, DEA avoids parametric specification of technology as well as the distributional assumption, e.g., half-normal or truncated normal, of the error term (Coelli et al. 2005).

In agriculture, parameters such as land, fertilizer, and water are considered. Thus, a multiple-input model is necessary to measure the efficiency. A variety of yield variables should be adopted to measure not only the quantity, but also the quality, which is linked to the market value. The input and output variables may be in different units, without any relevant parameters that can be assumed accurately beforehand. Moreover, the farmers can control the quantity of inputs rather than the outputs relatively freely. Meanwhile, farms are difficult to operate at an optimal scale, due to varying socio-economic factors, including natural and marketing risks, government regulations, and financial constraints. Therefore, we adopted an input-oriented DEA model with the assumption of VRS (variable returns to scale), which permits that not all firms are operating at the optimal scale (Coelli et al. 2005).

To interpret the differences in production efficiency and slack adjustment measured by DEA, we adopted irrigation management in the second stage. As an indispensable factor, water affects rice productivity in many aspects, e.g., nutrition supplication and weed control (Goto et al. 2000; Sellamuthua et al. 2011). Moreover, with the presence of global warming, it is increasingly important to stabilize the soil temperature, control the excessive decomposition of organic matter, and maintain soil capacity through proper irrigation management (Goto et al. 2000; Tsujimoto et al. 2009). Many studies have measured the effect of irrigation management from primarily two perspectives. Roel et al. (2005) estimated the effect of water temperature on rice production in California, US, by calculating the total number of hours and days the water temperature was below a given threshold. Saga et al. (2010) included the water temperature as a form of energy in estimating the high-yield rice plants of Japan. Tao et al. (2015) and Choudhury and Singh (2016) estimated the impact of irrigation management on the rice yield in China and India, respectively. As the effect of irrigation management may vary in different growth stages and conditions, its subsequent analysis is preferable rather than its inclusion in the first stage of the DEA model. This chapter included both the water temperature and water depth and analyzes their effects through a comparison among the grouped paddy fields by their technical efficiency. To amplify the impact of irrigation management on technical efficiency, a comparison was conducted involving 20 paddy fields of high and low technical efficiency, sampled from the whole sample.

We fulfilled the following targets in the ensuing sections: (1) formulating a DEA model appropriate to analyze the rice production efficiency, using the paddy fields as the decision making units (DMUs), i.e., the individual evaluation objects, (2) based on which, revealing the overall attributes of rice production efficiency, (3) determining the theoretical margins for increasing yields and saving inputs, (4) identifying the effects of water depth and water temperature, to rice production and technical efficiency as calculated in DEA, and (5) summarizing the major findings and putting forward recommendations to improve the rice yield.

2 Materials and Methods

2.1 Sample and Data

In this chapter, the data was sampled in 2015, from 110 paddy fields of a large-scale farm locating in the Kanto region of Japan. In DEA, the number of observations is typically small, e.g., 20–200 specified by Peter and Lars (2011). The rule of thumb for sufficient observation is three-fold of the number input-output variables. Thus, in this model with 12 input-output variables, the acceptable smallest sample size was 36 DMUs. Therefore, 110 paddy fields were enough for this chapter, and other agricultural envelopment analyses in general. As data was collected from the same farm, we can rule out the model bias arise from omitted variables of producer skill, knowledge, and ability. The rice yield was measured from the following six types of objects: raw paddy, paddy with 15% moisture, unsorted brown rice, sorted brown rice, milled rice, and full-grain rice (Table 1). The yield of raw paddy refers the weight of husked rice grain with moisture content measured directly after harvesting. In this chapter, using combine harvesters equipped with advanced ITs, we monitored weight and moisture content of raw paddy, based on which the yield of the paddy with 15% moisture was calculated. Brown rice was then weighed after hulling, and the sorted brown rice retains only grains thicker than 1.85 mm. Milled rice is the fluffy white-yellow rice with the bran and germ removed, and it is the finally processed grains for retail and table consumption. In contrast, full-grain rice refers to the normally ripened brown rice with husk-stuffed ovary, completely developed grain in mainly symmetrical shape, good luster, clear and transparent appearance (Goto et al. 2000). Percentage of full-grain rice to sorted brown rice is one of the key rice quality indicators. In this chapter, this indicator was measured using grain analyzer RGQ120A, product of Satake Co., Ltd. In Japanese market, the first-class rice, composed of about 70% full-grain rice, fetches the highest price. Quantity was the main concern with the first four outputs, while the last two outputs showcased more information about rice quality.

In the smart combine harvester, yield and moisture are monitored by a small matchbox sized sensor, set at the input slot of the grain tank. The sensor probes the grain flow rate, while a much larger load cell is set at the bottom to measure the total grain weight in the tank. This innovation enables real-time, precise, and low-cost monitoring, expelling the bias out of the grain tank stuffing state—whether the tank is filled or not. Meanwhile, the smart combine harvester can detect the threshing or screening yield loss, by loss sensors, and minimize it by automatic operation. Finally, the field-specific data of yield and moisture content is conveyed, via the global navigation satellite system (GNSS), to the cloud server shared by the company, institutes, and farms. Thereafter, the yield, moisture content, and farming time are automatically mapped, using Google Maps. The maps are essential for the ability of the farms to capture the yield variation among the paddy fields, and thus, to update their farming plans, accordingly (Nanseki et al. 2016).

Table 1 Six types of rice yield adopted as the DEA model outputs and the six determinants of the sampled paddy fields included as DEA model inputs

Variable	N	Min	Max	Mean	Std. D	CV (%)
Output: yield of (kg/ha)						
Raw paddy	110	4350.00	9090.26	6689.65	739.76	11.06
Paddy with 15% moisture	110	3976.42	8298.87	6143.82	644.80	10.50
Unsorted brown rice	110	3086.50	6572.70	4877.03	497.62	10.20
Sorted brown rice[a]	110	2664.60	5634.10	4292.91	432.02	10.06
Milled rice[b]	110	2273.16	4873.50	3760.61	387.95	10.32
Full-grain rice	110	1060.51	3791.05	2669.60	582.04	21.80
Input variables						
Field area (m^2)	110	200.00	14037.00	2513.99	2044.27	81.32
Air Temperature (°C/day)[c]	110	24.02	27.56	26.75	0.57	2.14
Solar radiation (MJ/m^2/day)[c]	110	15.65	21.15	19.16	0.91	4.77
Fertilizer nitrogen (kg/ha)[d]	110	37.50	200.00	74.52	35.81	48.06
Soil capacity[e]	110	0.00	1.00	0.56	0.22	40.23
Farming condition score[f]	110	26.80	37.90	32.65	2.31	7.07

[a]Grain thickness over 1.85 mm
[b]Fluffy white-yellow rice with the bran and germ removed
[c]Daily average values within 20 days since heading
[d]Calculation based on the amounts of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizers, and the corresponding nitrogen contents
[e]Compound value of 5 principals of 21 soil analysis indicators transformed using $(x_i - \min(X))/(\max(X) - \min(X))$
[f]Managers' appraisal of the farming condition of paddy fields, including height difference, water depth, water leakage, former crop, water inletting, fertility unevenness, illumination, and herbicide application
Data source Survey by the authors

As shown in Table 1, the inputs included the field area, the average air temperature, and solar radiation within 20 days after heading, the amount of fertilizer nitrogen, soil capacity, and farming conditions. The air temperature and solar radiation were monitored through meteorological observing devices every 10 min, and average values of these parameters were calculated. Fertilizer nitrogen was measured according to the amount of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizers, as well as the corresponding nitrogen content. The soil capacity was estimated by a constructed compound value, which was the mean sum weighted by the eigenvalues of the five principals of 21 soil chemical properties, including pH, cation exchange capacity, content of pyridine base elements, phosphoric acid, and silicic acid (Table 2). Values of soil capacity (X) were transformed using $(x_i - \min(X))/(\max(X) - \min(X))$, showcasing the relative soil capacity within the whole sample. Therefore, the larger value denoted higher soil capacity, and vice versa. The values of 0 and 1 indicated paddy fields with the lowest and largest soil capacity, respectively. The lowest soil capacity occurred in the paddy field with least

Table 2 The 21 soil chemical properties, based on which soil capacity was calculated for each of the sampled paddy fields

Soil chemical property	N	Min	Max	Mean	Std. D	CV (%)
pH	110	5.66	6.50	6.13	0.20	3.33
EC (ms/cm)	110	0.04	0.19	0.08	0.03	33.08
Humus (%)	110	2.51	9.20	5.25	1.60	30.49
Phosphate absorption coefficient	110	168.00	1295.69	852.41	212.98	24.99
CEC (meq/100 g)	110	6.35	31.00	19.85	5.97	30.05
Ammonium nitrogen (mg/100 g)	110	0.19	1.63	0.85	0.35	40.67
Nitrate nitrogen (mg/100 g)	110	0.10	2.99	0.34	0.36	106.85
Effective phosphoric acid (mg/100 g)	110	1.87	31.10	10.96	5.75	52.50
Exchangeable potassium (mg/100 g)	110	8.43	30.80	17.98	5.14	28.57
Exchangeable lime (mg/100 g)	110	122.00	472.50	312.29	90.03	28.83
Exchangeable magnesia (meq/100 g)	110	18.31	115.57	57.66	18.96	32.88
Potassium saturation (%)	110	0.86	3.51	2.01	0.55	27.13
Lime saturation (%)	110	34.02	68.52	56.64	5.77	10.19
Magnesia saturation (%)	110	8.57	24.92	14.71	3.40	23.11
Lime/magnesis	110	2.19	6.84	4.03	0.93	22.97
Magnesia/potassium	110	3.45	18.12	7.80	2.71	34.79
Exchangeable manganese (%)	110	1.38	64.94	13.01	13.61	104.60
Soluble zinc (%)	110	3.14	72.68	18.80	9.74	51.81
Soluble copper (%)	110	1.08	12.25	6.68	2.51	37.63
Free iron oxide (%)	110	0.28	6.78	2.00	1.23	61.28
Effective silicic acid (mg/100 g)	110	6.93	22.61	11.90	3.45	28.95

Data source Survey by the authors

content of exchangeable magnesia and its ratio to exchangeable potassium, both ranked the 110th. In contrast, paddy field with the highest soil capacity was mostly rich in free iron oxide and exchangeable potassium, ranked the 1st and 6th in the sample, respectively. Farming condition scores were the managers' appraisal of the farming condition of the paddy fields, including the height difference, water depth, water leakage, former crop, water inletting, fertility unevenness, illumination, and herbicide application.

Comparison on values of the CV indicated that among the output variables, the largest CV—21.8%—occurred for the full-grain rice, while CVs of other yield indicators were approximately equal to 11%. Among the input variables, field area showed the largest variability, followed by the amount of fertilizer nitrogen and soil capacity, both of which are measured as the most important yield determinants in Tsujimoto et al. (2009). Meanwhile, air temperature, solar radiation, and farming condition score varied with smaller CVs lesser than 8% (Table 1). Both the air temperature and solar radiation varied negatively with a later date of transplanting the rice. As

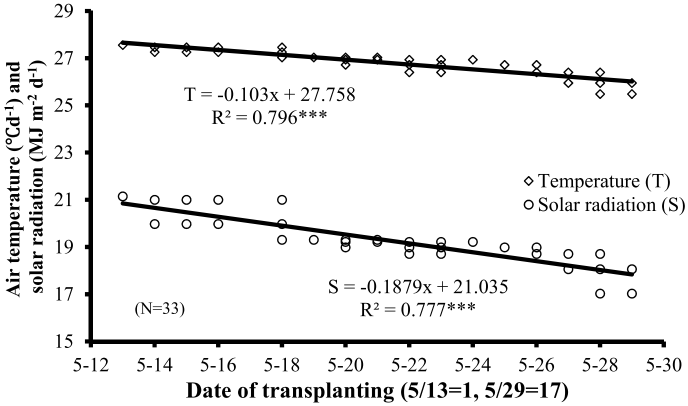

Fig. 1 Daily average air temperature and solar radiation of 20 days since heading on different date of transplanting in the sampled paddy fields, valid number of which decreased since the duplicate cases are merged *(Data source* Survey by the authors. *** indicates statistical significance at the 0.01 level)

shown in Fig. 1, the date number was much reduced than that of the paddy fields, because transplanting was conducted on multiple fields in the same day. However, even monitored in the same day, the values of air temperature and solar radiation varied slightly in some fields. Thus, merging the duplicate cases, 33 fields were included in the regression analysis. The estimated regression equation indicated that delaying transplanting by one day resulted in an approximately 0.1 °C reduction in the daily average air temperature, and a 0.18 MJ reduction in the daily average solar radiation per m^2. Hence, to some extent, the daily average air temperature and solar radiation of 20 days since heading were adjustable by changing the date of transplantation. Since both strongly affected by solar radiation, water temperature was identified as much significantly related to air temperature ($r = 0.89$) than it did to the water depth ($r = 0.32$). Nevertheless, this chapter aimed to improve irrigation management in practice, thus the controllable variable of water depth was included, while the uncontrollable air temperature was excluded.

2.2 Theory of the DEA Model

DEA measures the efficiency of the DMUs relative to a frontier constructed through linear programming. This nonparametric method was proposed by Charnes et al. (1978), with the assumption of CRS (constant returns to scale), which holds when all firms are operating at an optimal scale (Coelli et al. 2005). It was generalized by Banker et al. (1984), assuming VRS and that the weight of each DMU add up to unity. Thus, get the input oriented VRS model:

$$\min \theta_i$$

$$\text{subject to } -\mathbf{y}_i + \mathbf{Y}\lambda \geq 0$$

$$-\theta_i \mathbf{x}_i + \mathbf{X}\lambda \geq 0 \quad (i = 1,\ 2,\ \ldots,\ n) \tag{1}$$

$$\mathbf{I1}'\lambda = 1$$

$$\boldsymbol{\lambda} \geq 0,\ 0 \leq \theta_i \leq 1$$

where $\mathbf{Y}$ and $\mathbf{X}$ are the output and input matrix, respectively; $\mathbf{y}_i$ and $\mathbf{x}_i$ are the output and input vector of the *i*-th DMU, respectively; $\boldsymbol{\lambda}$ is an $n \times 1$ vector, serving as a weight system to each DMU in forming an optimal combination of inputs and outputs, the frontier, for the *i*-th DMU; θ_i is a scalar for the *i*-th DMU, used to scale the $\mathbf{x}_i$ to achieve the optimal combination of inputs, with a value of unity indicating a point on the frontier—a technically efficient DMU; and **I1** ($\mathbf{I1}'$ means its transpose) is an $n \times 1$ vector of unities, ensuring that the sum of all the weights assigned to the benchmarking DMUs equals 1. Thus, the fabricated benchmarks (the optimal combination of inputs and outputs) are similar in scale to the *i*-th DMU (Coelli et al. 2005), and so, the DEA model of Eq. (1) seeks to reduce the inputs as much as possible, relative to the empirically-constructed identical and optimal combination of inputs and outputs for each DMU.

Equation (1) represents the VRS DEA model, and the θ_i showcases the pure technical inefficiency. Removed the constraint of $\mathbf{I1}'\boldsymbol{\lambda} = 1$, Eq. (1) becomes the CRS DEA model, and the corresponding θ_i indicates the total inefficiency (i.e., production or economic efficiency). If the θ_i obtained from the CRS DEA, differs from that calculated by the VRS DEA, there exists scale inefficiency (Coelli et al. 2005), which is the ratio of the total efficiency (i.e. CRS θ_i) to the pure technical inefficiency (i.e. VRS θ_i). Thus, the total efficiency is decomposed into two components arising from scale inefficiency and pure technical inefficiency.

2.3 Effect of Irrigation Management

In the second stage, the High-10 and Low-10 paddy fields were the ten fields with the highest and lowest technical efficiency, respectively. They were analyzed based on the technical efficiency and slack measured in the DEA.

Based on Tsujimoto et al. (2009) and the model published by the Food and Agriculture Organization (Allen et al. 1998) and cited by Choudhury and Singh (2016), we divide the total growth duration into four stages. S_1 included the 40 days from

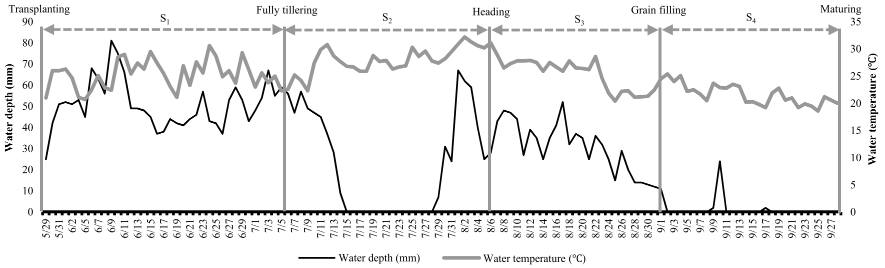

Fig. 2 Image of irrigation management in a paddy field of high production efficiency, where the water depth and water temperature are monitored at 18:30, divided into four growth stages from transplanting to maturing (*Data source* Survey by the authors)

transplanting to fully tillering, S_2 covered the duration from fully tillering to heading, S_3 referred to the 25 days from heading to grain filling, i.e., the early-middle maturity stage, and S_4 consisted of the remaining days until complete maturity (Fig. 2). The irrigation management was measured in terms of the water depth and water temperature. The monitoring device mainly consisted of three parts: (1) the sensor head immersed in water to detect the water depth and water temperature, (2) the sensor box to process the data gathered and sent to the farming visualization system (FVS) via (3) the antenna. The FVS can report the field-specific water depth and water temperature in forms of maps, graphs, and tables. All are accessible by internet terminals or mobile Apps, and thus, promote precise and efficient irrigation management (Nanseki et al. 2016). Although being monitored every 10 min, the data used in this chapter was collected at 18:30, when the soil temperature is most easily affected by the performance of irrigation management in the paddy field (Matsue 2016). Figure 2 shows an image of the varying water depth and water temperature at 18:30 for growth stages S1 through S_4, in a paddy field of high production efficiency. Fluctuation of the two curves illustrated the significant correlation ($r = 0.32$) between water depth and water temperature, thus as major aspect of irrigation management, the former determined the latter in a positive way.

3 Results and Discussion

3.1 DEA Analysis on Production Efficiency

(1) Efficiency summary

The efficiency summary in Table 3 shows that 29 paddy fields are in the status of full efficiency and serve as benchmarks for the other paddy fields. For convenience of analysis, they are defined as Type I. Furthermore, the rest 81 paddy fields had a total efficiency lesser than 1, within which 17 paddy fields had a technical efficiency

Table 3 Efficiency and the status of returns to scale for the different types of DMUs[a]

Type	Number of DMUs	Mean of efficiency			Number of DMUs with[b]		
		Total	Technical	Scale	*crs*	*irs*	*drs*
I	29	1.000	1.000	1.000	29	0	0
II	17	0.938	1.000	0.938	0	16	1
III	64	0.890	0.974	0.914	4	62	2
Total	110	0.927	0.985	0.940	29	78	3

[a]Decision making units, same to the paddy fields in this chapter
[b]*crs* =constant returns to scale; *irs* = increasing returns to scale; *drs* = decreasing returns to scale
Software DEAP 2.1
Data source Survey by the authors

score equal to 1 and were referred to as Type II. This indicated that in these paddy fields, the production efficiency can only be improved through equal proportional adjustment of the inputs. To be clear, the scale should be increased for 16 paddy fields, while decreased in the remaining fields. The average scale efficiency of 0.938 indicated that the scale adjustment can increase the production efficiency by 6.2%.

Meanwhile, there were 64 paddy fields, referred to as Type III, having technical and scale efficiency lesser than 1. In these paddy fields, the production efficiency can be improved by reducing the inputs and increasing the scales, keeping the outputs constant. The average technical efficiency of Type III was 0.974, implying that 2.6% of the inputs can be reduced by eliminating technical inefficiency. Meanwhile, production efficiency can still be improved by 8.6% through scale adjustment, according to the information of DMUs with different returns to scale shown in Table 3, i.e., increasing and decreasing the scale in 62 and two paddy fields, respectively.

Viewing from the whole sample, the total production efficiency can be improved by 7.3%, of which 1.5% can be fulfilled through technical improvement and, thus, input reduction, while about 6% would be realized by adjusting the scales, increasing in 78 and decreasing in three of the 110 paddy fields.

(2) Slack analysis of the outputs

In DEA analysis, the slack of an output shows the margin that a DMU can improve the output, referring to the benchmarking DMUs identified by DEA. Here, the output slacks occurred only in Type III; as summarized in Table 4, ratios of slack calculated in all paddy fields were lesser than those of Type III. For instance, considering the entire sample, the yields of the sorted brown rice can be increased by 1.70%, while it can be increased by as much as 2.94% for Type III. Meanwhile, due to the much larger dispersions among paddy fields of different efficiency, the yield of full-grain rice can be increased more than other kinds of yield. Within Type III, the average slack of full-grain rice yield was greater than 20%, while those of other kinds of yields vary from 2 to 4%. This indicated that compared to an increase in quantity, a much higher margin is associated with improvement in quality for the inefficient paddy fields.

Table 4 Output and input average slacks of rice yield, in terms of all the paddy fields and those of Type III. The average slacks are shown in terms of both absolute values and percentages

Variable	All paddy fields				Type III			
	Origin	Target	Slack	Slack (%)	Origin	Target	Slack	Slack (%)
	(1)	(2)	(3) = (2)−(1)	(4) = (3)/(1)	(5)	(6)	(7) = (6)−(5)	(8) = (7)/(5)
Output: Yield (kg/ha)								
Raw paddy	6689.65	6789.50	99.85	1.49	6665.18	6836.79	171.61	2.57
Paddy with 15% moisture	6143.82	6239.89	96.07	1.56	6114.71	6279.84	165.13	2.70
Unsorted brown rice	4877.03	4943.83	66.81	1.37	4859.63	4974.45	114.82	2.36
Sorted brown rice	4292.91	4365.97	73.07	1.70	4265.81	4391.39	125.58	2.94
Milled rice	3760.61	3851.60	90.99	2.42	3729.28	3885.67	156.38	4.19
Full-grain rice	2669.60	2974.57	304.98	11.42	2610.38	3134.56	524.18	20.08
Input variables								
Field area (m^2)	2513.99	2354.16	112.06	4.46	2717.48	2442.77	192.61	7.09
Air Temperature (°C/day)	26.75	26.33	0.01	0.03	26.86	26.14	0.01	0.05
Solar radiation (MJ/m^2/day)	19.16	18.52	0.34	1.77	19.31	18.21	0.58	3.03
Fertilizer nitrogen (kg/ha)	74.52	61.97	11.06	14.85	80.96	59.39	19.02	23.49
Soil capacity	0.56	0.50	0.05	9.34	0.63	0.52	0.09	14.28
Farming condition score	32.65	31.82	0.32	0.97	32.98	31.55	0.55	1.66

Software DEAP 2.1
Data source Survey by the authors (sample size = 110)

(3) Slack analysis of the inputs

In contrast, the slack of an input indicates the extent of excess supply or incomplete usage, reduction of which leads to higher efficiency (Martine et al. 2003). In case of input-oriented VRS model, the DEAP 2.1 divided the slack into two parts: the radial movement from origin of each inefficient DMU to the frontier, and the additional movement on the frontier to save some inputs, keeping the same output level. As mentioned above, for the paddy fields of Type I and II, the pure technical efficiencies equaled 1, and hence, there was no margin to adjust the input, maintaining a constant output level. Therefore, as sum of the radial additional movement, slack analysis was conducted only for Type III.

As shown in Table 4, fertilizer nitrogen had the largest slack of 14.85%, followed by soil capacity with 9.34%, for all paddy fields, and the corresponding slacks increase to 23.49 and 14.28%, respectively, for Type III. These ratios showed the relatively redundant or inefficient use of the two kinds of inputs. Meanwhile, the air temperature and farming condition demonstrate the efficient usage by the smallest slacks. The slack analysis of each variable, i.e., the constraining factor of each paddy field, can be beneficial in increasing the production efficiency through the appropriate adjustment of the inputs.

3.2 Irrigation Management to the Production Efficiency

(1) Comparison of the outputs and inputs

In the second stage, we analyzed the effect of irrigation management on the technical efficiency measured by DEA. As introduced above, we focused on 20 paddy fields to represent paddy fields with high and low technical efficiency. The average values of the output and input variables were summarized in Table 5. The paddy fields with high efficiency yielded more than those with low efficiency, in terms of all the output variables. Moreover, the results of the t-test showed that the average yield per hectare of efficient paddy fields, 3146 kilograms, was significantly higher than the yield of the inefficient fields, which was about 2500 kilograms. Among the input variables, the average values of the air temperature, solar radiation, fertilizer nitrogen, and farming condition of the efficient paddy fields, were lesser than the corresponding variables of the inefficient fields. The above comparison indicates that higher yield and less input relate to technical efficiency.

(2) Comparison of irrigation management practices

As shown in Table 6, the average water depth was the deepest in S_1, followed by S_3. Deeper water is adopted to protect the seedling from frost and strong wind in S_1 and to improve grain quality in S_3 by resisting strong evaporation and the over absorption of cadmium. The average water depth was at its lowest for harvest preparation in S_4, followed by S_2, when the lower average water depth facilitates the top dressing and the decomposition of organic survival substances (Goto et al. 2000).

Table 5 Average output and input of the High-10 and Low-10 paddy fields, in terms of the technical efficiency measured using DEA. A t-test is conducted to calculate the significance of their differences

Paddy field	Output: Yield (kg/ha)					
	Raw paddy	Paddy with 15% moisture	Unsorted brown rice	Sorted brown rice	Milled rice	Full-grain rice
High-10	6951.02	6397.68	5067.19	4476.07	3952.90	3145.92
Low-10	6791.05	6240.90	4944.66	4402.16	3815.57	2500.62
Differ[a]	159.97	156.78	122.53	73.91	137.33	645.30**

Paddy field	Input variables					
	Field area (m^2)	Tempe-rapture (°C)	Solar radiation (MJ/m^2)	Fertilizer nitrogen (kg/ha)	Soil capacity	Farming condition score
High-10	3286	25.99	18.06	61.99	0.52	31.80
Low-10	3369	27.13	19.68	125.03	0.66	34.11
Differ[a]	−83	−1.14***	−1.62***	−63.04***	−0.13	−2.31**

[a]The balance of high–low, ** and *** indicate statistical significance at 5 and 1%, respectively

Data source Survey by the authors (sample size = 110)

Table 6 Average water depth and water temperature of the High-10 and Low-10 paddy fields, in terms of the technical efficiency measured using DEA. A t-test is conducted to calculate the significance of their differences

Paddy field	Peer count[a]	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
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[b]	18.4	0.054	2.17	1.25	−3.68	3.02	0.32	1.08^{***}	-1.27^{**}	0.11

[a]The times of being benchmark for other DMUs. b: the balance of high–low, ** and *** indicate significance at 5 and 1%, respectively. c: S1 includes the 40 days from transplanting to fully tillering, S2 covers the duration from fully tillering to heading, S3 refers to the 25 days from heading to grain filling, i.e., the early-middle maturity stage, and S4 consists of the remaining days until complete maturity

Data source Survey by the authors (sample size = 110)

Nevertheless, no significant difference was detected in the average water depth of the High-10 and Low-10 paddy fields. In contrast, the average water temperature of the High-10 paddy fields was significantly lower than that of the Low-10 paddy fields, in S_2 and S_3. Figure 2 shows the average water depth and average water temperature in a paddy field of high production efficiency.

In addition, the average technical efficiency of the Low-10 paddy fields was 0.946, only 0.054 lower than that of the High-10 paddy fields (Table 6). It suggests that little inequality exists in the efficiency of the paddy fields sampled from the same farm.

Figure 3 plots the similar relationship between water temperature and yield of full-grain rice, within the growth stages of S_2 in (a) and S_3 in (b), respectively, in the whole sample of 97 paddy fields with water temperature monitored. For comparison, the 20 paddy fields of high and low efficiency are illustrated as well. As illustrated

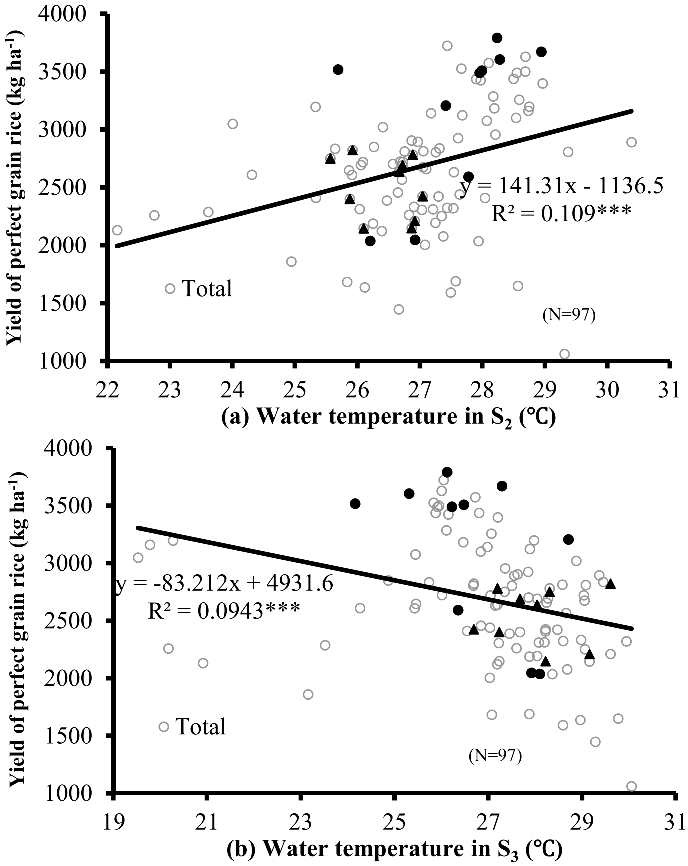

Fig. 3 Relationship between yield of full-grain rice and the average water temperature monitored daily at 18:30 in the growth stages of (**a**) S_2 and (**b**) S_3 (*Data source* Survey by the authors. *** indicates statistical significance at the 0.01 level)

in the two figures, some high efficiency points were lower than those of other paddy fields. Thus, it is not necessarily that high yield results in high technical efficiency. In S_2, from fully tillering to heading, the young panicle is in the under-growing phase and, thus, susceptible to low air temperature and drought. In addition, after the end of the rainy season, the soil capacity recovers together with the increasing air temperature. Hence, the higher water temperature needs to be maintained at this stage to avoid sterility failure due to low air temperature (Goto et al. 2000). As shown in Fig. 3a, higher water temperature was significantly related to higher rice yield in the whole sample. In contrast, S_3, the early-middle maturity stage, included 25 days from heading to grain filling, vital for starch accumulation. In this stage, especially after flowering occurs, lower temperatures are necessary to facilitate the branching, extension, and vitality maintenance of the roots (Asaoka et al. 1985). As shown in Fig. 3b, lower water temperature contributed to higher rice yield. Therefore, yield is much more affected by the water temperature than by the water depth. This finding was in accordance with Roel et al. (2005) and Saga et al. (2010), where water temperature was identified as a determinant of rice production. Meanwhile, the water temperature can be increased through a higher water depth, due to the positive relationship identified between them, in the growth stages of both S_2 and S_3.

From the perspective of farm management, we analyzed the relationship between the date of transplantation, and average water temperature sampled daily at 18:30 in S_2 and S_3. As shown in Fig. 4, significantly quadratic relationships were identified in both stages. This indicated that the average water temperature in both stages decreased at first and then increased after the turning points, which the corresponding transplantation date were 19th and 27th of May, respectively. Thus, from May 19th to 27th, the earlier transplanting of rice negatively affected the yield via the higher average water temperature of each 18:30 in S_2, but positively affects the yield via lower average water temperature of each 18:30 in S_3. Considering the offsetting effect shown in Fig. 3, changing the date of transplantation can slightly affect the yield via the water temperature.

3.3 Effects of the Irrigation Management on the Technical Efficiency

The effects of the water depth and water temperature were evaluated with the Tobit regression, to deal with the inconsistency of the ordinary least squares regression that arises from the over-existence of the single-valued efficiency (Tobin 1958). Through the application of EViews 7.2, maximum likelihood estimation was conducted. The effect of each determinant on the technical efficiency was estimated and presented in Table 7. Model I included the paddy fields with highest and lowest production efficiencies, while Model II extends the paddy fields to the whole sample.

A comparison between the two models indicated that a significant effect of irrigation management was identified in Model I. In contrast, both the water depth and

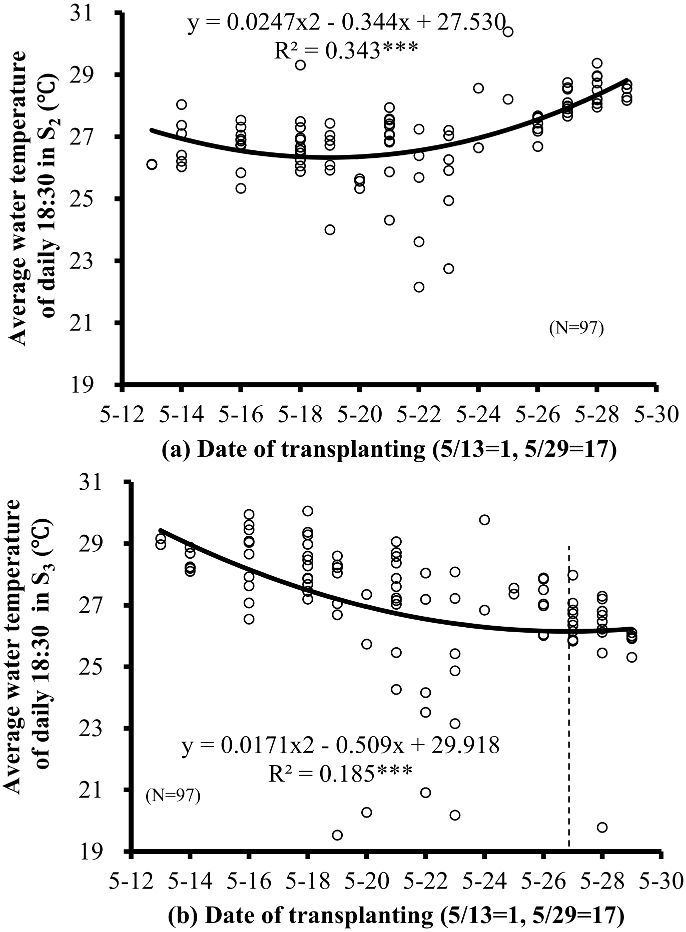

Fig. 4 Date of transplanting and average water temperature of daily 18:30 in (**a**) S_2 and (**b**) S_3 (*Data source* Survey by the authors. The lowest water temperature occurs when rice was transplanted on 19th and 27th of May, respectively. *** indicates statistical significance at the 0.01 level)

water temperature were insignificant in affecting the technical efficiency in all four stages. Thus, we concentrated the analysis on the paddy fields with the highest and lowest production efficiencies. Like the above analysis, the water temperatures in S_2 and S_3 were measured to be significant at 5 and 10% respectively, for the technical efficiency. According to the coefficients, an increase of 1 °C in water temperature in S_2 tended to increase the efficiency by 0.012, while in S_3 a decrease in efficiency by the same amount was realized. As measured by Tsujimoto et al. (2009), high water temperature in S_2 increased the rice yield through high levels of redox potential. In contrast, lower water temperatures in S_3 favored nutrition used for grain growth, while maintaining the activity of the root and stem.

Table 7 Result of the Tobit regression between the technical efficiency measured using DEA and irrigation management, in different growth stages

Variable	Model I		Model II	
	Coefficient	z-Statistic	Coefficient	z-Statistic
Water depth in S_1	0.000722	1.348	0.000131	0.768
Water depth in S_2	−0.000886	−1.215	0.000202	0.685
Water depth in S_3	−0.000216	−0.497	−0.000207	−1.449
Water depth in S_4	0.001057	1.298	−0.000482	−1.857
Water temperature in S_1	−0.003342	−0.748	0.001624	0.782
Water temperature in S_2	0.012140^{**}	2.022	0.002913	1.705
Water temperature in S_3	-0.011817^{***}	−2.972	−0.001509	−1.471
Water temperature in S_4	0.008341	1.366	−0.001177	−1.492
(Constant term)	0.839491	3.055	0.934307	20.829
Included observations	18		94	
Log likelihood	49.602		250.550	

Dependent variable Technical efficiency
Method ML-censored normal Tobit; Software: EViews 7.2
Data source Survey by the authors

4 Conclusion

The results of DEA analysis showed that among the 110 paddy fields, 29 were scored as full efficiency and act as benchmarks for the other inefficient paddy fields. There were 17 paddy fields with technical efficiency scores of 1, indicating that an input adjustment will not change the output efficiency. Consequently, increasing the scales was the only solution to improve production efficiency. Meanwhile, there were remaining 64 paddy fields with technical efficiencies lesser than 1, where inputs can be reduced. In more than 70% of the paddy fields, the efficiency can be increased by increasing the scales. Slack analysis of the outputs showed that the full-grain rice yield has the largest average margin of more than 20%, while those of the other yields have margins lesser than 4%. This finding indicated that compared to an increase in quantity, a much higher margin lied in the improvement in quality for the inefficient paddy fields. Meanwhile, slack analysis of the inputs indicated that fertilizer nitrogen has the largest slack, followed by soil capacity, in terms of relatively redundant or inefficient usage. In contrast, the air temperature and farming condition showed efficient usage with the smallest slacks. Further comparison indicated that the efficient paddy fields yield significantly more than those with low efficiency, particularly for full-grain rice. Among the input variables, air temperature, solar radiation, fertilizer nitrogen, and farming condition of the high-efficiency paddy fields, had lower values than those of the inefficient fields. Thus, higher yield and less input related to efficient production.

A comparison of irrigation management indicated that the water depth of the High-10 paddy fields was not significantly different compared to that of the Low-10 paddy fields. In contrast, the average water temperature of the High-10 paddy fields was significantly different compared to that of the Low-10 paddy fields—higher in S_2 and lower in S_3. Similarly, using a Tobit regression, water temperature in S_2 and S_3 was identified as significant to the measurement of technical efficiency, in a positive and negative manner, respectively. Therefore, the rice yield was much more affected by the water temperature than by the water depth.

Water temperature is an essential indicator for rice production. In addition to real-time monitoring, analysis on the determinants and effects of water temperature are necessary to increase the rice yield. In future studies, more empirical models—e.g., covariance structure analysis and multivariate regression—can be adopted to determine the effect of the yield determinants and the interactions among them, including water temperature.

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Two-Stage DEA of 122 Paddy Fields in Hokuriku Region

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In Japan, rice production is undergoing a transition from acreage reduction to an improvement in efficiency and competitiveness. Owing to the global warming, irrigation management is increasingly important in maintaining soil temperature and fertility for rice productivity. This chapter aimed to measure the production efficiency of rice yield, using a two-stage DEA like the former chapter. The data comprised of 122 paddy fields of Koshihikari, one of the most popular Japanese rice varieties. The data was sampled from a large-scale farm located in the Hokuriku Region of Japan in 2015. In the first stage of the analysis, the outputs included yields of raw paddy, paddy with 15% moisture, unsorted, sorted, fully shaped, and milled brown rice. The inputs included the field area, temperature, solar radiation, fertilizer nitrogen, soil capacity, and farming conditions. The results indicated that there was a large margin to increase the yields, and an enlarged scale could increase the efficiency of most paddy fields. The largest input slacks occurred in land capacity and field area. In the second stage, we determined the significant effects of irrigation management on rice production efficiency at different growth stages in the 20 paddy fields of highest and lowest efficiency. Finally, we discussed the interactions between air temperature, water depth and water temperature.

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1 Introduction

Confronting decreases in gross production and high input costs of rice (Oryza sativa L.), the Japanese government is promoting the transition from acreage reduction to improvements in efficiency and competitiveness. In 2014, the production of sorted brown rice was 8.43×10^6 t, 40% lower than the 1985 production of 11.83×10^6 t (MAFF 2016a). Meanwhile, the average production cost of sorted brown rice was 256.9 JPY per kilogram (MAFF 2016b). The cost typically decreased as farming scale increased. In the large farms over 15 hectares, the average production cost of sorted rice was 193 JPY per kilogram. From our research consortium, we found that the cost per kilogram decreased further to 155 JPY and 150 JPY for farms with 30 hectares and over 100 hectares of farmland, respectively (Nanseki et al. 2016). Nevertheless, it was difficult to reduce the production costs further by merely increasing the scale, thereby increasing production efficiency, without technological innovation. Thus, we analyzed rice production from the perspective of technical efficiency using field-level data from a large-scale farm. To isolate the bias arising from the differences in rice varieties, we concentrated the study on Koshihikari. As one of the most popular rice varieties in Japan, it accounts for approximately 35.6% of the total domestic planting area (Komenet 2020).

Many studies, including Abdullah and Ali (2014), Barrett et al. (2010), and Kozak et al. (2007), focused on the determinants of rice yield using overseas field-level on-farm data. In addition to these studies, a study by Hirai et al. (2012) used experimental data sampled in Japan. In our prior study, we analyzed the determinants of Koshihikari yield, using 2014 data from a large-scale farm in the Kanto Region of Japan (Li et al. 2016). However, we found few similar studies sampling field-level on-farm data in Japan. Therefore, it is important to accumulate further empirical evidences on the research fields.

In this chapter, we applied the analytical flamework employed in our previous study to another farm in the different prefecture and analyzed the determinants of the 2015 rice yield, using DEA in the first stage. The effect of irrigation management on rice production efficiency was analyzed in the second stage. Irrigation management is the control and movement of water resources to minimize damage to life and property and to maximize efficient beneficial use. Irrigation systems make the most efficient use of limited water supplies for agriculture (NRCS 2017).

Based on the pioneering work of Farrell (1957), studies devoted to the estimation of efficiency mainly embrace two approaches: the parametric function symbolized by the stochastic frontier production (SFP, Aigner et al. 1977) and the nonparametric approach of DEA (Charnes et al. 1978). SFP requires the specification of the function between inputs and outputs. In contrast, DEA is advantageous in that it includes multiple inputs and outputs with different units, simultaneously. Moreover, it avoids the parametric specification of technology and the distributional assumption (Coelli et al. 2005).

A multi-input model is necessary to measure agricultural efficiency when parameters such as land, fertilizer, and water are considered. Furthermore, a variety of yield variables should be used to measure not only quantity, but also quality, which is linked to the market value. The input and output variables may be in different units without any relevant parameters that can be assumed accurately beforehand. Moreover, the farmers can control the quantity of inputs rather than the outputs relatively freely. Farms are difficult to operate at an optimal scale because of varying socio-economic factors, including natural and marketing risks, government regulations, and financial constraints (Nanseki et al. 2016). Therefore, we adopted an input-oriented DEA model assuming VRS.

To interpret the differences in production efficiency and adjustable slacks measured by DEA, we adopted irrigation management practices in the second stage. As an indispensable factor, water affects many aspects of rice productivity e.g., nutrition supplication and weed control (Goto et al. 2000; Sellamuthua et al. 2011). Rice is also a major water-consuming crop and in Asia, about 80% of the irrigated fresh water is consumed by rice (Bouman and Tuong 2001; Wang et al. 2016). Moreover, with global warming, it is increasingly important to stabilize soil temperature, control excessive decomposition of organic matter, and maintain soil capacity through proper irrigation management (Goto et al. 2000; Tsujimoto et al. 2009). Many studies have measured the effects of irrigation management from two perspectives. Roel et al. (2005) estimated the effects of water temperature on rice production in California, US, by calculating the total number of hours and days it was below a given threshold. Saga et al. (2010) included water temperature as a form of energy in estimating the high-yield rice plants of Japan. Tao et al. (2015), Choudhury and Singh (2016) estimated the impact of irrigation management on rice yield in China and India, respectively. As the effects of irrigation management may vary at different growth stages and conditions, its subsequent analysis rather than its inclusion in the first stage of the DEA model was preferable. Based on the analyzing model presented in Li et al. (2018), this chapter included both water temperature and water depth, and analyzed their effects on various paddy fields. To further amplify the effects, a comparison of 20 paddy fields of high and low efficiency was conducted.

We composed this manuscript based on an oral presentation conducted on the annual symposium of the Japan Farm Management Society (Li et al. 2017), to fulfill several objectives in this chapter. (1) We formulated a DEA model appropriate for analyzing the efficiency of rice production using the paddy fields as the decision making units (DMUs); (2) revealed the overall attributes of rice production efficiency; (3) determined the theoretical margins for increasing yields and saving inputs; (4) identified the effects of the depth and temperature of water on rice production and technical efficiency; and (5) summarized our major findings, and put forward recommendations to improve rice yield.

2 Materials and Methods

2.1 Sample and Data

The dataset used in this book was constructed in the "NoshoNavi1000" projects (Nanseki et al. 2016; Nanseki 2019). In this chapter, the DEA model shown in Chapter "Production Efficiency and Irrigation of 110 Paddy Fields in Kanto Region" in Eq. 1 was adopted, and the following six rice yield variables were measured: raw paddy, paddy with 15% moisture, unsorted, sorted, fully shaped, and milled brown rice (Table 1). The raw paddy weight and percentage of moisture content were monitored directly by the combine harvester equipped with advanced ITs. Furthermore, the yield of the paddy with 15% moisture was calculated using the raw paddy yield and average moisture content measured by smart combine harvester. Brown rice was then weighed after hulling, and for sorted brown rice we retained only grains thicker than 1.85 mm. Milled rice referred to the fluffy white-yellow rice with the bran and germ removed, while fully shaped rice excluded the deformed, crashed, immature,

Table 1 The yield of six forms of rice constituting the outputs and six determinants as inputs in the DEA model of the sampled paddy fields

Variable	N	Min	Max	Mean	Std.D	CV (%)
Output: yield of (kg/ha)						
Raw paddy	122	5948.64	9983.33	8058.98	758.36	9.41
Paddy with 15% moisture	122	5423.76	9114.20	7358.73	666.46	9.06
Unsorted brown rice	122	4401.63	7360.44	5934.22	530.20	8.93
Sorted brown rice[a]	122	4172.75	6753.21	5438.19	493.49	9.07
Milled rice[b]	122	3613.42	5843.36	4797.12	436.53	9.10
Full-grain rice	122	2934.91	5226.98	4111.93	408.09	9.92
Input variables						
Field area (m^2)	122	452.00	4458.00	1354.70	1028.80	75.94
Temperature (°C)[c]	122	25.55	26.60	26.19	0.29	1.11
Solar radiation (MJ/m^2)[c]	122	18.07	21.82	20.37	1.17	5.73
Fertilizer nitrogen (kg/ha)[d]	122	92.01	136.01	112.49	7.71	92.01
Land capacity[e]	122	0.00	0.92	0.48	0.18	37.98
Farming condition score[f]	122	27.00	38.00	33.97	1.68	4.93

[a]Grains with the thickness over 1.85 mm. [b]Fluffy white-yellow grain with the bran and germ removed. [c]Average values within 20 days after the heading. [d]Calculated according to the amounts of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizers and the corresponding nitrogen contents. [e]Compound value of 5 principals of 21 soil analysis indicators transformed using $(x_i - \max X)/(\max X - \min X)$. [f]Managers' appraisal of the farming condition of paddy fields, including height difference, water depth, water leakage, former crop, water inletting, fertility unevenness, illumination, and herbicide application

Data source Survey by the authors

and dead grains. Quantity was the focus of the first four outputs, while the last two outputs were more focused on quality. In the domestic market of Japan, the first-class rice, composed of about 70% full-grain rice, fetches the highest price.

Within the smart combine harvester, a small matchbox sized sensor, set at the input slot of the grain tank, monitored yield. The sensor probed the grain flow rate, whereas conventionally a much larger load cell is set at the bottom to measure the total grain weight in the tank. This innovation enabled real-time, precise, and low-cost monitoring, expelling the bias out of the grain tank stuffing state—whether the tank is filled or not. The smart combine harvester could detect the threshing or screening yield with loss sensors and minimize it by automatic operation. Finally, the field-specific data was conveyed, via the global navigation satellite system (GNSS), to the cloud server shared by the company, institutes, and farms. Thereafter, the yield, moisture content, and farming time were automatically mapped, using Google Maps. The maps were essential for farms to capture the yield variations among the paddy fields, and update their farming plans, accordingly (Nanseki et al. 2016).

The inputs included the field area, average temperature, and solar radiation within 20 days after heading, the amount of fertilizer nitrogen, soil capacity, and farming conditions. The temperature and solar radiation were monitored through meteorological observation devices every 10 min, and average values of these parameters were calculated. Fertilizer nitrogen was estimated based on the amount of chicken manure, chemical fertilizer, ammonium sulfate, and urea fertilizers, as well as their corresponding nitrogen contents, used. The soil capacity was measured using the compound values of five principals of 21 soil analysis indicators. Farming condition scores consisted of the managers' appraisal of the farming conditions of the paddy fields, including height difference, water depth, water leakage, former crop, water inletting, fertility unevenness, illumination, and herbicide application (Table 1).

Comparing the CVs, we found that among the output variables, full-grain rice had the largest CV (9.92%), while the CVs of other yield indicators were approximately 9%. Among the input variables, the largest CV was observed in the field area, followed by land capacity and amount of fertilizer nitrogen, respectively, both of which were measured as the most important yield determinants by Tsujimoto et al. (2009). At the same time, the temperature, solar radiation, and farming conditions score varied to a lesser degree, with CVs less than 6% (Table 1). Both the temperature and solar radiation varied negatively with a later date of transplantation (Fig. 1). The estimated regression equations indicated that delaying transplanting by 1 d resulted in an approximately 0.06 °C reduction in temperature and a 0.21 MJ reduction in solar radiation per m^2. Hence, to some extent, the average temperature and solar radiation within 20 days after heading were discretionary variables, when adjusting the date of transplantation.

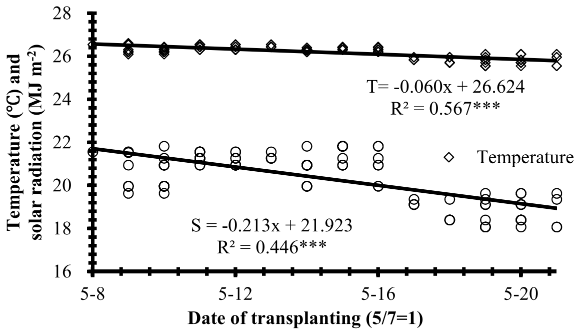

Fig. 1 Temperature and solar radiation at different dates of transplanting in the sampled paddy fields, where significant linear and negative relationships were identified

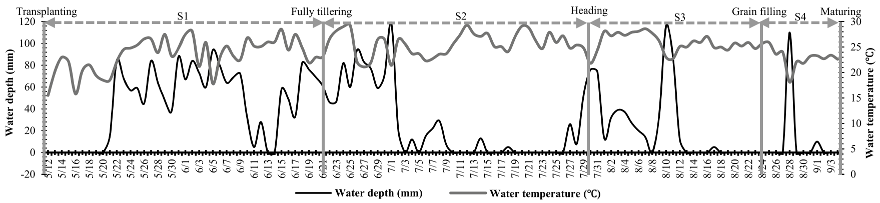

Fig. 2 Irrigation in a paddy field of high production efficiency, where the depth and temperature of water were monitored at 18:30 h, and divided into four growth stages from transplanting to maturation

2.2 *Effects of Irrigation Management*

In the second stage, the High-10 and Low-10 paddy fields, the ten fields with the highest and lowest technical efficiency, respectively, were analyzed based on the technical efficiency and slack measured in the DEA.

Based on Tsujimoto et al. (2009) and the model published by the Food and Agriculture Organization (Allen et al. 1998) and cited by Choudhury and Singh (2016), we divided the total growth duration into four stages. S_1 included the 40 d from transplanting to fully tillering, S_2 covered the duration from fully tillering to heading, S_3 referred to the 25 d from heading to grain filling, i.e., the early-middle maturity stage, and S_4 consisted of the remaining days until complete maturity (Fig. 2). Irrigation management was measured in terms of water depth and temperature. The monitoring device consisted mainly of three parts: (1) the sensor head immersed in water to detect the depth and temperature, (2) the sensor box to process the data gathered and sent to the farming visualization system (FVS) via (3) the antenna. The FVS can report field-specific water depth and water temperature in form of maps, graphs, and tables. All are accessible by internet terminals or mobile apps, and thus, promote precise and efficient irrigation management (Nanseki et al. 2016). Although being monitored every 10 min, the data used in this chapter was collected at 18:30 h, when the soil temperature was most easily affected by the performance of irrigation management in the paddy fields (Matsue 2016). Figure 2 showed the varying water depths and temperatures at 18:30 h for all growth stages, in a paddy field of high production efficiency across the sample.

3 Results

3.1 DEA Analysis of Production Efficiency

The summary of efficiency in Table 2 shows that 19 paddy fields were fully efficient and served as benchmarks for the other paddy fields. For convenience of analysis, they were defined as Type I. The remaining 103 paddy fields had a total efficiency less than 1, within which 27 paddy fields had a technical efficiency score equal to 1 and were referred to as Type II. This indicated that in these paddy fields, the production efficiency could only be improved through equal-proportional adjustments of all the inputs. Here, the scale should be increased according to the returns to scale information provided in the last columns of Table 2. An average scale efficiency of 0.921 indicated that the scale adjustment could increase the production efficiency by 7.9% (Coelli et al. 2005).

The 76 paddy fields left were referred to as Type III, having a technical and scale efficiency less than 1. In these paddy fields, the production efficiency could be improved by reducing the inputs and increasing the scales, while keeping the outputs constant. The average technical efficiency of Type III was 0.987, implying that 1.3% of the inputs could be reduced by eliminating technical inefficiency. Meanwhile, production efficiency could only be improved by 10.5% through increases in the scales of the paddy fields. For the entire sample, the total production efficiency could be improved by 9.0%, of which 0.8% could be fulfilled through technical improvement and, thus, input reduction, while about 8.3% could be realized by increasing the scales of 103 of the 122 paddy fields.

Table 2 Efficiency and status of returns to scale for the paddy fields in different types categorized in terms of their total, technical and scale efficiencies

Type	Number of DMUs	Mean of efficiency			Number of DMUs		
		Total	Technical	Scale	crs	irs	drs
I	19	1.000	1.000	1.000	19	0	0
II	27	0.921	1.000	0.921	0	27	0
III	76	0.884	0.987	0.895	0	76	0
Total	122	0.910	0.992	0.917	19	103	0

Note crs =constant returns to scale; irs = increasing returns to scale; drs = decreasing returns to scale
Software DEAP 2.1
Data source Li et al. (2017)

The slack of an output shows the margin for output improvement by a benchmarking DMU identified by DEA. Here, the output slacks occurred only in Type III; the ratio of slack calculated in all paddy fields were less than that of Type III (Table 3). For instance, considering the entire sample, the yields of the sorted brown rice and Type III could be increased by 1.76 and 2.82%, respectively. Not much dispersion existed among the paddy fields, in terms of the different types of rice yields. Within the entire sample, the ratios of yield slack ranged from 1.7 to 3.0%, while in Type III, they ranged from 2.8 to 5.0%. The largest and smallest slack ratios occurred in the raw paddy and sorted brown rice, respectively.

The DEAP 2.1 provided the input slack movement for each DMU. As mentioned above, for the paddy fields of Type I and II, the pure technical efficiencies equaled 1, and hence, there was no margin needed to adjust the input, maintaining a constant output level. Therefore, the radial and slack were analyzed only for Type III.

Table 3 Output and input slacks of rice yield, of all the paddy fields and of Type III. The slacks are shown in terms of both absolute values and percentages

Variable	All paddy fields				Type III			
	Origin	Target	Slack	Slack (%)	Origin	Target	Slack	Slack (%)
Output: Yield (kg/ha)								
Raw paddy	8058.98	8304.34	245.36	3.04	7926.96	8317.86	390.90	4.93
Paddy with 15% moisture	7358.73	7560.70	201.97	2.74	7257.63	7578.49	320.86	4.42
Unsorted brown rice	5934.22	6090.75	156.53	2.64	5855.25	6103.27	248.02	4.24
Sorted brown ricesorted brown rice	5438.19	5533.67	95.48	1.76	5378.64	5530.29	151.66	2.82
Milled rice	4797.12	4902.08	104.96	2.19	4728.70	4890.35	161.65	3.42
Full-grain rice	4111.93	4202.37	90.44	2.20	4083.58	4228.28	144.70	3.54
Input								
Field area (m^2)	1354.70	1274.25	80.44	5.94	1189.57	1060.43	129.14	10.86
Temperature (°C)	26.19	25.98	0.21	0.80	26.26	25.93	0.33	1.27
Solar radiation (MJ/m^2)	20.37	19.58	0.80	3.91	20.62	19.34	1.28	6.20
Fertilizer nitrogen (kg/ha)	112.49	110.84	1.66	1.47	112.89	110.46	2.43	2.16
Land capacity	0.48	0.41	0.07	13.81	0.47	0.37	0.10	21.64
Farming condition score	33.97	33.41	0.55	1.63	34.35	33.47	0.88	2.56

Software DEAP 2.1
Data source Li et al. (2017)

In the DEA analysis, the slacks showed the inputs that were in excess supply or not completely used (Audibert et al. 2003). As shown in Table 3, land capacity had the largest slack of 13.81%, followed by field area with 5.94%, for all paddy fields, and the corresponding slacks increased to 21.64 and 10.86%, respectively, for Type III. These ratios showed the relatively redundant or inefficient use of the two kinds of inputs. Meanwhile, the temperature, fertilizer nitrogen, and farming conditions demonstrated an efficient use by the much smaller slacks. The slack analysis of each variable, i.e., the constraining factor of each paddy field, could be beneficial in increasing the production efficiency through the appropriate adjustment of the inputs.

3.2 *Effects of Irrigation Management on Production Efficiency*

In the second stage, we analyzed the effects of irrigation management on the production efficiency measured by DEA. As mentioned above, we chose 20 paddy fields to represent paddy fields with high and low efficiency. The output and input variables were summarized in Table 4.

The paddy fields with high efficiency had higher yields than those with low efficiency for all the output variables. Moreover, the results of the t-test showed that the average yield per hectare of efficient paddy fields were significantly higher than that

Table 4 Outputs and inputs of the High-10 and Low-10 paddy fields in terms of the technical efficiency measured using DEA. A t-test was conducted to calculate the significance of their differences

Paddy field	Output: Yield (kg/ha)					
	Raw paddy	Paddy with 15% moisture	Unsorted brown rice	Sorted brown ricesorted brown rice	Milled rice	Full-grain rice
High-10	8521.72	7770.51	6251.73	5715.04	5086.84	4467.55
Low-10	7108.40	6518.14	5281.32	4919.50	4320.11	3809.73
Differ[a]	1413.32***	1252.37***	970.41***	795.53***	766.73***	657.82***
Paddy field	Input variables					
	Field area (m^2)	Temperature (°C)	Solar radiation ($MJ\ m^{-2}$)	Fertilizer nitrogen (kg/ha)	Land capacity	Farming condition score
High-10	1336	26.07	19.98	108.52	0.48	32.80
Low-10	1151	26.46	21.35	113.40	0.38	34.90
Differ[1]	185	−0.39***	−1.38**	−4.87	0.10	−2.10***

[a]The balance of high–low, ** and *** indicate significance at 5 and 1% probability levels, respectively

of the inefficient fields. For instance, according to the mostly used rice yield indicator in Japan, the average yield of sorted brown ricesorted brown rice in High-10 paddy fields was 5715 kilograms per hectare, 795 kilograms (approximately 16%) higher than that of the Low-10 fields. Among the input variables, temperature, solar radiation, fertilizer nitrogen, and farming conditions of the efficient paddy fields were less than the corresponding variables of the inefficient fields. This indicated that higher yields and lower inputs were related to efficient production.

As shown in Table 5, the average water level was the deepest in S_1. In this stage, a higher water depth may result in rotten roots or even plants thus, inhibiting yield and production efficiency. The average water depth of the Low-10 paddy fields was 51.68 mm, which was 40% higher than the average for the Top-10 fields. Thus, a lower average water depth benefitted the production efficiency. In these efficient fields, the average water depth for harvest preparation was the lowest in S_4 followed by S_3, where the lower water levels facilitated the top dressing and the decomposition of organic survival substances. On the other hand, higher water depths in S_3 may have improved efficiency by resisting the strong evaporation and over-absorption of cadmium (Goto et al. 2000).

In contrast, the water temperature of the High-10 paddy fields was significantly lower than that of the Low-10 paddy fields, in S_1, S_3, and S_4. In S_3, the early-middle maturity stage included the 25 d from heading to grain filling, vital for starch accumulation. In this stage, especially after flowering occurs, lower temperature is necessary to facilitate the branching, extension, and vitality maintenance of the roots (Asaoka et al. 1985). In S_4, a lower water depth and water temperature may help to resist lodging, constrain the activity of the plant, and facilitate harvesting conducted soon after the end of this stage. In the entire growth season, lower water temperature may limit over-evaporation thereby, preventing the withering of plants (Goto et al. 2000) thus, contributing to higher rice yields. Therefore, for the 20 paddy fields, technical efficiency was much more affected by water temperature than water depth. This finding was in accordance with Roel et al. (2005) and Saga et al. (2010), where water temperature was identified as the determining factor in rice production.

4 Discussion

The DEA analysis conducted above mainly indicated two ways to increase rice production efficiency. The first was to eliminate the input slacks under the present scale and level of returns. This was adoptable in DMUs with a technical efficiency less than 1, i.e., the paddy fields of Type III. According to the results summarized in Table 3, the largest average slack ratio occurred in land capacity. For each paddy field, land capacity was the compound value of five principals of 21 soil analysis indicators. Thus, in some paddy fields, land capacity was not completely cultivated because of the constraints of other resources. The field area was estimated to be positively related to rice yield in our previous studies (Li et al. 2016; Nanseki et al. 2016). The large average slack ratio indicated that an enlarged area of some paddy fields could increase

Table 5 Water depth and temperature of the High-10 and Low-10 paddy fields, in terms of the technical efficiency measured using DEA. A t-test was conducted to calculate the significance of their differences

Paddy field	Peer count[a]	Technical efficiency	Water depth (Mean at 18:30 h, mm)				Water temperature (Mean of 18:30, °C)			
			S_1	S_2	S_3	S_4	S_1	S_2	S_3	S_4
High-10	24.9	1.000	36.72	22.18	16.43	5.58	23.26	26.23	26.16	23.00
Low-10	00.0	0.974	51.68	29.90	12.75	9.55	24.42	26.36	27.39	24.24
Differ[b]	24.9	0.026	-14.96^{**}	-7.71	3.68	-3.97	-1.16^{**}	-0.13	-1.23^{**}	-1.24^{***}

[a]The number of times it was a benchmark for other DMUs; [b]the balance of high–low, **and *** indicate significance at 5 and 1% probability levels, respectively
Data source Li et al. (2017)

efficiency. Although much smaller than the above two inputs, the average slack ratios of other input variables indicated additional ways and extents to which the inputs could be adjusted. Considering the significantly negative relationship as illustrated in Fig. 1, lower temperature and solar radiation were acceptable in some paddy fields, from dispersed farming plans and hence, postponed the dates of transplanting or sowing. Some paddy fields yielded less, relative to the improved farming conditions including a leveled height difference and fertility, irrigating system, illumination, and herbicide application. In addition, efficiency could be increased by reducing the amount of fertilizer, with a given content of nitrogen, used. In the second approach, the production efficiency could be increased by changing the scales. In other words, by increasing or decreasing the inputs with the same proportions, according to the status of returns to scale. As shown in Table 2, scale adjustments were applied to Type II and III, where scales of all the 103 paddy fields could be enlarged. Nevertheless, due to the law of diminishing returns to scale, there should be boundary values for the inputs. For instance, a significant quadratic relationship was detected between the average solar radiation during the 20 days after heading and rice yields, of which the optimal values ranged from 20.27 to 20.39 °C. In addition, roughly 0.7 hectares was measured as the optimal paddy area for the highest yields (Li et al. 2016). Thus, in establishing farming plans, it was necessary to conduct a general optimization considering interactions of the inputs and tradeoffs from costs and revenue, using professional technologies.

In the second stage, water temperature was measured as significantly affecting production efficiency. Thus, it was necessary to identify the determinants of water temperature from the perspectives of air temperature and water depth. Figure 3 illustrated the average water depth (AWD), average air temperature (AAT), and average water temperature (AWT) at 18:30 h, of the 117 paddy fields in the growth stages of S_1 through S_4. It was obvious that the AWT varied closely with the AAT. In fact, a high correlation coefficient of 0.90, significant at 0.01, existed between the AWT and AAT. It indicated that the former was highly affected by the latter. Moreover, the AWT was higher than the AAT in each growth stage. In total, the AWT was 1.45 °C higher than the AAT, across the four stages.

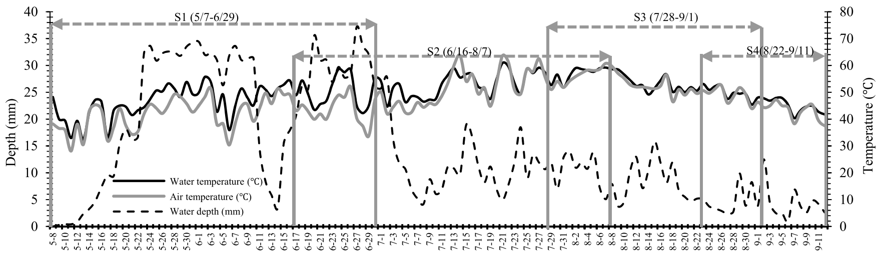

Fig. 3 Average water depth, air temperature, and water temperature, at 18:30 h, of the 117 paddy fields across the four growth stages

These relationships were illustrated in Fig. 4a, where a significantly linear regression was fitted between the AAT and AWT; the AWT was larger than the AAT in most cases, as represented by the diagonal line. However, the CVs of AWT and AAT were 11.94 and 15.49%, respectively. Thus, it showed that water temperature was more stabilized, and it helped to maintain the land temperature, which promoted plant growth. In addition, the average technical efficiency of the Low-10 paddy fields was 0.974, only 0.026 lower than that of the High-10 paddy fields (Table 5). This

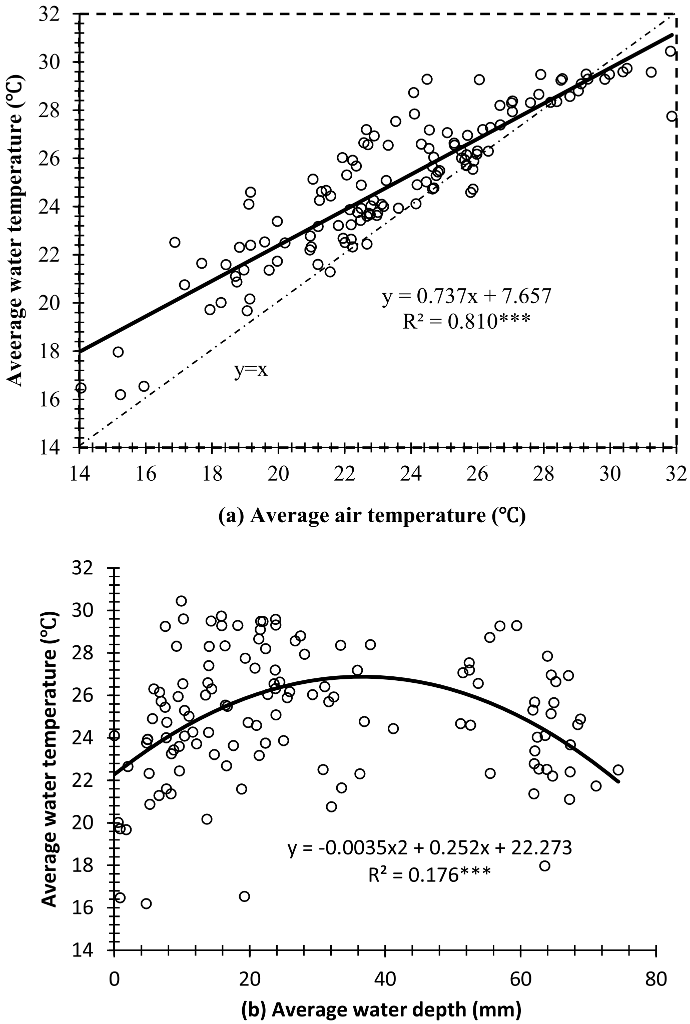

Fig. 4 Average air temperature (AAT), water temperature (AWT), and water depth (AWD) at 18:30 h across the four growth stages in the 20 paddy fields. **a** Average air temperature (°C), **b** Average water depth (mm)

indicated that little inequality existed in the efficiency of the paddy fields sampled from the same farm. In total, the means of water temperature and air temperature were 25.02 and 23.57 °C, respectively, while the CVs were 11.94 and 15.49%, respectively. Hence, water functioned in maintaining the land temperature.

In contrast, no significant linearity was observed between water depth and water temperature, as shown in Figs. 3 and 4b. Nevertheless, a significant quadratic relationship was identified and fitted between the variables. Calculations based on the equation shown in Fig. 4b, showed that the AWT peaked when the AWD was roughly 36 mm, over the entire growth season. This implied that before reaching this threshold, the water temperature was preserved with increasing depths. On the other hand, heat from solar radiation and the air was separated when the water depth exceeded this threshold. Thus, to some extent, the water temperature could be adjusted by properly controlling the water depth.

5 Conclusion

The results of the DEA showed that among the 122 paddy fields, 19 paddy fields were fully efficient and acted as benchmarks for the other inefficient paddy fields. There were 27 paddy fields with technical efficiency scores of 1, indicating that an input adjustment did not change the output efficiency. Thus, in these paddy fields, increasing the scales was the only solution for improving production efficiency. There remained 76 paddy fields with technical efficiencies less than 1, where inputs could be reduced further. Altogether, in more than 84% of the paddy fields, the efficiency could be increased by increasing the scales. Slack analysis of the outputs showed that not much of a margin existed between the yields of the six types of rice. The largest slack ratios were observed in the raw paddy and sorted brown ricesorted brown rice, respectively. From our analyses and the similar CVs of the yields shown in Table 1, we concluded that that the quantity and quality were balanced by large, among the paddy fields. On the other hand, slack analysis of the inputs indicated that land capacity had the largest slack, followed by field area, in terms of relatively redundant or inefficient usage. In contrast, the temperature, fertilizer nitrogen, and farming conditions showed efficient usage with the smallest slacks. Further comparisons indicated that the efficient paddy fields yielded significantly more than those with low efficiency. Among the input variables, temperature, solar radiation, fertilizer nitrogen, and farming conditions of the high-efficiency paddy fields had lower values than those of the inefficient fields. Thus, higher yields and lower inputs related to efficient production.

A comparison of irrigation management indicated that in S_1 alone, the water depth of the High-10 paddy fields was significantly lower than that of the Low-10 paddy fields. In contrast, the average water temperature of the High-10 paddy fields was significantly lower than that of the Low-10 paddy fields, in all stages, except for S_3. In these 20 paddy fields, water temperature and depth in all the four growth stages except for S_3 were identified as significant to the measurement of technical efficiency, although the direction of the effect, positive or negative, varied in different stages. Within all the sampled paddy fields, further discussion revealed that water temperature was linearly affected by air temperature. Moreover, a significant quadratic relationship showed that water temperature peaked at a water depth of approximately 36 mm, thus the water temperature could be adjusted by properly controlling the water temperature.

Therefore, irrigation management including the water depth and water temperature, is an essential factor affecting rice production. In addition to real-time monitoring, an analysis of the interactions, effects, and determinants of water managerial indicators are necessary for increasing rice yield and technical efficiency. Thus, in future studies, the DEA models should be expanded to incorporate non-discretionary variables, e.g., the stage-specific average and the corresponding daily ranges of air temperature and solar radiation. Furthermore, other empirical models—e.g., covariance structure analysis and multivariate regression—could be adopted to identify the effects of the yield determinants, including water temperature, and the interactions between them.

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