Smart Rice Farming, Managerial Model and Empirical Analysis

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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

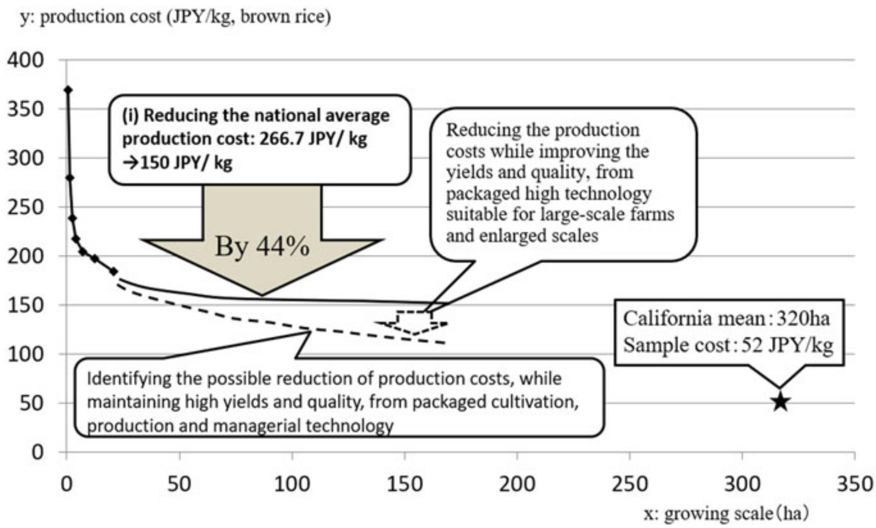

Fig. 1 Scale and production costs of rice in Japan, 2011 (*Source* Nanseki [2019])

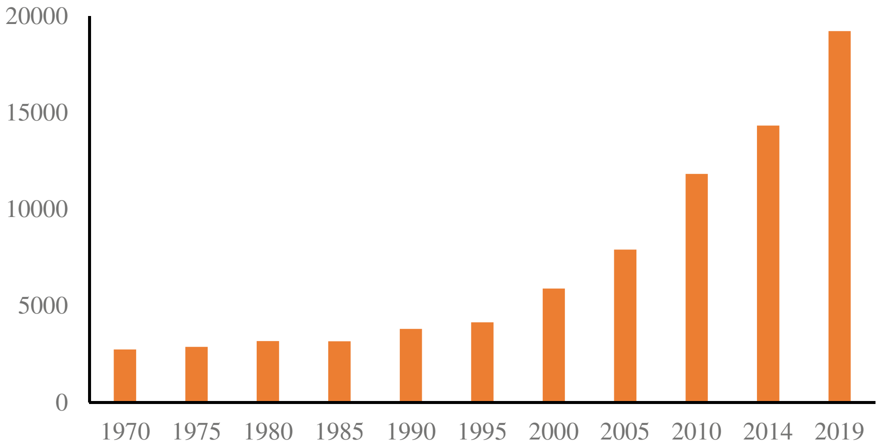

Fig. 2 Number of Japanese agro-corps (corporations qualified to own farmland) in 1970–2019 (*Source* MAFF 2020)

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

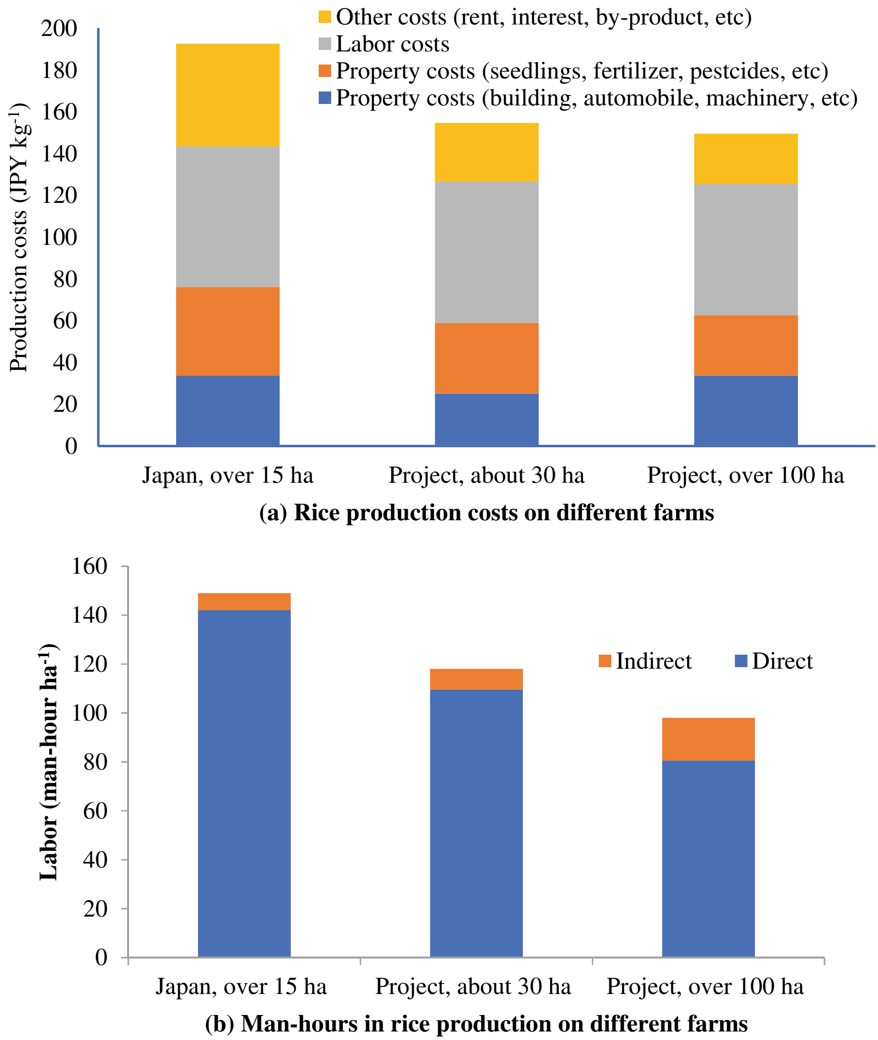

Fig. 3 Total cost and labor hours of rice production large-scale farms, on the average of nation-level of Japan and member farms of the research project. **a** Rice production costs on different farms. **b** Man-hours in rice production on different farms (*Source* Nanseki et al. 2016, pp. 9–10)

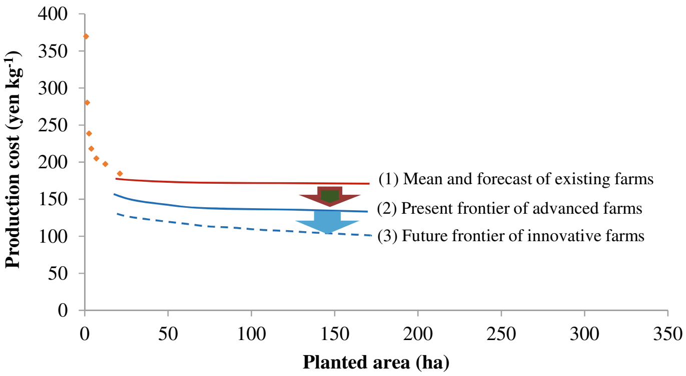

Fig. 4 Planted area expansion and rice production cost reduction in Japan (*Source* Nanseki et al. 2016, p. 5)

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

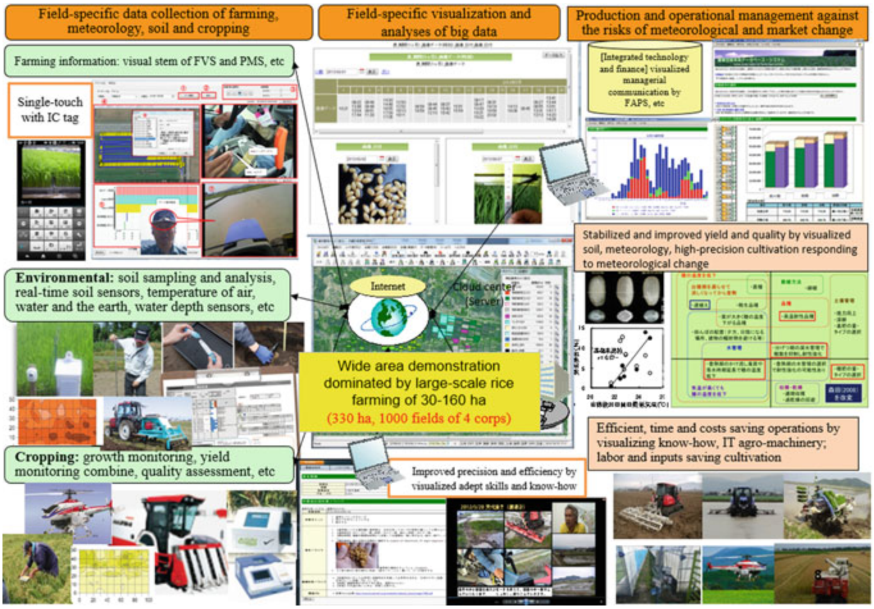

Fig. 5 Development and demonstration of new generation large-scale rice farming technological system integrating with agro-machinery, field sensors, visualized farming, and skill-transferring system (*Source* Nanseki et al. 2016, p. 167)

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

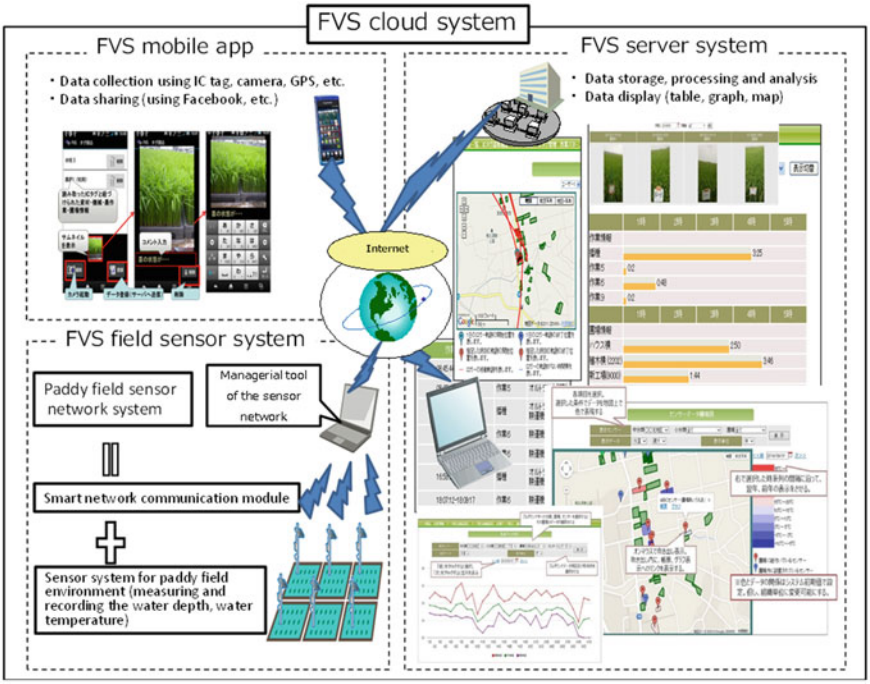

Fig. 6 Image of the FVS cloud system combining the paddy field sensors (*Source* Nanseki et al. 2016, p. 170)

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.

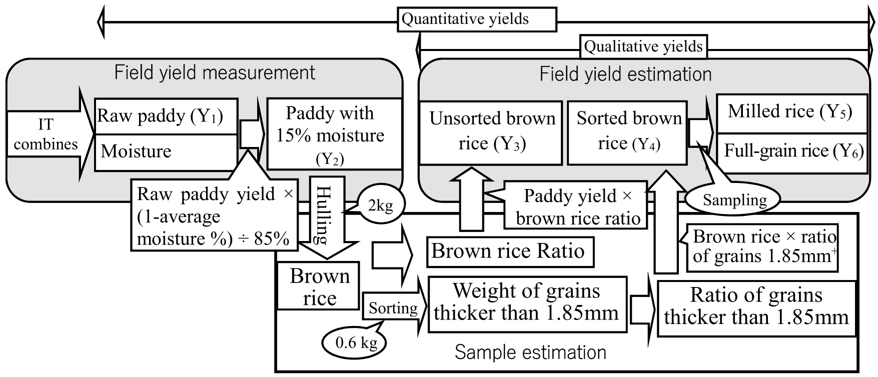

Fig. 7 Process of estimating rice yield from raw paddy to milled and full-grain rice (*Source* Nanseki 2019, p. 166)

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

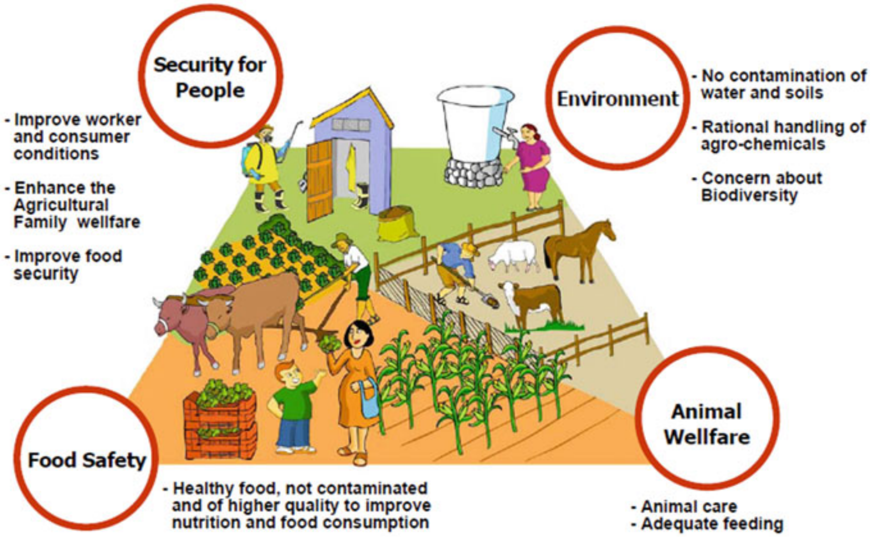

Fig. 8 Four major objectives of GAP (*Source* FAO [2007] Guidelines on "Good Agricultural Practices for Family Agriculture")

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,

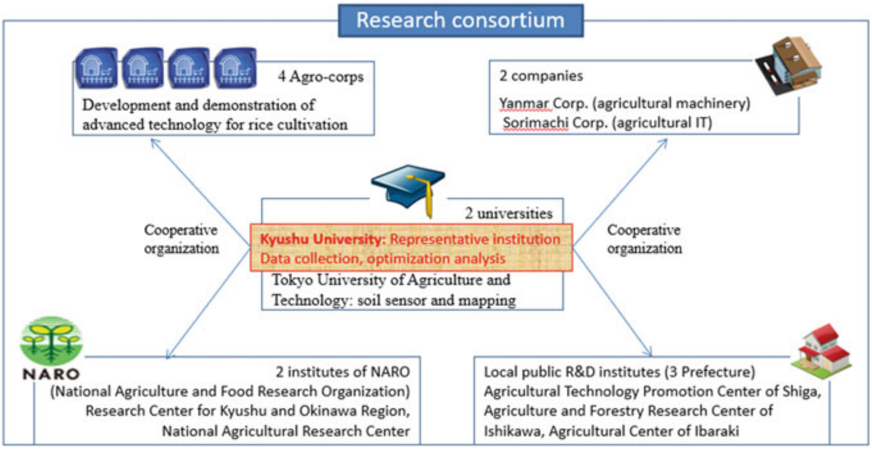

Fig. 11 Research consortium of the project

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.

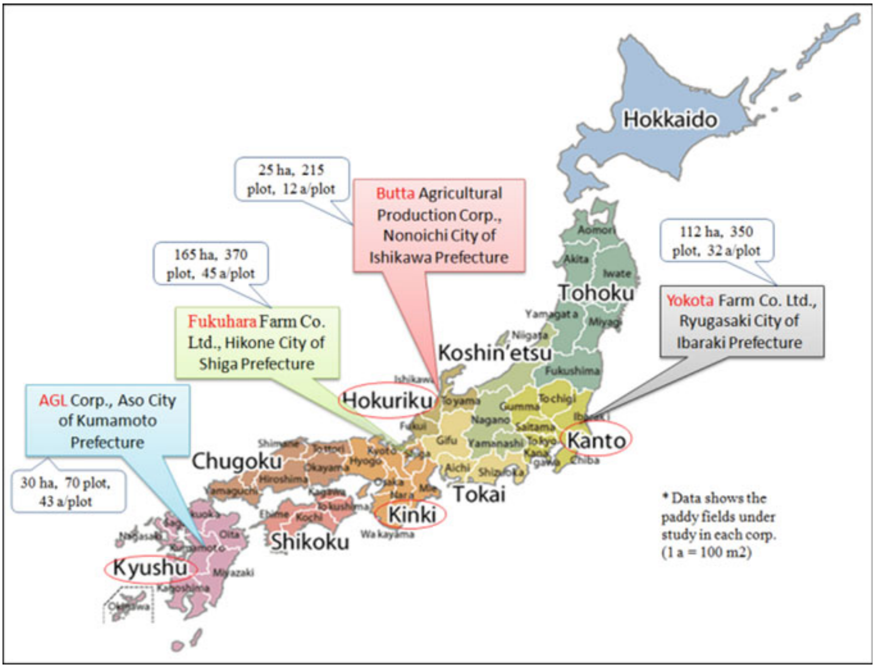

Fig. 12 Location of the 4 agricultural corporations

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.

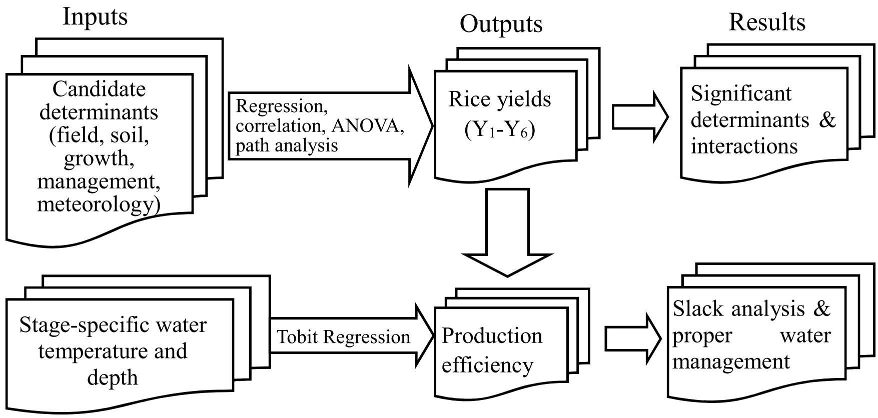

Fig. 13 General scenario of estimating the results in the empirical analyses summarized in this book

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

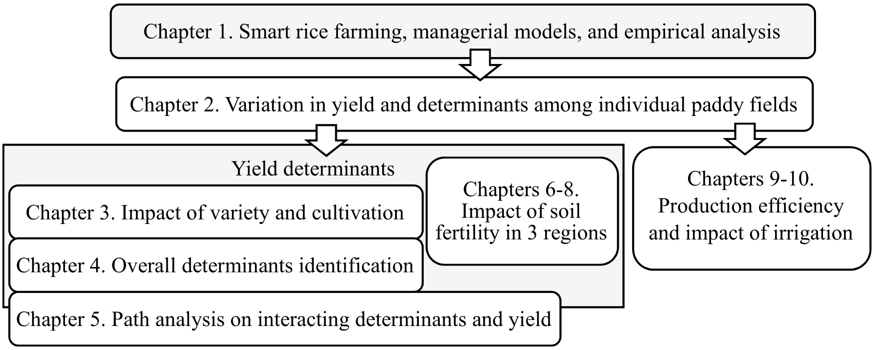

Fig. 14 Organization of this book

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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