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Exploring the characteristics of smart agricultural development in Japan: Analysis using a smart agricultural kaizen level technology map

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ABSTRACT

This study aims to clarify the Japanese characteristics of the spread of smart agriculture utilizing digital technology, which is expected to spread worldwide, and to provide policy implications for further dissemination of the technology. We conducted a questionnaire survey on actual conditions related to smart agriculture on Japanese farms. We have also proposed creation of a Smart Agricultural Kaizen Level (SAKL) technology map by applying the evaluation method used in management technology theory for the manufacturing industry. Using the results of the questionnaire survey and the proposed SAKL technology map, we analyzed the current pattern of expansion of smart agricultural technologies in Japan. Our results suggest that production efficiency in Japanese agriculture could be improved by raising the data visualization level and introducing smart agricultural technology. We also found that Japanese agriculture efficiency can be improved by introducing smart agricultural technology even if the data visualization level remains low. Smart agricultural technology automatically visualizes information and optimizes conditions without relying on the farmer's information literacy. At Japanese agriculture sites, the current smart agricultural technology introduction rate is less than 50%. To effectively disseminate smart agricultural technologies in the future, a policy should be implemented that promotes the development of a standardized package of smart agricultural technologies that can improve efficiency to some extent through default operation. With such a package, smart agriculture could be expanded without resorting to improving farmers' information literacy. Agricultural sites in Japan are thought to be currently engaged in developing such a standardized package of smart agricultural technologies.

1. Introduction

This study aims to clarify the Japanese characteristics of the spread of smart agriculture utilizing digital technology, which is expected to spread worldwide[1], and to provide policy implications for further dissemination of the technology. We define smart technology as an advanced management technology for eliminating input waste and produce products with higher value, by thoroughly managing the site using information and communication technology (ICT) and the Internet of Things (IoT). We defined smart agriculture as agricultural practices that utilize smart technology. Munz et al. (2020) stated that smart agriculture is related to a knowledge-based approach in which mechanical work is automated under a certain management system.

We conducted a survey on smart agriculture in cooperation with the Japan Agricultural Corporations Association (JACA). As a tool for systematically analyzing the results of the survey, we then propose creating a smart agricultural kaizen[2] level (SAKL) technology map. The SAKL technology map is an applied development of the smart manufacturing kaizen level (SMKL) technology map (Fujishima, 2020), which is a tool for promoting information technology (IT) in the manufacturing industry.

As mentioned above, smart agriculture is agriculture with advanced management that requires data collection and analysis. With remarkable innovations in software and hardware ICT, data collection and analysis, and agricultural management principles have undergone major changes over the last few years.

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[1] FAO Digital agriculture http://www.fao.org/digital-agriculture/en/(Last access August 27, 2021)

[2] Kaizen is a constantly ongoing process of changing the means for accomplishing a task in order to streamline, improve accuracy and/or speed, therebyeliminating redundancy and allowing labor to concentrate on more important work. https://www.berlitz.com/ja-jp/blog/kaizen

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First, agricultural technological development was advanced in the methodology of collecting and integrating various data at the farm site (Khalid et al., 2019; Eitzinger et al., 2019; Sanches et al., 2019; Patil et al., 2019; Tan Gar Tan Gar Heng et al., 2020). In the next phase, the concept of individual farm management was extended to the concept of management for the entire region or agricultural supply chain (Markovska and Dudchenko, 2021; Arkhipov et al., 2020; Belikova et al., 2021; Yue, 2020; Kolesnikov et al., 2020). Recently, it has been established that developing smart agriculture in some contexts for the spread of smart agriculture is necessary. Since smart agriculture spreads to agricultural sites only when its merits are convinced by the farmer, a context that convinces the farmer is necessary (Cisternas et al., 2020; Vecchio et al., 2020; Perea et al., 2019; Li et al., 2021; Solntseva and Yashina, 2021; Micle et al., 2021; Munz et al., 2020; Veronice et al., 2019). Contextual understanding of smart agriculture is developing smart agriculture research in social sciences. Similarly, construction of information platforms, improvement of big data analysis technologies, and standardization of those technologies are driving progress in agricultural research through informatics (Ngo et al., 2020; Bhaskara and Bawa, 2021; Chergui et al., 2020; Ma et al., 2021). Furthermore, improving information security is a major issue in smart agricultural research in informatics (Dey and Shekhawat, 2021; Yang et al., 2021; Zhu and Li, 2021; Kristen et al., 2021).

The principles of smart agriculture, i.e., the principles of advanced management in agriculture, have undergone major changes over the last few years. The sophistication of management first proceeded in the form of the evolution of methodologies for collecting and integrating various information, and then the concept of management was extended to cover the entire region or the entire agricultural supply chain. Recently, research on the formation of a social context for establishing smart agricultural technology at the site has progressed simultaneously with technological progress in the field of informatics for smart agriculture. Nakano and Washizu (2018) clarified that the spread of smart agricultural technology will build a new industrial structure between the manufacturing, agriculture, information, and communication services industries, and contribute to moderate economic growth. Therefore, for green innovation after COVID-19, further research is required on the refinement of the social context that promotes the establishment of smart agricultural technology at the site, and the direction of the next development of smart agricultural technology is necessary. This study will include such research required to promote dissemination of smart agricultural technologies.

2. Need for data-oriented management: A case study of a smart large-scale rice farmer in Japan

This section summarizes the content of the interview with Mr. Shuichi Yokota, a representative of Yokota Nojo Co., Ltd., conducted in January 2021. Mr. Yokota is one of the farmers in Japan who practice smart advanced large-scale rice farming and has achieved a significant reduction in production costs through enhanced data-oriented management. The Yokota Nojo example suggests that smartening—that is, strengthening management based on data analysis—is the most important issue for Japanese agriculture, which is at a turning point.

According to Mr. Yokota, Japanese agriculture is currently at a historic turning point. The generations that experienced land reform after World War II have changed, and farmers' awareness of land is changing, creating an environment in which large-scale agglomeration is likely to proceed. The purpose of mechanization in conventional agricultural management was to avoid heavy labor, but there is little room for further labor reduction by mechanization at rice cultivation sites in Japan. As an initiative in smart agriculture, automation of tractors and combines (automatic driving) is attracting attention, but automatic driving is restricted in narrow Japanese farms. Even if the farming area expands, the narrow Japanese terrain does not change, and automation would not be facilitated.

As the farming scale grows, increasing labor productivity is important. Therefore, farmers divide the work process, placing one person in charge of each process to facilitate efficiency of the production process. In addition, "management" becomes more important as the farming scale increases. For example, management maximizes yield and combines the cultivars considering the harvest time, making a cropping plan so that the amount of work required for harvesting and the required number of machines are optimized. Since the required technology (agricultural method) changes according to the farming scale, managing the optimum technology selection according to the farming scale is necessary. For example, in small- and medium-sized farms, loading fertilizer (including top dressing), pesticides, and seedlings into one agricultural machine and completing all work processes simultaneously, is efficient. However, this is not the case for large-scale farmers.

To summarize, the farming scale of Japanese farmers is currently growing spontaneously. However, the productivity improvement required for the expansion of the farming scale cannot be achieved only by the automation of agricultural machinery. As the scale of farming expands, it is important to improve the efficiency of the production processes by implementing detailed management. The essential purpose of introducing smart agriculture is supporting detailed management.

3. Materials: Questionnaire survey on the actual situation of smart agriculture in Japan

To obtain the data necessary for the analysis, with the cooperation of JACA, we conducted questionnaire surveys on the actual situation of smart agriculture for farms that are members of the JACA. Two surveys were conducted. The JACA conducts an annual "national agricultural corporation fact-finding survey" for its members. Our first qualitative survey was conducted as part of the survey (the first survey is referred to below as the "fact-finding survey"). A fact-finding survey was conducted from November to December 2020, and 1149 responses (response rate 56.2%) were obtained. Of these, 1122 farms, whose main business is agricultural production rather than sales and processing, were included in this study's analysis. In addition, we conducted a second survey in January 2021 regarding the contents, including numerical data of the financial status of each farm (the second survey is referred to as "individual survey" below); 134 responses were obtained from the individual survey (response rate 13.4%), of which 108 also responded to the fact-finding survey.

Fig. 1 shows the composition ratio of target farms by farm type obtained from the fact-finding and individual surveys. Similarly, Fig. 2 shows the composition ratio by the sales scale. Rice cultivation was the most common (33% and 45%, respectively), with open-field and facility vegetables accounting for approximately 10% each. Farms with JPY $\geq$ 100 million accounted for 43% and 54%, respectively. According to the Japanese Agricultural Census, only 0.8% of farms have sales of 100 million yen or more; therefore, JACA members are mainly large-scale farms.[3]

In the fact-finding survey, we enquired about the types of smart agricultural technologies[4] introduced by each farm, whether or not they received technical advice and subsidies associated with the introduction, and the objectives and outcomes of introducing smart technologies. We also asked farms that did not introduce smart agriculture their reasons for not doing so. As mentioned in Section 2, the collection and management of data in the production and accounting processes is the basic principle of smart agriculture. Over the past few years, efforts have been made to improve management by having all stakeholders, including companies and governments, manage information through the

[3] JACA, *2020 Agricultural Corporation White Paper* (in Japanese) https://hojin.or.jp/wp-content/uploads/hakusho2020.pdf

[4] See the survey questions in Appendix 1 for the names of the technologies we specifically investigated.

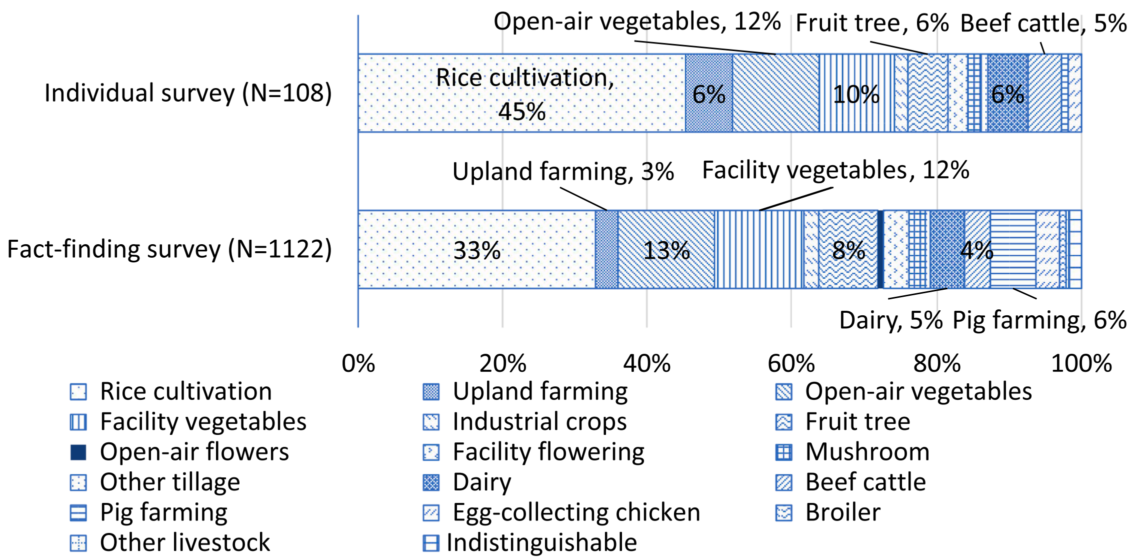

Fig. 1. The composition ratio of the target farms by farm type.

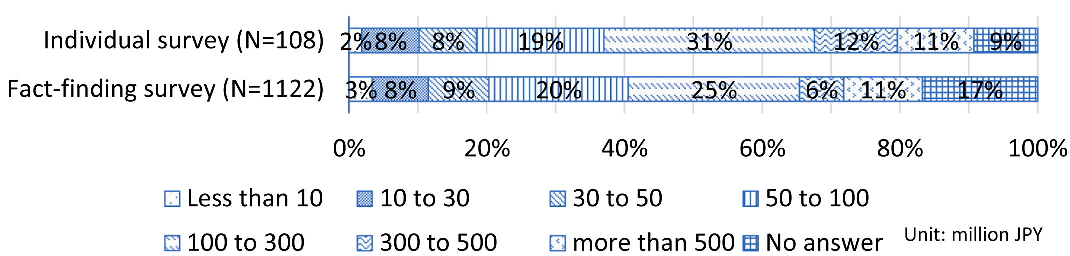

Fig. 2. The composition ratio of the target farms by sales scale.

cloud, rather than requiring individual farmers to complete it. Therefore, we also considered how active farmers are in such information disclosure.

In the individual survey, we asked each farmer whether they had introduced smart agricultural technologies, and if so, the year of introduction. In addition, we asked each farmer to answer the data utilization status at the following four levels: 1. We did not collect the data necessary for management, 2. We collected the data, 3. We collected the data and visually compared them, and 4. We collected and analyzed the data using ICT. This question is based on the principle that the essence of smartness lies in management, which is conducted by collecting and analyzing data. In addition, to consider the relevance to the adoption of smart agricultural technologies, we asked each farmer about financial information for the past five years, and input information such as the latest labor force and IT investment. Appendix 1 presents the survey questions in the fact-finding and individual surveys.

4. Analytical method: Development of the SAKL technology map diagnostic method

We developed a SAKL technology map diagnosis as a criterion for evaluating the degree of smartness of individual farmers. The SAKL technology map diagnosis is an agricultural application of the SMKL technology map diagnosis method practiced in the manufacturing industry. The purpose of the SAKL technology map diagnosis is to provide a common endpoint for individual farms with different characteristics. The effects of the diagnostic results on farms' productivity were verified by the regression analysis described in section 6. Section 4.1 describes the SMKL technology map and Section 4.2 describes its application to the SAKL technology map.

4.1. SMKL technology map

The SMKL technology map is an analytical method in management technology theory and an evaluation tool for smart production processes in the manufacturing industry. It can be used by a factory site supervisor for assessing the current level of smartness in their field and consider measures for promoting smartness without needing process management expertise (Fujishima, 2020). By utilizing this SMKL technology map, companies will be able to continuously invest in smart devices. Similarly, by presenting a SAKL technology map applied to the agricultural field and evaluating the degree of smartness of individual farms, considering the path of continuous investment in smart agriculture is possible.

Fig. 3 shows the SMKL technology map of Fujishima (2020). The vertical axis direction shows four visualization levels, and the horizontal axis shows four managed levels. Each business operator can easily evaluate the smartness of their manufacturing site by determining the current state of their site in these 16 squares. The visualization level in the vertical direction evaluates whether data collection and analysis at a manufacturing site is performed electronically and automatically rather than on paper or manually.

Conversely, the managed level in the horizontal axis direction evaluates the control range of the business operator However, Fujishima (2020) established that changing the criteria for division of managed levels in the horizontal axis direction based on the characteristics of each industry is necessary.

The equipment designer diagnoses the current SMKL level and simultaneously decides the key performance indicator (KPI) that they want to improve. For improving the selected KPI, a smart investment plan will be created based on the current SMKL level. The KPI is an index

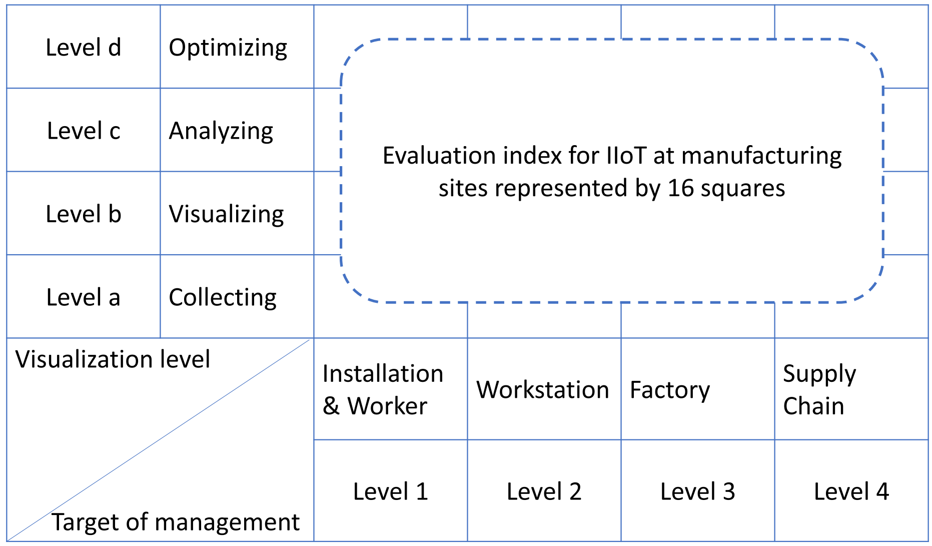

Fig. 3. SMKL technology map (Fujishima, 2020).

defined in ISO 22400 (ISO, 2014), which was established for the standardization of production control.

4.2. SAKL technology map

In this study, we propose a SAKL technology map for evaluating the current state of smartening on individual farms by applying the concept of the SMKL technology map. By analyzing the results of the questionnaire survey based on this technology map, we will be able to consider smart investment strategies in agriculture.

Fig. 4 shows a conceptual diagram of the SAKL technology map. Based on the answers to the question "Please answer about the data utilization status at your farm" in the individual survey, the vertical axis in Fig. 4 is divided into the following four levels: data necessary for management are not collected (Level 0), collected (Level 1), collected and analyzed visually (Level 2), and collected and analyzed using ICT (Level 3).

In the SMKL technology map shown in Fig. 3, the horizontal axis was divided according to the managed level. However, Fig. 3 is an example of a technology map in a factory, such as an automobile production factory in which individual production processes are clearly separated. Fujishima (2020) stated that changing the evaluation scale on the horizontal axis for each industry based on its characteristics is necessary.

We set the evaluation scale on the horizontal axis based on the characteristics of agriculture, as follows: In our individual survey, we asked respondents whether they introduced 12 types of individual technologies related to smart agriculture on their farms, along with the year of their first introduction. The results are summarized in Fig. 5. Smart agricultural technology can be roughly divided into technologies that were introduced in the 1990s, 2000s, and the 2010s. Therefore, according to the time at which the technologies began to spread, we divided smart agricultural technologies into the following three categories: early, medium-term, and late. Early technologies include shipping management support systems, whereas medium-term technologies include production process support systems. The late-type technologies are technologies that make heavy use of GPS and internet communication, such as smart rice transplanters and smart harvesters. Thus, the horizontal axis in Fig. 4 is divided into the following levels: smart agriculture technologies are not introduced (level 0), early type technologies are introduced (level 1), medium-term technologies are introduced (level 2), and late-type technologies are introduced (level 3).

In our fact-finding survey, we asked level 1 or higher farms on the horizontal axis of the SAKL technology map qualitative questions about their objectives of working on smart agriculture and the outcomes. By summarizing the contents of these questions into five indicators (efficiency, quality, capacity, environment, and maintenance), the objectives and outcomes of smartening of each farm were evaluated. The indicators adopted here correspond to five of the six KPI fields (excluding inventory management) defined in ISO 22400, which was established as the standard used in the management technology theory of the manufacturing industry. Table 1 presents the question items that comprise the five types of agricultural KPIs for evaluating the objectives and outcomes of smart agriculture. The agricultural KPI (objectives and outcomes) in Table 1 is a variable that becomes one when any one of the corresponding questions is answered "yes."

Presently, the extent of the diffusion of smart agriculture is limited, and many farms are in the level 0 status of the horizontal axis division of the SAKL technology map in Fig. 4. The items mentioned by Rogers (2003) are prominent among the factors that hinder the diffusion of innovation. According to Rogers (2003), innovation does not diffuse because of the lack of any of the following five factors: comparative advantage (superiority compared to prior art), suitability (no distance from current status), comprehensibility, trialability (experimental use), and visibility (technology adoption is easily observed from the surroundings).

In our fact-finding survey, we asked farms that did not introduce any smart agriculture technologies to state the reason for doing so. We associated these options with one of the five factors listed by Rogers (2003) and evaluated the factors that influenced the farms' decision of not introducing smart agriculture. If a farm answered "yes" to any one of the options related to a factor in Table 2, it was evaluated that the farm had not introduced smart agricultural technologies due to the missing factor.

5. Diagnostic results

5.1. Results by technology type using the fact-finding survey

This section summarizes the characteristics of farmers by technology type used, which is the evaluation level in the horizontal axis direction of the SAKL technology map based on the results of the fact-finding survey. We investigated the current adoption status of smart agricultural technology at each farm. We also investigated the objectives and outcomes of technology introduction when a farm adopted the technology, and reasons for instances where a farm did not adopt the technology.

SAKL: Smart Agricultural Kaizen Level

Level 3	(Data necessary for management are) Collected and analyzed using ICT				
Level 2	Collected and analyzed visually				
Level 1	Collected				
Level 0	Not collected				
Visualization level / Technology type		Not introduced	Work process assist advanced equipment Shipping management support system Coordination between production process support system and shipping management support system	Smart tractor Advanced equipment for spraying pesticides and fertilizers Sensing equipment Production process support system	Smart rice transplanter Smart harvester Water management / irrigation / watering system Advanced fertilization control equipment Other diagnostic business
		Level 0	Level 1(Early type)	Level 2 (Medium-term type)	Level 3(Late-type)

Fig. 4. SAKL technology map.

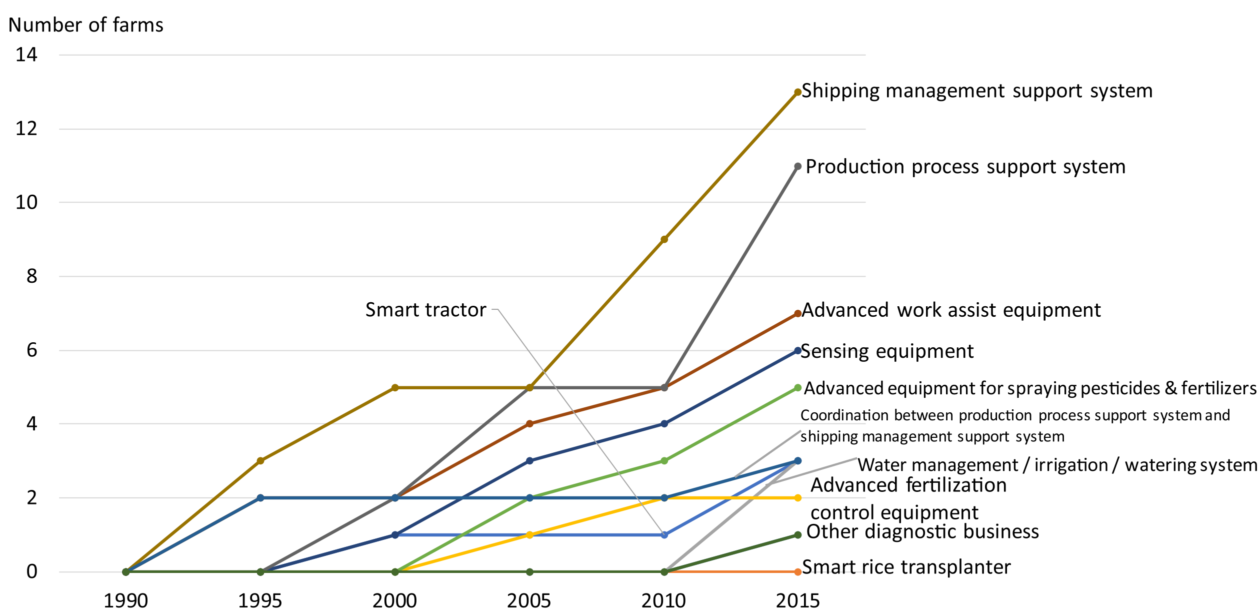

Fig. 5. Technology introduction status from individual surveys: The evaluation scale on the horizontal axis of the SAKL technology map.

Of 1122 farms whose main business is agriculture, we were able to determine the technology type of the 873 farms. Fig. 6 shows the composition ratio of the technologies introduced by farm type, for a total of 813 farms that could identify the farm type out of 873 fact-finding respondents. According to Fig. 6, rice farms, dairy farms, and beef cattle farms were 73%, 90%, and 69% more likely to adopt smart agricultural technologies, respectively. Rice farms have a high proportion of late-type technology, and dairy and beef cattle farms have a high proportion of medium-term technology. Fig. 6 shows that each farm type is adequately characterized by the technology type classification, as defined in Section 4.2.

In addition, 73% of the 873 farms that have introduced some smart agricultural technologies have received some technical advice for smartening, and 51% have used subsidies to introduce the technologies. It is noteworthy that approximately half of the cases adopted smart agricultural technologies without subsidies.

Fig. 7 shows the percentage of farms that use some kind of smart agricultural technologies for which each item of KPI in Table 1 was the objective of introduction, and the percentage of farms that could improve each item of KPI as a result of their introduction. For all technology types, 50%–70% of farms have introduced technologies for improving the KPIs of efficiency, production capacity, working environment, and maintenance. As a result of technology introduction, the KPIs improved in almost 90% of the farms. A large proportion of farms

Table 1
Key performance indicators (KPI) for agriculture.

	KPI (Objectives of technology introduction)	KPI (Results of technology introduction)
Efficiency indicators	To reduce working hours and man-hours. To solve the labor shortage. To reduce production costs (raw material input costs).	Work speed has improved. Production costs have been reduced. The rate of return has improved.
Quality indicators	To increase added value.	Ingenuity has been realized, improving quality and adding value.
Capacity index	To improve yield, profit, and land use rate. For scale expansion For training of unskilled people. To expand the business field.	Expansion of new business and expansion of scale have been realized. New workers and young workers participated. New business opportunities have been created.
Environmental indicators	To reduce workload and make work more ergonomic.	Work efficiency has improved, and the working environment has improved.
Maintenance indicators	To optimize production and process management (including cultivation management, fertilization management, water management, feeding system, etc.). To optimize business management practices including production cost and financial data management. For new IT business use, including sharing of agricultural machinery and use of cultivation management services.	Work and process simplification, and labor savings have been achieved. Regional cooperation has been strengthened.

Table 2
Factors that hinder the diffusion of smart technologies (Rogers, 2003).

Spread factor	Applicable question items
Comparative advantage	Unprofitable, suspicious
Suitability	Insufficient performance, unsuitable for the actual situation, poor internet environment, difficult data collection
Comprehensibility	Unable to operate, do not know how to install, difficult to acquire technology, uncertain knowledge
Trialability	High initial investment
Visibility	Surroundings are negative

that adopted late-type technology aimed to improve each KPI. The KPI for improving product quality is not well recognized by farms, both as an objective and an outcome of the introduction of the technology.

Fig. 8 presents the reasons why farms that do not use any of the smart agricultural technologies do not introduce them, as listed by Rogers (2003). It was observed that the biggest factor hindering the introduction of technologies was the lack of compatibility. Even if a farmer acknowledges the novelty of smart agricultural technologies, they may not introduce them because they consider such technology incompatible with the current state of their farm. This study defines trialability as low when the initial investment amount is high, and this factor is the second largest obstacle to the introduction of technologies. However, about half of the farms that use smart agricultural technologies have introduced them without subsidies, so the high initial investment amount may be feasible.

5.2. Results by visualization level using individual surveys

This section summarizes the characteristics of farmers by visualization level, which is the evaluation level in the vertical axis direction of the SAKL technology map, for farms that participated in both fact-finding and individual surveys. In the individual survey, we considered the adoption status of smart agriculture, its adoption time, and the utilization status of data, which is a measure of the visualization level (a four-step scale from not collecting data to utilizing it with ICT). We also considered the financial situation and employee composition ratio for the past five years. These numerical data are used for the quantitative analysis in Section 6.

Fig. 9 shows the results of the answers from 73 farms whose visualization levels were identified by answering questions about data utilization.[5] Of these farms, 40% collect data and analyze them visually. Approximately 20% of the farms did not collect data, 20% only collected data, and 20% collected data and analyzed it using ICT.

Fig. 10 shows the percentage of farms that adopted each smart agriculture technology among the farms classified into each visualization level. Approximately 50% of farms with visualization level 2 or higher (farms that analyze data visually or by ICT) have introduced a production process management support system (system for cultivation, work, environmental control, transportation, fruit selection, storage, etc., mixed feed systems, systems for cattle health management, etc.). In addition, 20%–30% of farms that analyze data using ICT use late-type smart technologies such as water management systems, irrigation/sprinkling systems, and advanced equipment for controlling and automating fertilization. On farms with a visualization level of 3 or higher, the proportion of farms adopting medium-term technology is higher than the proportion adopting late-type technology. Of the farms with a visualization level of 0 or 1, the percentage of farms that use early type technology is close to zero, while some of these farms use medium-term or late-type technology. It is interesting to note that a relatively large proportion of farms with advanced data analysis employ medium-term technologies, and some farms with less data analysis employ late-type technologies. If smart agricultural equipment automatically collects data and automatically makes optimization decisions, the farmers do not need to collect and analyze the data. Our observations reflect this situation.

We calculated the age composition of farm employees based on the visualization level. At farms with visualization level 2 or higher (data are analyzed visually or by ICT), the percentage of employees in their 30 s or younger is 42%, which is higher than 24% at farms with visualization level 1 or lower.

5.3. Diagnostic results of the SAKL technology map

Of the 134 respondents in individual survey, we were able to diagnose the location of 73 farms on the SAKL technology map. Fig. 11 shows the result. The cell at the intersection of the level *i* visualization and level *j* technology type is indicated by M (*i, j*). As shown in Fig. 11, peaks were observed at M (0,0) and M (2,2). In some cases, such as M (0,3) and M (3,0), the levels of visualization and technology type are significantly different from each other. There are 32 farms (44% of the total) located in the upper right cell of the SAKL technology map, where both visualization levels and technology types are considered advanced (cells where $i > 3$, $j > 3$).[6]

Fig. 12 shows the percentage of farms located in the upper right of the SAKL technology map for which each item of KPI in Table 1 is the

[5] Among the 73 farms studied, 43.8% were involved in rice cultivation, and 14.1% in facility vegetables. Additionally, farms with sales of ≥JPY 100 million accounted for 50.7% of these farms. These conditions were similar to the distributions shown in Figs. 1 and 2.

[6] Of these 32 farms, 43.8% were involved in rice cultivation, followed by 13.3% for both vegetable and dairy farming. Farms with sales of ≥JPY 100 million accounted for 71.9% of these farms, a relatively high proportion of large-scale farms.

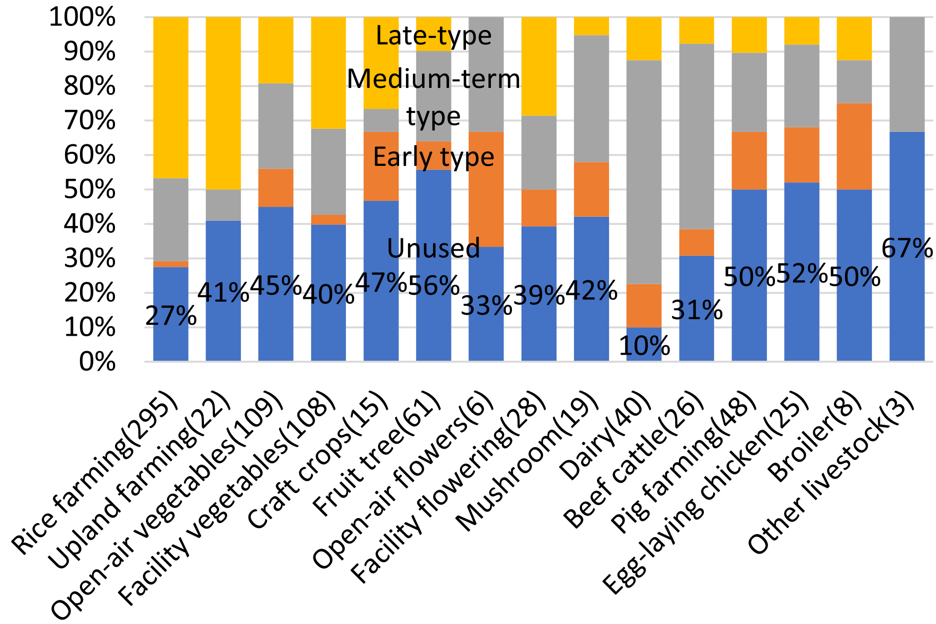

Fig. 6. The composition ratio of the technologies introduced by farm type (numbers in parentheses are the number of farms; a total of 813 farms could identify the farm type and the technology type.)

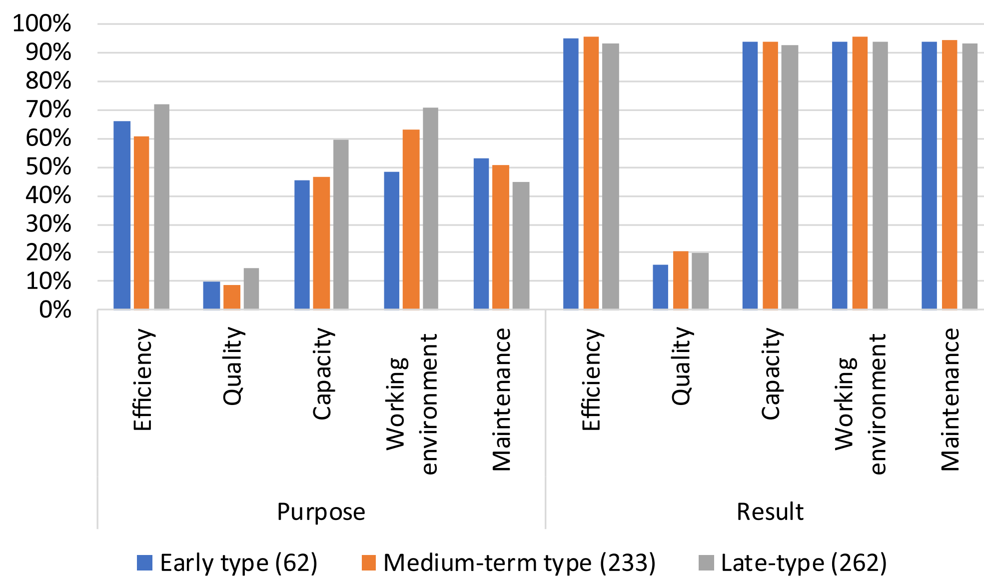

Fig. 7. Objectives and results of using smart agricultural technologies by technology type (Numbers in parentheses are the numbers of responses; 557 responses were obtained from a total of 873 farms).

objective or outcome of technology introduction. In Fig. 12 a high percentage (80% or more) of farms corresponding to M (3, 3) set efficiency, production capacity, and improvement of working environment as clear KPI objectives for the introduction of smart agricultural technologies. In addition, 80% to 90% of all 32 farms, not limited to farms that correspond to M (3, 3), responded that the introduction of smart technologies resulted in improvements in efficiency, production capacity, and working environment. Considering Fig. 12 in detail, if the visualization level is fixed at two or three and the technology type is improved from two to three, the effect of introducing smart technologies tends to be more pronounced. Conversely, if the technology type is fixed at two or three and the visualization level is improved from two to three, the effect of introducing smart technologies tends to diminish. The improvement of the technology type may not need to be accompanied by an improvement in the visualization level, but the improvement of the visualization level seems to be more effective as the technology type progresses.

6. Regression analysis: Detailed explanation of farm characteristics

In the previous section, we described methods for diagnosing the degree of smartness of various farms and showed that the higher the degree of smartness, the better the KPI of farms. In this section, we first analyze in detail the effects of the various characteristics of farms identified in the questionnaire based on their smartness level. In addition, we analyze how the degree of farms' smartness, along with their farming type, affects their productivity.

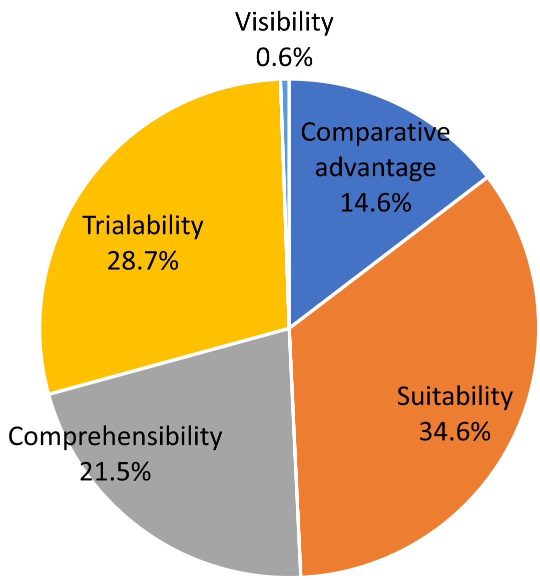

Fig. 8. Factors hindering the introduction of smart agricultural technologies (Percentages of the 540 total responses obtained from 316 farms).

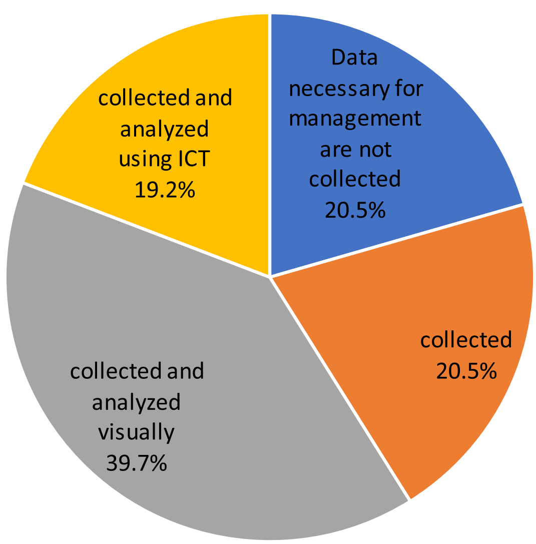

Fig. 9. Composition ratio obtained by visualization level of 73 farms.

6.1. Estimating the Heckman selection model of smart agricultural technology type: Analyzing factors for introducing smart technology in farms

Based on the results of the fact-finding survey, we analyzed the selection behavior of smart agricultural technologies among the early, medium-term, and late-types on the farms using Heckman correction for sample selection. In the first stage of the model, we conducted a probit analysis of the adoption behavior of smart agricultural technologies (Eq. (1)). When some types of smart agricultural technologies were introduced, we performed an ordered probit analysis of selection behavior between early-and late-type technologies in the second stage of the model (Eq. (2)). Currently, approximately 40% of farms have not introduced smart agricultural technologies. Therefore, to obtain unbiased results, performing two stage estimation of equations (1) and (2) is necessary. By adding farms that have not introduced smart agricultural technologies to the dataset, it is possible to obtain unbiased estimation results for the selection factors of technology types and adoption factors for smart agricultural technology.

$$\text{The first stage}: d = \alpha_0 + \sum_{i=1}^{m} \alpha_i x_i \tag{1}$$

$$\text{The second stage}: y_k = \beta_0 + \sum_{i=1}^{n} \beta_i x_i y_k = 1, 2, 3 \tag{2}$$

Here, d is a dummy variable that becomes 1 when smart agricultural technologies are introduced, and is 0 in its absence. y_k is an ordinal number indicating each technology type from early to late. $x_i(i = 1, \cdots n)$ are variables that explain the adoption behavior of smart agricultural technologies or the selection behavior of the technology types, which are selected from the question items of the fact-finding survey. The estimation results are presented in the Appendix 2. Table 3 shows the significantly measured coefficient values extracted from the Appendix 2.

According to the estimation results of the first stage in Table 3, the farming types that are not aggressive in introducing smart agricultural technologies (compared to other cultivation) are open-field vegetables, pig farming, and chicken eggs. The younger generation is actively adopting smart agricultural technologies. Experience acting on technical advice, and high literacy regarding information provision are factors that promote the adoption of smart agricultural technologies. Among the technology dissemination factors mentioned by Rogers (2003), the lack of comparative advantage, suitability, comprehensibility, and trial possibility, hinder the adoption of smart agricultural technologies.[7]

The estimation results of the second stage indicate the factors that encourage the adoption of later-type smart agricultural technologies. According to the results, later-type smart agricultural technologies will be adopted when capacity expansion among KPI items is the objective of introducing smart technology, when the farming type is rice and upland farming (compared to other farming cases), when sales are high, and when taxation and advanced processing are mentioned as business challenges. Sales do not have a significant impact on the decision to adopt smart agricultural technologies, but when these technologies are deployed, they do have a significant impact on the adoption of late-type technology. Conversely, late-type technologies will not always be required when maintenance management among KPIs is the objective of introducing smart technology, when the farming type is dairy and beef cattle (compared to other farming cases), and when the labor force is mentioned as a business challenge. According to the detailed observations of the fact-finding survey, dairy farming and beef cattle are farming types in which the introduction of smart technology was relatively advanced, but the late-type technologies defined in this study were not adopted. The results of the simultaneous estimation of Eqs. (1) and (2) are consistent with this observation.

6.2. Estimating plant-based production function: Analyzing the effects of smart technology on farms' productivity

Based on the financial data for the past five years in the individual survey, plant-based production function of each cost item for annual sales, which detected the scale effects in manufacturing plants (Ozaki and Shimizu, 1980), was estimated using the following formula:

$$\ln y = \beta_0 + \beta_1 \ln x + \beta_2 z \tag{3}$$

y is the input amount of each input element (number of employees, tangible fixed assets excluding land and intangible fixed assets, software among intangible fixed assets, information processing costs and communication costs, labor costs, or material costs). x is the annual sales. z is an ordinal variable indicating the type of smart agricultural technology and farming type (Appendix 3), or diagnostic results for the SAKL technology map (Appendix 4). By inputting the above variables

[7] Among the technology diffusion factors mentioned by Rogers (2003), the sign of the coefficient estimated for visibility is contrary to expectations, so further investigation and examination are required in the future.

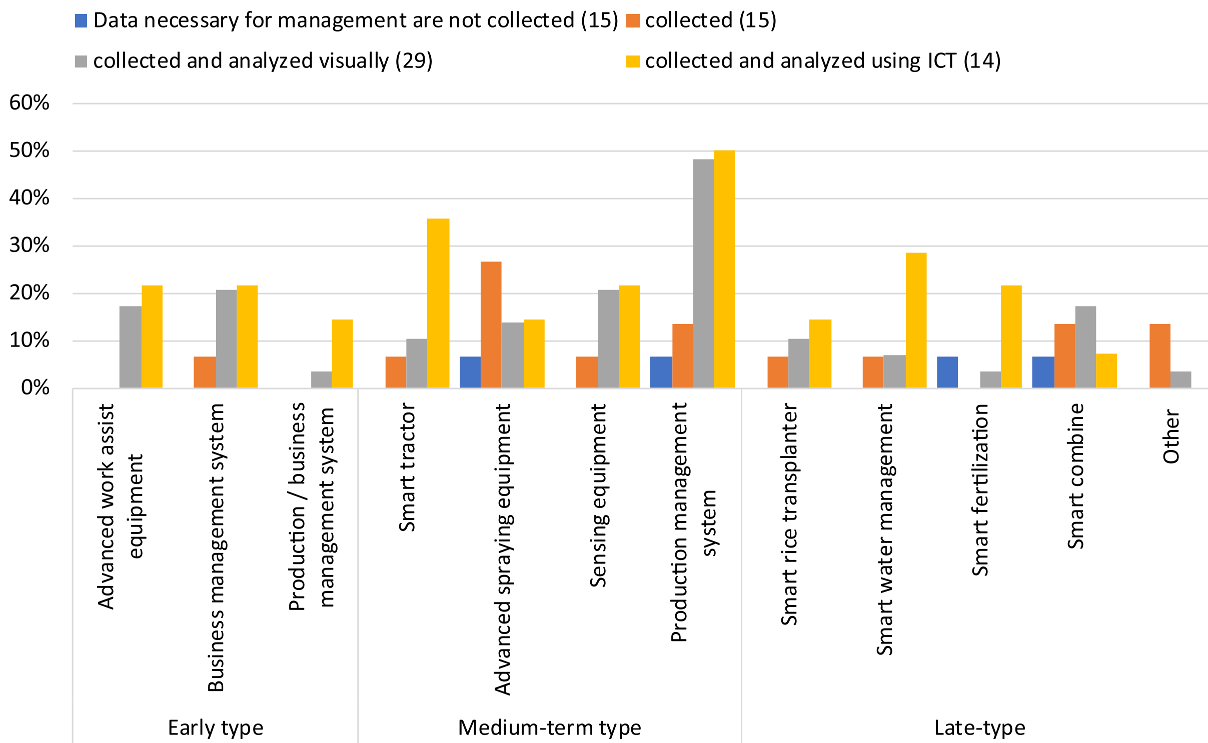

Fig. 10. Smart agricultural technology adopted by visualization level on 73 farms (A farm may own multiple technologies. This figure shows the results for a total of 105 technologies owned by 73 farms.)

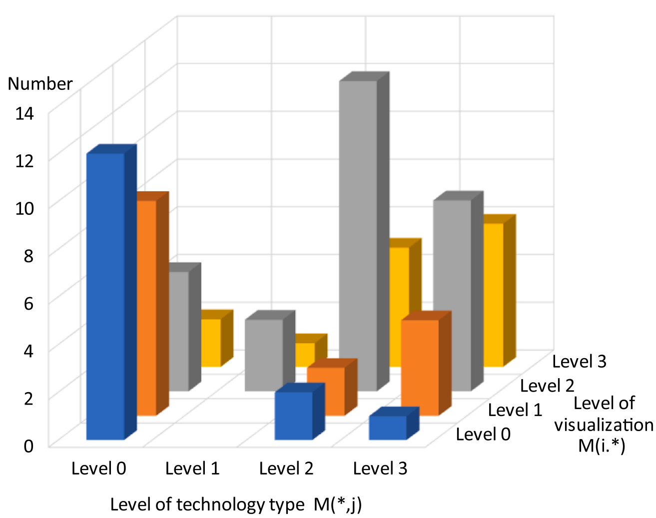

Fig. 11. SAKL technology map of 73 farms. Note: The division of visualization levels was as follows: data necessary for management were not collected (Level 0), collected (Level 1), collected and analyzed visually (Level 2), and collected and analyzed using ICT (Level 3). The classification of technology types was as follows: smart agriculture technologies were not introduced (level 0), early type technologies were introduced (level 1), medium-term type technologies were introduced (level 2), and late type technologies were introduced (level 3).

into Eq. (3), we can observe the cost-reduction effect by changing the technology type or the farming type. When the dependent variable is the number of employees, labor costs, or material costs, Eq. (3) was estimated for a dataset that pooled the survey results for the five years from FY 2015 to FY 2019. Regarding tangible fixed assets and intangible fixed assets excluding land, software among intangible fixed assets, information processing costs and communication costs, we required only the data for 2019. Therefore, when the explained variable is one of these items, Eq. (3) is estimated for the 2019 dataset.

Table 4 presents the estimation results of Eq. (3)[8]. We also estimated the case in which the farming type was added to the explanatory variables in Eq. (3), and the case in which the ordinal number of the technology type in Eq. (3) was replaced with ordinal numbers 1 to 16, indicating the cell positions of the SAKL technology map. The results are shown in Appendixes 3 and 4, respectively.

According to Table 4, the coefficient of sales in Eq. (3) was estimated to have a positive value significantly less than 1 for any input factor. This shows that the scale effect works on the input of each factor against the increase in sales. Particularly, there are large-scale effects on the number of employees, information processing costs and communication costs. Of the coefficients related to technology type in Eq. (3), the coefficient estimated for labor costs is positive and significant. Hence, the adoption of later-type smart agricultural technology boosts labor costs. High labor costs are also interpreted as high wages; therefore, further investigation is needed on the background of this estimation result.

Looking at the estimation results when the farming type is added to the explanatory variables in Eq. (3) in Appendix 3, the coefficient of the technology type is a positive and significant value for the plant-based production function of the number of employees. The adoption of more advanced late-type smart agricultural technology increases the number of employees.

In particular, many coefficients related to farming types are significant in the plant-based production function of the number of employees and material costs. This means that the expected value of the number of employees and the expected value of material costs differ depending on the type of farming.

Appendix 4 shows the estimation results when the ordinal number indicating the technology type is replaced with the ordinal numbers 1 to 16, indicating the cell position of the SAKL technology map in Eq. (3). According to it, in estimating the plant-based production function of the

[8] The issue of endogeneity should be addressed in the future.

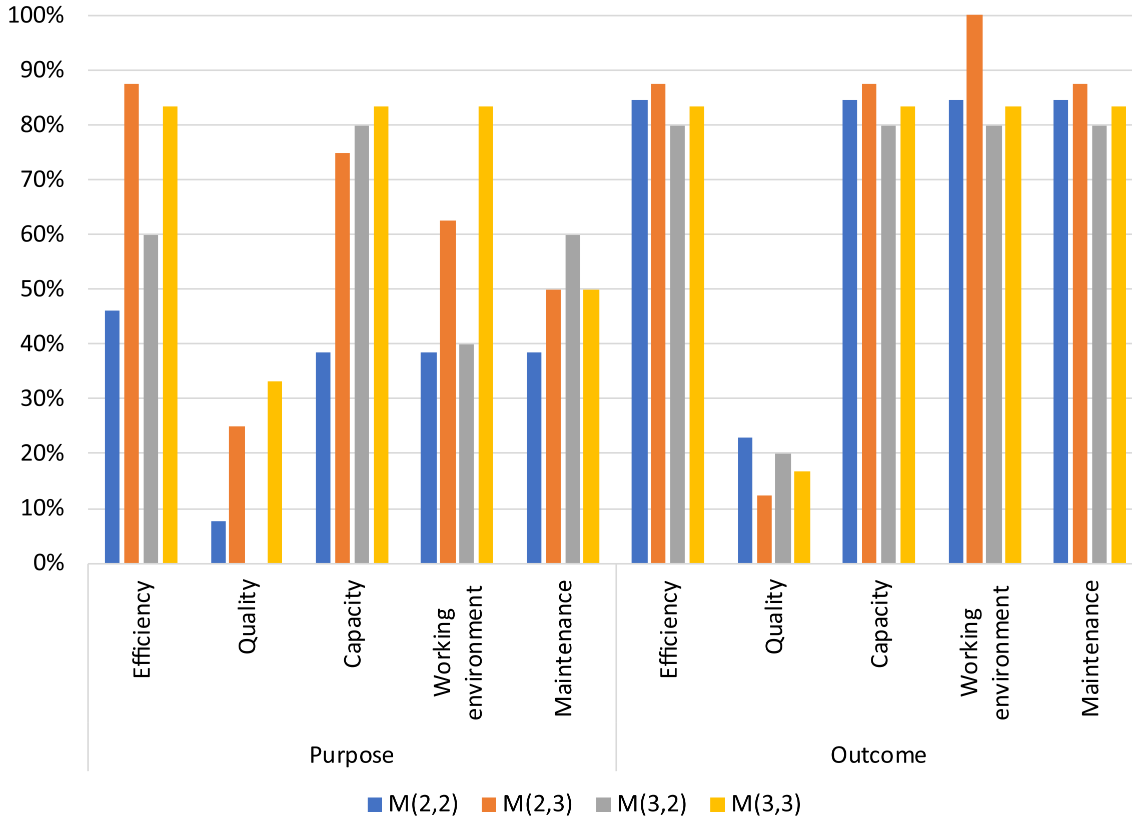

Fig. 12. Objectives and results of using smart agricultural technologies of farms located in the upper right of the SAKL technology map in 32 farms.

Table 3
Results of ordered probit analysis.

Stage 2: Whether to use later type technology				Stage 1: Whether to introduce technology			
KPI: Purpose	Capacity	0.371	**	Farming type	Open-air vegetables	−0.812	**
	Maintenance	-0.307	**		Pig farming	−1.215	***
Farming type	Rice farming	0.681	**		Egg-laying chicken	−0.930	*
	Upland farming	1.078	*	Average age of employees		−0.014	*
	Dairy	−1.134	***	Current management issues: Tax system		0.921	*
	Beef cattle	−0.735	*	Smart farming advice		0.671	***
Sales (10^4JPY)		0.00000004	***	Information provision		0.081	***
Current management issues	Labor force	−0.274	*	Factors to deny	Comparative advantage	−1.001	**
	Tax system	0.486	*		Suitability	−2.302	***
	Advanced processing	0.544	**		Comprehensibility	−1.264	***
					Trialability	−1.821	***
					Visibility	2.264	*
					Constant term	1.636	***

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
Estimation of plant-based production function.

	Number of employees (logarithm)		Capital (logarithm)		Software (logarithm)		Information processing & communication costs (logarithm)		Labor costs (logarithm)		Material cost (logarithm)	
Sales (logarithm)	0.407		0.736		0.725		0.432		0.797		0.980	
	(0.038)	***	(0.097)	***	(0.192)	***	(0.123)	***	(0.040)	***	(0.062)	***
Technology type	0.025		0.139		0.182		−0.041		0.105		−0.021	
	(0.031)		(0.101)		(0.241)		(0.093)		(0.045)	**	(0.055)	
Constant term	−1.060		1.391		−3.501		−0.082		0.009		−1.762	
	(0.353)	***	(0.890)		(1.757)	*	(1.216)		(0.394)		(0.577)	***
Number of observations	542		101		20		71		231		231	
Adj R-squared	0.308		0.421		0.424		0.261		0.577		0.563	

Note: Capital is tangible fixed assets, excluding land and intangible fixed assets.
Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

number of employees, there are relatively many significant results with respect to the coefficient related to the cell position of the SAKL technology map. In the case of M (0,3), M (1,2), M (1,3), and M (2,1), the number of employees tends to be lowered on average. In contrast, in the case of M (2,2) and M (3,1), the opposite trend is observed. Even if the visualization level is not high, the adoption of smart agricultural technology is effective in saving labor for employees. Conversely, having a high level of visualization alone does not save labor for employees.

7. Discussions

In this study, we conducted two questionnaire surveys (the fact-finding survey and the individual survey) on the actual situation of smart agriculture at Japanese farming sites with the cooperation of JACA. By analyzing the survey results, we proposed a SAKL technology map for smart agriculture and determined the degree of smartness of farms based on the survey results. This is an application of the SMKL technology map (Fujishima, 2020) to promote the introduction of IT in the manufacturing industry. The SAKL technology map is represented by 16 squares, with the vertical axis divided by four visualization levels and the horizontal axis divided by four smart agricultural technology types (no introduction, early-type, medium-term type, and late-type). The analytical results of the two surveys are summarized below.

First, based on the fact-finding survey, we summarized the observation facts by smart agricultural technology type, which is the classification in the horizontal axis direction of the SAKL technology map. According to the results, 64% of the 873 farms for which the type of technology could be identified have introduced some kind of smart agricultural technologies from the early to late-types, and the technologies are being introduced, especially at rice farms. Approximately 50% of the farms that have introduced some kind of smart agricultural technology made use of subsidies. We asked farms using smart agricultural technologies about the objectives and outcomes of introducing the technologies, and tabulated the answers using five KPI items. 50%–70% of farms have introduced technologies for improving the KPIs of efficiency, production capacity, working environment, and maintenance. As outcomes of the introduction of technologies, the KPIs improved in almost 90% of the farms using smart agricultural technologies. The KPI of "product quality" was less conscious of both the objective and the outcome of technology introduction. For farms that do not use any of the smart agricultural technologies, the biggest impediment to technology adoption was the lack of compatibility of the technology with their farm site.

Second, based on the individual survey, we summarized the observation facts by visualization level, which is the vertical scale of the SAKL technology map. Of the 73 farms whose visualization levels were determined, 40% of the farms collected data and analyzed them visually. The percentages of farms that did not collect data, farms that only collected data, and farms that collected data and analyzed by ICT were approximately 20% each. Farms with a visualization level of 3 or higher have a relatively high proportion of medium-term and late-type technologies. Conversely, it was noteworthy that a certain percentage of farms with a visualization level of 0 or 1 adopted medium-to late-type technologies. If smart agricultural equipment automatically collects data and optimizes it, optimization based on data analysis will be executed without the farmers collecting and analyzing the data. Farms with visualization level 2 or higher (data analyzed visually or by ICT) have a relatively high proportion of young employees.

Third, looking at the diagnostic results from the SAKL technology map, there were peaks in M (0,0) (the case where data were not collected and smart technologies were not adopted) and M (2,2) (the case where data were visually analyzed and medium-term technologies were adopted). In some cases, such as M (0,3) and M (3,0), the levels of visualization and technology type are significantly different from each other. When observing the effects of introducing smart technologies on the farms corresponding to the cells on the upper right of the SAKL technology map, the improvement of the technology type may not need to be accompanied by an improvement in the visualization level, but the improvement of the visualization level seems to be more effective as the technology type progresses.

Fourth, by performing a regression analysis, we analyzed in detail the effects of the various characteristics of farms identified in the questionnaire on their smartness. In addition, we analyze how the degree of farms' smartness, along with their farming type, affects productivity. From the results of the regression analysis, it was found that the experience of taking technical advice and high information provision literacy promoted the adoption of smart agricultural technologies. Conversely, the lack of comparative advantage, suitability, comprehensibility, and trial possibility of smart agricultural technologies are obstacles to technology adoption. Even if the visualization level is not very high, the adoption of smart agricultural technologies is effective in saving labor on the farm, but even if only the visualization level is high, labor saving cannot be achieved. This result, together with the diagnostic results from the SAKL technology map mentioned earlier, are as follows. The sophistication of management level (visualization) largely affects farm site efficiency when combined with the introduction of more advanced smart agricultural technologies. However, even if the management level (visualization) is not very sophisticated, the same effect may be obtained by introducing more advanced smart agricultural technologies. It should be noted that presently, approximately 50% of farms are not making efforts for visualization or adopting smart agricultural technologies.

In the manufacturing industry, it could be considered that the improvement in the upper right direction of the SMKL technology map would bring about an improvement in the efficiency of the production process. Therefore, moving to the upper right of the technology map is considered to be a unique direction for smart management. Conversely, according to our analytical results, the efficiency of the agricultural production process is expected to improve without necessarily moving to the upper right of the SAKL technology map. The transition to the upper right of the SAKL technology map will evidently improve the efficiency of the production process. In addition, it was observed that simply skidding at the bottom of the technology map (even by adopting later-type smart agricultural technologies while the visualization level was low) could improve the efficiency of the production process.

According to the information on the web page of an agricultural machinery manufacturer,[9] one of the late-type technologies, smart combine, efficiently performs rice harvesting by automatic operation using GPS. It simultaneously uses on-board sensors to measure the composition and yield of rice. If the smart combine is used, a field map showing the composition and yield of rice for each position is automatically created from the data collected during harvesting, and detailed information is provided to improve the harvest the following year. The collection and analysis of data on the harvest is integrated into the harvesting work, and the data are collected and analyzed without the farmers being aware of it. If a farm that does not currently have smart agricultural technologies introduces the smart combine, the change will manifest as a skid at the bottom of the SAKL technology map.

Based on the above considerations, the path to establishing smart agriculture is as follows:

First step involves promoting the introduction of smart agricultural technologies by supporting farmers who are willing to raise the level of visualization and technology types by themselves. To train such farmers, it is effective to increase opportunities for receiving technical advice on smart agriculture and for enhancing information provision literacy. Additionally, efforts are needed to eliminate the factors that impede the introduction of smart agricultural technologies: the lack of comparative advantage, suitability, comprehensibility, and trial possibility.

[9] Kubota Web Page Co., Ltd. https://agriculture.kubota.co.jp/product/combine/dr6130a/

Second step is advancing the efforts of the 1st step; the smart technologies will be refined by accumulating various data collections and the standardization and packaging of the technology will be promoted. If packaged technology is introduced and operated at default settings, some efficiency improvement will be achieved without relying on the degree of information provision literacy of the farmer.

Third step is the strategy to disseminate the technologies of 2nd step, i.e., subsidies, demonstrations, institutional reforms related to land ownership, sharing of agricultural machinery, education of farmers and operators of agricultural machinery.

In Japan, the “Smart Agriculture Demonstration Project” has been implemented as a national project since FY 2019.[10] Under the project, demonstration projects are being conducted in 202 farms nationwide for implementing “smart agriculture” that utilizes cutting-edge technologies such as robots, AI, and IoT, and accelerating the social implementation of smart agriculture. This project represents the progress of the first-stage process. To generalize the precedents of the first stage, it is necessary to proceed to the processes of the second and third stages. The research subjects to be carried out for this study are as follows.

In the second stage, it is necessary to consider the specific content of the standardized packaging technology. For example, the smart combine that integrates information collection, analysis, and harvesting work, is an example of standardized packaging technology. In this case, data collection and analysis are integrated into the harvesting work, and there is no need for farmers to consciously collect and analyze data. In the future, proposing a standardized packaging technology for various farm operations and verifying whether the proposed technology is truly useful for agricultural sites is necessary.

For that purpose, investigating the actual situation of agricultural machinery development and analyzing the outcomes of advanced efforts using machinery in detail, is necessary. When analyzing outcomes, it is important to summarize the outcomes of case studies from a unified perspective and compare the outcomes between cases with rational standards. Applying management technology methods, which are often used to improve manufacturing processes, are useful for organizing such analytical concepts. The SAKL technology map proposed in this study is an example of an application of management technology methods in the manufacturing industry. In future research, we will further enhance analytical methods such as the SAKL technology map and use those methods to accumulate detailed case analysis. Furthermore, based on the analytical results, we consider the technology dissemination strategy in the third stage. Such research could contribute to improving agricultural productivity through the spread of smart agriculture.

The limitations of this study are as follows. The questionnaire survey conducted in this study spanned all farming types, and the sample size was not large. Therefore, it is necessary to confirm that the facts found in the results of this survey are the universal nature of smart agriculture based on more detailed case studies by farming type and farm size. In addition, this study applied the SAKL technology map to entire farm management for comprehensively evaluating the farm performance. In future studies, we need to apply the SAKL technology map to individual activities on the farm, activities such as rice planting, harvesting, weeding, and livestock feeding, and evaluate the performance of each activity.

Despite these limitations, this study clarified the path to smart agriculture that Japanese agriculture should presently choose. As mentioned in Section 2, context building for advancing smart agriculture is being sought worldwide. The results of this study add a context for the establishment of smart agriculture in the literature. In addition, according to an interview with one of Japan’s smart farmers in Section 2, Japanese agricultural sites need a flexible application of smart agriculture. The SAKL technology map proposed in this study will help satisfy the needs of such agricultural sites.

[10] Agriculture, Forestry and Fisheries Technology Conference Web Page https://www.affrc.maff.go.jp/docs/smart_agri_pro/smart_agri_pro.htm

8. Conclusion

The use of smart agriculture that utilizes digital technology is expected to spread worldwide. As typical smart farmers in Japan show, smartening (strengthening management based on data analysis) is the most important issue for Japanese agriculture, and is at a turning point.

Given this background, we conducted a questionnaire survey on the actual conditions of smart agriculture among relatively large-scale farms in Japan. We also propose a SAKL technology map by applying the evaluation method used in management technology theory in the manufacturing industry. Using the results of the questionnaire survey and the proposed SAKL technology map, we determined the current state of the spread of smart agricultural technologies in Japan. It was found that the higher the degree of smartness, the better the KPI of farms.

We then quantitatively determined farm characteristics that are more likely to accept later-type smart agricultural technologies. We also quantitatively confirmed that the degree of farms’ smartness, along with their farming type, affects their productivity. The scale effect works on the input of each factor against an increase in sales.

Regarding the impact of the technical map’s diagnostic results on the productivity of farms, even if the visualization level is not high, the adoption of smart agricultural technology is effective in saving labor for employees. Conversely, having a high level of visualization alone does not save labor for employees. In other words, it seems that the production process efficiency in Japanese agriculture could be improved without necessarily moving to the upper right of the SAKL technology map. The shift to the upper right of the SAKL technology map would improve the efficiency of the production process, but simply skidding at the bottom of the technology map (adopting later-type smart agricultural technology when the visualization level was low) would improve the efficiency of the production process. This is a unique feature of agriculture in Japan.

Since the questionnaire survey conducted in this study was comprehensive and the sample size was not large, the characteristics of farms by farm type and size have not been sufficiently analyzed. This is a limitation of this study. It is our future research subject to perform SAKL technology map diagnosis by farm type and size through more detailed case studies and to create a detailed roadmap for smartening Japanese agriculture.

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CRediT authorship contribution statement

Ayu Washizu: Methodology, Conceptualization, Supervision, Writing – original draft, Writing – review & editing, Formal analysis, Project administration. **Satoshi Nakano:** Methodology, Data curation, Writing – review & editing, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This study was funded by a JSPS KAKENHI Grant-in-Aid for Scientific Research (JP21H03676, JP19KT0037, JP20K22139) and a Waseda University Grant for Special Research Projects (2022C-190, 2021C-263), the Environment Research and Technology Development Fund (JPMEERF20202008) of MOE, and the Environmental Restoration and Conservation Agency.

We would also like to thank Mr. Shu-ichi Yokota, the representative of Yokota Nojo Co., Ltd., for participating in the interview, and the Japan Agricultural Corporation Association for their cooperation in conducting the questionnaire.

Appendix 1. Survey questions list

Fact-finding survey

Please tell us about your farm's commitment to smart farming. (In this survey, "smart" means high-performance technology that utilizes information and communication technology (ICT), automation technology, and robotic technology.

Q1 In relation to smart agriculture, do you ever participate in technical exchange meetings organized by national, prefectural, agricultural co-operatives, research institutes, manufacturers, etc., receive their visits, or receive advice?

Q2 Please encircle the smart farming technology you are using (any number).

1. Smart tractor
2. Smart rice transplanter
3. Water management system, irrigation / sprinkling system
4. Advanced equipment for controlling and automating fertilization
5. Smart harvester (smart combine)
6. Advanced equipment for spraying pesticides and fertilizers (aerial spraying, ground spraying)
7. Sensing equipment (aerial photography, satellite, and field server), camera, advanced monitoring equipment such as estrus detectors
8. Advanced equipment that assists the work process (such as robots, radio-controlled mowers, assist suits, packing machines, pruners, and automatic feeders)
9. Production process management support system (such as systems for cultivation, work, environmental control, transportation, fruit selection, control, storage, mixed feed system, and system for cattle health management)
10. Management and shipping management support system (such as collection of market data, harvest forecasting system, order management system, and shipping support system)
11. Coordination between the production process management support system and the business and shipping management support system
12. Others
13. Smart farming technology is not used.

Q3 For those who have introduced smart agricultural technology in Q2

Q3-1 Did you use the subsidies provided by the national, prefectural, and research institutes to introduce the technology in Q2?

Q3-2 Please tell us the purpose of introducing the Q2 technology.

1. To reduce working hours and man-hours
2. To reduce the workload and make work more comfortable
3. To improve yield, profit, and land use rate
4. To reduce production costs (raw material input costs)
5. To improve added value (such as improvement of taste and improvement of unit sales price)
6. For optimization of production / process management such as cultivation management, fertilization management, water management, feeding system.
7. For optimizing business management such as data management related to production costs and finance
8. To scale up
9. For training unskilled people
10. To solve the labor shortage
11. For new IT business use such as sharing agricultural machinery and using cultivation management services
12. To expand the business field
13. Others

Q3-3 Please answer the following questions regarding the results of introducing the technology in Q2.

1. Did you improve work efficiency and work environment?
2. Did it improve your profit margin?
3. Did you find new workers or young people working?
4. Has regional cooperation been strengthened?
5. Have new business opportunities been created?

Q3-4 Please tell us why you are happy to use Q2 (any number).

1. Work speed has improved.

2. Production cost has been reduced.
3. We were able to achieve simplification and labor saving of work and processes.
4. We were able to expand new businesses and scale.
5. We were able to realize measures to improve quality and added value.
6. Others

Q3-5 Please tell us about the points that should be improved in Q2 (any number).

1. Excessive data provided.
2. The performance of the technology is not sufficient.
3. The content of the technology does not match the actual situation at the site.
4. The cost is high for the results obtained.
5. Setting up a contact point where you can feel free to consult about maintenance services and explanations of functions.
6. Providing consultant services to apply expert knowledge to farm sites.
7. Providing agency services for smart agriculture.
8. Others

Q3-6 I would like to ask those who marked 5 to 7 in Q3-5. How far do you think the business establishment that provides such services should be from your address?

1. Within the same village
2. Within the same municipality
3. Within the same prefecture
4. Neighboring prefecture
5. If the internet is connected, the location does not really matter
6. Others

Q4 For those who have not introduced smart agricultural technology in Q2
Please tell us why you are not introducing smart farming technology.

1. Because the initial investment is high
2. Because workers cannot operate computers and high-performance machines
3. The performance of the equipment is inadequate or uncertain
4. Because the people around me are negative about smart farming
5. Because it does not match the actual situation at the work site
6. I do not know how to introduce it
7. Because the internet connection is bad
8. Because collecting or inputting data is troublesome
9. It takes time or is troublesome to learn the technique
10. Knowledge for proper use of IT technology is uncertain, and it is troublesome to make a mistake in using the technology.
11. Even if smart agriculture is adopted, it is not expected to increase profits.
12. It is doubtful that delicious crops can be produced even if smart agriculture is adopted.
13. Others

Q5 For everyone
The technology in Q2 utilizes information and communication technology (ICT). Can information about your farm be provided to a third party for the following purposes with appropriate consent and the necessary safeguards?

1. To improve the accuracy of your farm's agricultural machinery control technology, farming plan support function, growth model, and so on.
2. To improve the general accuracy of agricultural machinery control technology, farming plan support function, growth model, and so on.
3. To improve local technical capabilities and pass on skills
4. To improve the accuracy of logistics / commercial distribution systems
5. For cooperation between production information and distribution / commercial distribution information
6. For new business development in collaboration with different industries
7. To help the development of academics such as education and research
8. To help deal with climate change and prevent epidemics

Individual survey

Q1. Please indicate whether you have introduced the smart agricultural technology you are using and include the year of introduction.

1. Smart tractor
2. Smart rice transplanter
3. Water management system, irrigation / sprinkling system
4. Advanced equipment for controlling and automating fertilization
5. Smart harvester (smart combine)

6. Advanced equipment for spraying pesticides and fertilizers (aerial spraying, ground spraying)
7. Sensing equipment (aerial photography, satellite, field server), camera, advanced monitoring equipment such as estrus detectors
8. Advanced equipment that assists the work process (such as robots, radio-controlled mowers, assist suits, packing machines, pruners, and automatic feeders)
9. Production process management support system (such as systems for cultivation, work, environmental control, transportation, fruit selection, control, storage, etc., mixed feed system, system for cattle health management)
10. Management and shipping management support system (such as collection of market data, harvest forecasting system, order management system, shipping support system)
11. Coordination between the production process management support system and the business and shipping management support system
12. Others

Q2. Please tell us about the data utilization status at your farm.

1. Not collecting the data required for management
2. Collecting data necessary for management
3. We collect data necessary for management and compare and analyze it visually.
4. We collect data necessary for management and analyze it using ICT.

Q3. Please tell us the following values for the last 5 years at your farm:

1. Annual sales (10,000 yen)
2. Operating profit (10,000 yen)
3. Material cost (10,000 yen)
4. Labor costs (10,000 yen)
5. Manufacturing cost (10,000 yen)
6. Selling, general, and administrative expenses (10,000 yen)
7. Employees (executives, full-time employees, full-time part) (unit: person)

Q4. Please tell us about the values of assets and information and communication costs for FY2019.

1. Tangible fixed assets (10,000 yen)
2. Of which, land assets (10,000 yen)
3. Information processing cost + communication cost (10,000 yen)
4. Intangible fixed assets (10,000 yen)
5. Of which, software assets (10,000 yen)
6. Acquisition amount of tangible (excluding land) and intangible fixed assets for the current period (10,000 yen)
7. Of which, informatization investment (10,000 yen)

Q5. Please tell us about the composition of employees (executives, full-time employees, full-time part) for FY2019.

1. 10 s to 30 s (Unit: person)
2. 40 s to 50 s (Unit: person)
3. 60 s and over (unit: person)

Q6. Regarding FY2019, please tell us the number of employees (executives, full-time employees, full-time part-time employees) who are engaged in ICT-related work (such as operation and maintenance) in each of the following processes. If one person has both ICT-related work and other work, count that person as 0.5.

1. Production (unit: person)
2. Sales (unit: person)
3. Accounting (Unit: Person)

Appendix 2. Results of ordered probit analysis

Stage 2: Whether to use later type technology					Stage 1: Whether to introduce technology				
KPI: Purpose	Efficiency	0.135	(0.174)		Farming type	Rice farming	−0.246	(0.348)	
	Product quality	0.314	(0.262)			Upland farming	−0.043	(0.483)	
	Production capacity	0.371	(0.155)	**		Open-air vegetables	−0.812	(0.345)	**
	Working environment	0.044	(0.174)			Facility vegetables	−0.474	(0.363)	
	Maintenance management	−0.307	(0.155)	**		Craft crops	1.378	(1.111)	
Farming type	Rice farming	0.681	(0.272)	**		Fruit tree	−0.271	(0.553)	
	Upland farming	1.078	(0.637)	*		Open-air flowers	−0.363	(0.832)	
	Open-air vegetables	−0.221	(0.325)			Facility flowering	0.244	(0.746)	
	Facility vegetables	0.548	(0.350)			Mushroom	−0.482	(0.498)	
	Craft crops	0.913	(0.716)			Other tillage			
	Fruit tree	−0.422	(0.396)			Dairy	0.709	(0.587)	

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Stage 2: Whether to use later type technology					Stage 1: Whether to introduce technology				
	Open-air flowers	−0.172	(0.442)			Beef cattle	−0.728	(0.545)	
	Facility flowering	0.358	(0.562)			Pig farming	−1.215	(0.372)	***
	Mushroom	−0.010	(0.416)			Egg-laying chicken	−0.930	(0.483)	*
	Other tillage					Broiler	−0.224	(0.536)	
	Dairy	−1.134	(0.339)	***		Other livestock	−0.310	(0.578)	
	Beef cattle	−0.735	(0.417)	*	Sales (10^4JPY)		0.000	(0.000)	
	Pig farming	−0.541	(0.447)		Increase / decrease in sales		0.026	(0.110)	
	Egg-laying chicken	−0.277	(0.627)		Officers, full-time employees, full-time part-time workers		0.002	(0.005)	
	Broiler	−0.668	(0.906)		Average age of full-time employees		−0.014	(0.007)	*
	Other livestock	−0.336	(0.370)		Current management issues	Labor force	−0.024	(0.178)	
Sales (10^4JPY)		0.00000004	(0.000)	***		Agricultural land system	−0.199	(0.249)	
Increase / decrease in sales		−0.060	(0.101)			Infrastructure maintenance	0.456	(0.321)	
Officers, full-time employees, full-time part-time workers		0.003	(0.002)			Financing	0.034	(0.331)	
Average age of full-time employees		0.000	(0.007)			Material cost	0.228	(0.238)	
Current management issues	Labor force	−0.274	(0.160)	*		Distribution cost	0.059	(0.246)	
	Agricultural land system	0.323	(0.243)			Product price	−0.290	(0.258)	
	Infrastructure maintenance	−0.058	(0.192)			Domestic sales channel development	−0.211	(0.276)	
	Financing	−0.037	(0.220)			Technology development	−0.352	(0.277)	
	Material cost	−0.029	(0.169)			Technology development	0.921	(0.470)	*
	Distribution cost	−0.076	(0.205)			Advanced processing	0.282	(0.308)	
	Product price	−0.176	(0.171)			Export	0.081	(0.264)	
	Domestic sales channel development	0.096	(0.259)			safe and secure	0.425	(0.523)	
	Technology development	0.021	(0.210)			Safety net	−0.493	(0.410)	
	Technology development	0.486	(0.263)	*		Others	−0.548	(0.582)	
	Advanced processing	0.544	(0.248)	**	Smart farming advice		0.671	(0.202)	***
	Export	−0.017	(0.305)		Information provision		0.081	(0.026)	***
	safe and secure	0.229	(0.273)		Factors to deny	Comparative advantage	−1.001	(0.497)	**
	Safety net	0.154	(0.351)			Suitability	−2.302	(0.311)	***
	Others	−0.268	(0.545)			Comprehensibility	−1.264	(0.356)	***
Smart farming advice		0.263	(0.172)			Trialability	−1.821	(0.364)	***
Subsidy		0.214	(0.145)			Visibility	2.264	(1.217)	*
Information provision		−0.002	(0.020)		Constant term		1.636	(0.453)	***
	Number of observations	498				rho	0.301		
	Log pseudolikelihood	−358.6288				Ho: rho = 0			
						chi2(1)	4.02		
						Prob > chi2	0.045		

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 3. Estimation of plant-based production functions (cases where farming type is added to explanatory variables)

	Number of employees (logarithm)		Capital (logarithm)		Software (logarithm)		Information processing & communication costs (logarithm)		Labor costs (logarithm)		Material cost (logarithm)	
Sales (logarithm)	0.415		0.761		0.426		0.414		0.827		0.929	
	(0.124)	***	(0.122)	***	(0.372)		(0.205)	**	(0.114)	***	(0.081)	***
Technology type	0.126		0.161		−0.082		−0.085		0.080		0.054	
	(0.071)	*	(0.161)		(0.145)		(0.140)		(0.108)		(0.128)	
Rice farming	−0.944		−0.367		2.808		0.319		0.269		−1.132	
	(0.151)	***	(0.299)		(0.953)	**	(1.427)		(0.362)		(0.237)	***
Upland farming	−0.946		−0.423		1.923		0.205		0.468		−2.086	
	(0.237)	***	(0.229)	*	(1.214)		(1.406)		(0.428)		(0.630)	***
Open-air vegetables	−0.685		−0.022		3.031		0.598		0.368		−1.977	
	(0.196)	***	(0.343)		(1.690)		(1.421)		(0.603)		(0.807)	**
Facility vegetables	−0.501		−0.274				0.060		0.962		−1.215	
	(0.306)		(0.365)				(1.402)		(0.271)	***	(0.265)	***
Craft crops	−1.292		−0.590				−0.697		−0.146		−1.659	
	(0.099)	***	(0.166)	***			(1.214)		(0.241)		(0.293)	***
Fruit tree	−0.613		0.175		1.774		1.018		0.360		−1.578	
	(0.245)	**	(0.454)		(1.695)		(1.342)		(0.549)		(0.276)	***
Open-air flowers												
Facility flowering	−0.720		−0.946		4.783		0.668		0.168		0.045	
	(0.285)	**	(0.274)	***	(1.883)	**	(1.178)		(0.474)		(0.311)	
Mushroom	−0.397		0.204		−0.003		1.153		1.162		−1.463	
	(0.022)	***	(0.186)		(1.449)		(1.299)		(0.266)	***	(0.312)	***
Other tillage			−1.106				−0.095					
			(0.174)	***			(1.336)					
Dairy	−1.177		1.103		1.563		1.333					
	(0.244)	***	(0.365)	***	(1.680)		(1.150)					
Beef cattle	−1.273		−1.217				−0.075					

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	Number of employees (logarithm)	Capital (logarithm)	Software (logarithm)	Information processing & communication costs (logarithm)	Labor costs (logarithm)	Material cost (logarithm)
	(0.236) ***	(1.091)		(1.364)		
Pig farming	−1.876	0.172				
	(0.136) ***	(0.266)				
Egg-laying chicken	−0.403			1.438	0.300	−0.298
	(0.332)			(1.431)	(0.243)	(0.230)
Broiler	−0.182	−1.981				
	(0.807)	(0.891) **				
Other livestock						
Constant term	−0.533	1.399	−2.469	−0.106	−0.733	−0.174
	(1.164)	(1.070)	(2.121)	(3.262)	(1.262)	(0.994)
Number of observations	99	87	17	64	42	43
Adj R-squared	0.428	0.399	0.587	0.183	0.542	0.652

Note: Capital is tangible fixed assets, excluding land and intangible fixed assets.
Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 4. Estimation of plant-based production functions (case where the cell position of the SAKL technology map is added to the explanatory variable)

	Number of employees (logarithm)	Capital (logarithm)	Software (logarithm)	Information processing & communication costs (logarithm)	Labor costs (logarithm)	Material cost (logarithm)
Sales (logarithm)	0.382	0.748	0.896	0.412	0.819	0.950
	(0.038) ***	(0.118) ***	(0.215) ***	(0.126) ***	(0.040) ***	(0.069) ***
1_M(0,0)						
2_M(0,1)						
3_M(0,2)	−0.216	0.993		−1.021	0.400	−1.347
	(0.234)	(0.196) ***		(0.175) ***	(0.116) ***	(1.922)
4_M(0,3)	−0.809	−0.857				
	(0.056) ***	(0.174) ***				
5_M(1,0)						
6_M(1,1)						
7_M(1,2)	−0.631	0.597		−1.492	−1.040	−1.271
	(0.118) ***	(0.178) ***		(0.208) ***	(0.218) ***	(0.144) ***
8_M(1,3)	−0.357	0.215	0.120	−0.436	0.238	0.426
	(0.116) ***	(0.371)	(0.352)	(0.600)	(0.195)	(0.140) ***
9_M(2,0)						
10_M(2,1)	−0.264	0.363		0.583	−0.190	0.724
	(0.082) ***	(0.275)		(0.464)	(0.121)	(0.183) ***
11_M(2,2)	0.446	0.012	−0.669	0.282	0.121	0.451
	(0.108) ***	(0.391)	(1.002)	(0.353)	(0.190)	(0.140) ***
12_M(2,3)	0.008	0.184		−0.010	0.190	−0.047
	(0.131)	(0.396)		(0.437)	(0.146)	(0.136)
13_M(3,0)						
14_M(3,1)	0.983	2.056	−1.136		0.874	−0.112
	(0.065) ***	(0.234) ***	(0.495) **		(0.095) ***	(0.148)
15_M(3,2)	−0.171	0.048	−0.883	0.046	−0.943	−0.550
	(0.123)	(1.103)	(0.852)	(0.719)	(0.243) ***	(0.587)
16_M(3,3)	0.058	0.527		−0.136	0.448	−0.340
	(0.069)	(0.377)		(0.483)	(0.182) **	(0.265)
Constant term	−0.827	1.369	−4.595	0.052	−0.115	−1.478
	(0.358) **	(1.104)	(1.947) **	(1.273)	(0.411)	(0.656) **
Number of observations	542	101	20	71	231	231
Adj R-squared	0.348	0.387	0.363	0.248	0.615	0.601

Note: Capital is tangible fixed assets, excluding land and intangible fixed assets.
Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
The cell positions on the SAKL technology map were entered into the regression equation in the corresponding ordinal numbers of 1–16.

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