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Life-Cycle Greenhouse Gas Mitigation Potential of the Transition to Smart Farming Systems Using a Smart Farming Extended Input–Output Framework

Jun Taguchi, Hiroki Hondo * and Yue Moriizumi

Graduate School of Environment and Information Sciences, Yokohama National University, 79-7 Tokiwadai Hodogaya-ku, Yokohama 240-8501, Japan; taguchi-jun-wy@ynu.jp (J.T.); moriizumi-yue-sv@ynu.ac.jp (Y.M.)
* Correspondence: hondo@ynu.ac.jp

Abstract

Smart agricultural technologies (SATs) are gaining attention as means of addressing agricultural labor shortages. SATs are also expected to reduce greenhouse gas (GHG) emissions from agriculture; however, their life-cycle mitigation potential remains insufficiently quantified. This study conducts a model-based simulation analysis to assess the impact of SAT adoption in open-field cultivation on life-cycle GHG (LC-GHG) emissions in Japan, focusing on paddy rice and vegetable production. A Smart Farming Extended Input–Output (SFEIO) framework was developed by incorporating four smart farming sectors into a conventional input–output framework. Results indicate that the transition to smart farming can reduce LC-GHG emissions by 9% for paddy rice and 11% for open-field vegetables. These reductions reflect improved crop yields and input-use efficiency resulting from SAT adoption, including variable-rate fertilization and autonomous agricultural machinery. If smart farming were adopted in all rice and open-field vegetable cropping systems in Japan, the annual GHG emissions from the crop production sector could be reduced by up to 5%. However, SAT adoption also increased GHG emissions in some upstream industrial sectors. Furthermore, sensitivity analysis revealed that improvements in crop yield per unit area associated with SAT adoption are an important factor in enhancing LC-GHG emission reductions. These findings suggest that SAT adoption in open-field cultivation can contribute to agricultural decarbonization, although additional mitigation measures are required to achieve carbon neutrality.

Keywords: life cycle assessment (LCA); smart farming; precision agriculture; smart agricultural technologies; open-field cultivation; input–output analysis; greenhouse gas emissions

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1. Introduction

In Japan, agricultural production is increasingly challenged by an aging and declining agricultural workforce. According to the Ministry of Agriculture, Forestry and Fisheries, the agricultural workforce is projected to decline to approximately one-quarter of its current level over the next 20 years [1]. Continued workforce decline could threaten the sustainability of agricultural production and, consequently, food security. Therefore, alternative cultivation methods that maintain productivity while reducing labor requirements are increasingly important. Increasing attention has been paid to the transition from conventional farming to smart farming. Smart farming integrates advanced technologies, such as robots, artificial intelligence (AI), and information and communication technologies (ICTs), collectively referred to as smart agricultural technologies (SATs) [1]. These technologies enable

automation and precise control of agricultural operations, which are expected to improve productivity. Furthermore, smart farming may alleviate labor shortages and encourage new entrants into the agricultural sector. Despite challenges to SAT adoption, including the difficulty of developing technologies adaptable to diverse field conditions and the need for farmers to modify conventional farming practices, SATs were used on approximately 20% of Japan's cultivated area as of 2024 [1].

SAT adoption may also contribute to reducing agriculture-associated greenhouse gas (GHG) emissions. For example, Japan's agricultural policy framework, the MIDORI Strategy for Sustainable Food Systems, identifies SATs, such as automated tractor steering in open-field cultivation, as a measure to reduce GHG emissions [2]. This strategy aims to achieve zero CO_2 emissions from the agriculture, forestry, and fishery sectors by 2050. Although this policy identifies SATs in open-field cultivation as a potential measure for reducing GHG emissions, their quantitative mitigation potential has not been fully established. Quantitative information that can serve as the basis for policy formulation is indispensable for enhancing the effectiveness of agricultural and environmental policies. Therefore, quantitatively clarifying the GHG emission reduction potential associated with adoption of SATs in open-field agriculture is important for the development of effective agricultural and environmental policies.

Several studies have analyzed the potential to reduce life-cycle greenhouse gas (LC-GHG) emissions through the application of SATs in open-field cultivation. Medel-Jiménez et al. [3] conducted a life cycle assessment (LCA) to evaluate the environmental impacts of SAT adoption in a five-year crop rotation system comprising spring barley, soybean, winter wheat, rapeseed, and winter barley in Austria. Karagkounis et al. [4] evaluated the environmental impacts of multiple SATs, including remote-sensing technologies and farm management systems, across 11 fields and eight different crops (fruit trees, vegetables, and cereals) in Greece. Sanches et al. [5] evaluated the life cycle economic and environmental impacts of adopting automatic steering, automatic section control, and variable-rate fertilization technologies in Brazilian sugarcane production for ethanol. Tascione et al. [6] investigated the potential to reduce LC-GHG from grape cultivation in Sardinia through optimized management of fertilizers, water, and pesticides, using data obtained from various sensors and farm management systems. Bacenetti et al. [7] and Paleari et al. [8] analyzed the environmental impacts of introducing variable-rate fertilization technologies in paddy rice cultivation in Italy. Vatsanidou et al. [9] and Núñez-Cárdenas et al. [10] evaluated the environmental effects of adopting variable-rate fertilization technologies for pear cultivation in Greece and stone fruit production systems in Spain, respectively. Jovarauskas et al. [11] revealed the environmental impacts associated with the application of variable-rate fertilization technologies in wheat cultivation in Lithuania; similar work has also been reported by Medel-Jiménez et al. [12] in Austria and by Sponagel et al. [13] in Germany. In Japan, Seo et al. [14] evaluated the environmental impacts of agricultural drones for pesticide application in paddy rice production.

Despite the growing body of research on smart farming, important gaps remain in the literature. First, few studies have evaluated agricultural production systems in which multiple SATs are adopted simultaneously. Most previous studies focused on individual SATs, whereas multiple SATs are likely to be implemented simultaneously within agricultural production systems, highlighting the need for system-level assessments. Furthermore, the influence of additional GHG emissions associated with manufacturing of machinery and equipment required for SAT adoption on the overall LC-GHG mitigation potential remains unclear. Because the introduction of new technologies may involve trade-offs between increased upstream emissions and reduced on-farm emissions, life-cycle assessments are required to capture these effects. However, few studies have focused on quantitatively

assessing how transitions toward smart farming systems alter agricultural production structures, including capital goods, and how these changes affect life-cycle GHG emissions. Input–output (IO) analysis is well suited to addressing this gap because it enables the estimation of both direct GHG emissions from agricultural production and indirect emissions throughout upstream supply chains. However, conventional IO tables do not explicitly represent emerging SATs, limiting their ability to capture the environmental impacts of their adoption. The study by Choi et al. [15] is one of the few that have developed an input–output table incorporating smart farming systems, contributing to the quantitative analysis of their role in South Korea's economic growth. However, the table was not extended for environmental analysis, and its sectoral classification was relatively coarse, limiting its ability to represent the detailed production structures of smart farming systems. In addition, the geographical coverage of previous studies has been concentrated mainly in Europe [16]. GHG emission estimates from open-field cultivation may be influenced by regional characteristics, including climatic conditions, geographic settings, and crop types. In Japan, however, studies on smart farming that account for region-specific conditions remain limited, with Seo et al. [14] representing one of the few examples. Therefore, further research in underrepresented regions, including Japan, is important for building a body of evidence on the implications of smart farming transitions across diverse regional contexts.

This study aimed to quantitatively evaluate LC-GHG emissions associated with the transition to smart farming systems. Focusing on paddy rice and open-field vegetable production systems, two major cropping systems in Japan, we quantified the effects of adopting multiple SATs on LC-GHG emissions in the crop production sector. To achieve this objective, we developed a Smart Farming Extended Input–Output (SFEIO) table. Although the framework was demonstrated using Japan as a case study, its application provides insights that can contribute to the development of policies for sustainable agricultural production systems in other regions. It should be noted that the present study focuses on the environmental impacts of smart farming transitions and does not assess their economic performance or effects on employment.

2. Materials and Methods

To analyze the changes in LC-GHG emissions associated with the adoption of SATs in open-field cultivation, an SFEIO table was constructed by extending the industrial sectors related to smart farming.

The SFEIO table was developed based on the 2015 Japanese IO table (391 sectors) [17]. Figure 1 illustrates the conceptual structure of the SFEIO table and its construction workflow. First, based on the results of demonstration experiments and previous studies, the quantitative changes in agricultural inputs and crop yields associated with the adoption of SATs for paddy rice and open-field vegetable production were estimated. Next, the estimated changes in agricultural inputs and crop yields were combined with the input structures of the corresponding sectors in the existing IO table to define the input structures of smart-farming-related sectors. In this process, changes in input values were estimated based on the ratios of input values between conventional and smart farming in the years when the data were collected, rather than their absolute monetary values. We assumed that these ratios remain constant over time. In this study, the smart-farming-related sectors for which input structures were defined were (1) smart rice, (2) smart open-field vegetables, (3) smart agricultural machinery, and (4) agricultural drones. Based on the defined input structures, technology coefficient vectors were constructed for these four sectors. These vectors were then incorporated into the input coefficient matrix of the existing IO table to construct the SFEIO table. Sector-specific direct GHG emission intensities were developed for the SFEIO table. Finally, an IO analysis was conducted using the SFEIO table and a sector-specific

direct GHG emission intensity vector to estimate the LC-GHG emissions. The potential of SAT adoption to reduce LC-GHG emissions was quantitatively evaluated by comparing estimated LC-GHG emissions of paddy rice and open-field vegetable production under conventional and smart farming systems.

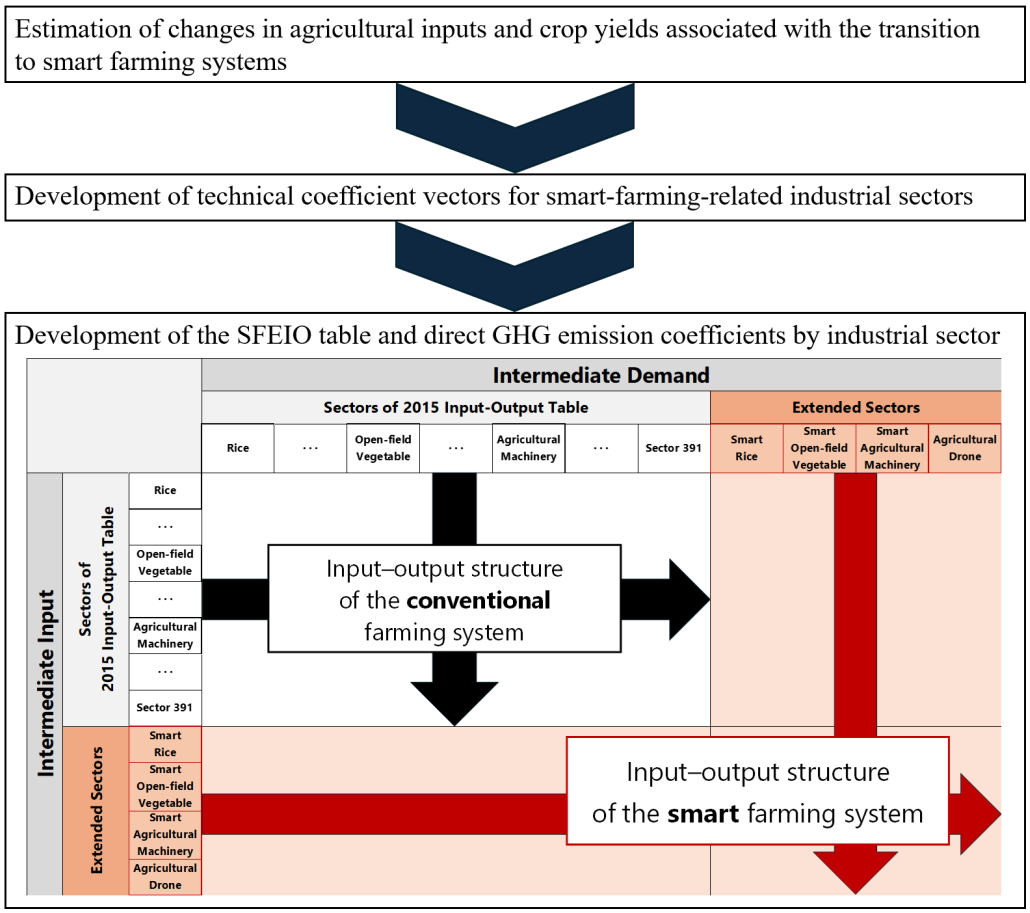


Figure 1. Workflow for constructing the SFEIO table and its conceptual structure.

The 2015 IO table was used for this study because the adoption of SATs in Japan was still limited at the time, providing a suitable basis for identifying changes in input structures associated with the transition from conventional to smart farming systems and estimating their potential LC-GHG emission reductions. However, technological and structural changes in the economic system since 2015, including changes in production cost structures and the electricity mix, may affect the estimated LC-GHG emissions. It should be noted that these changes were not fully accounted for in this study.

2.1. Changes in Agricultural Inputs and Crop Yields Associated with Smart Farming Practices in Open-Field Cultivation

2.1.1. Paddy Rice Cultivation

Rice (*Oryza sativa*) is the most important cereal crop in Japan, accounting for approximately 27% of the total crop farming production in 2023 [18]. Rice is typically cultivated in flooded paddy fields involving several agricultural processes. Almost all farming operations are mechanized, and various agricultural machines are used. The primary agricultural machinery includes tractors used in various field operations, rice transplanters, and combine harvesters.

In this study, a typical mechanized cultivation system was defined as the conventional farming system for paddy rice production. We assumed that the agricultural inputs and crop yields of this conventional farming system were identical to those of the rice sector in the IO table. In contrast, smart farming systems were defined based on smart farming demonstration projects conducted by national and local governments [19,20]. The cultivation systems analyzed were designed for a 100-ha farm. Several SAT-enabled agricultural machines and products have been introduced into smart farming systems, including autonomous tractors (73.6 kW), autonomous rice transplanters, autonomous combine harvesters, agricultural drones, and farm management systems. Table A1 presents the agricultural machinery and services used in conventional and smart farming systems. Autonomous agricultural machinery, such as tractors, rice transplanters, and combine harvesters, performs high-precision positioning using a real-time kinematic (RTK) Global Navigation Satellite System (GNSS), thereby enabling automated and precise farm operations. Autonomous agricultural machinery is capable of fully unmanned autonomous operation under human supervision. Autonomous rice transplanters and combine harvesters perform variable-rate fertilization through integration with a farm management system. Combine harvesters measure the crop yield at each location within the field using onboard sensors and transfer the yield data to the farm management system. Using the transmitted information, the system generates a prescription map for variable-rate fertilization. In the following year, the autonomous rice transplanter used the generated prescription map from the previous year to perform variable-rate fertilization during rice transplanting. In addition to creating and outputting prescription maps, the farm management system functions as software for personal computers and smartphones that collects and organizes data related to various farm operations. Agricultural drones are used for pest and disease control and topdressing. This technology level corresponds to human-controlled remotely operated drones.

The effects of SAT adoption on the agricultural inputs and crop yields of paddy rice cultivation, together with the factors driving these effects, are summarized in Table 1. Changes in fertilizer, pesticide, diesel, and labor inputs, as well as crop yields, were estimated based on average values from multiple smart farming demonstration projects conducted by national and local governments. Changes in information and telecommunications services were estimated by adding the additional costs associated with SAT adoption to the conventional input costs obtained from the IO table. Changes in machinery capital investment were estimated by comparing the prices of conventional and SAT-equipped agricultural machinery. The resulting rate of change in machinery capital investment was also applied to machinery-related services, such as repairs and leasing. Data sources are provided in Table A2, while details of the demonstration fields from which data were collected are provided in Table S1a of the Supplementary Materials.

Table 1. Changes in direct inputs and outputs associated with SAT adoption in paddy rice cultivation and influencing factors.

Direct Input/ Output Items	Change Rate	Factors
Fertilizers	−9%	• Optimization of basal fertilization through variable-rate fertilization • Improved efficiency of topdressing using drones
Pesticides	−40%	• Improved efficiency of pesticide application using drones
Diesel (agricultural fuel)	−17%	• Improved efficiency of agricultural operations through autonomous technologies
Information and telecommunications services	429%	• Increased costs associated with the introduction of farm management systems and the use of internet and GNSS communication services
Machinery capital and related services	24%	• Increased costs associated with the adoption and maintenance of SATs

Table 1. *Cont.*

Direct Input/ Output Items	Change Rate	Factors
Labor	−12%	• Improved efficiency of agricultural operations through SAT adoption
Yield	8%	• Increased operational precision through autonomous technologies • Reduced yield variability within fields due to variable-rate fertilization

2.1.2. Open-Field Vegetable Cultivation

Vegetable production is also important in Japan. In 2023, vegetable production accounted for 41% of total crop production in Japan [18]. Within open-field vegetable production, leafy and stem vegetables accounted for 52% of the total production value, while fruit vegetables and root vegetables accounted for 27% and 21%, respectively [17]. Because cultivation methods differ significantly among vegetable types, it is difficult to define a single generalized cultivation system for open-field vegetable production.

To improve the representativeness of an open-field vegetable production system, therefore, this study considered the changes in agricultural inputs and crop yields associated with the transition from conventional to smart farming for three representative crops. The weighted average was then calculated using production values as weights. Green onion (*Allium fistulosum*) and cabbage (*Brassica oleracea* var. *capitata*) were selected as representative stem and leafy vegetables, respectively. The Japanese radish (*Raphanus sativus* var. *hortensis*) was selected as the representative root vegetable. In terms of production value, green onion, cabbage, and Japanese radish ranked first, second, and fourth, respectively, among open-field vegetable crops in Japan, accounting for approximately 9%, 7%, and 6% of the total production value of open-field vegetables [17]. Therefore, the three selected crops together accounted for approximately 22% of the total production value of open-field vegetables in Japan. This selection was intended to reflect the diversity of cultivation systems among major open-field vegetable crops. However, these three crops cannot fully represent the diversity of open-field vegetable production in Japan. Notably, fruit vegetables were excluded from the data collection for modeling changes in agricultural inputs and crop yields because the demonstration and implementation of SATs in open-field fruit vegetable production have been less advanced than those for leafy and stem vegetables and root vegetables. The estimated changes in agricultural inputs and crop yields may differ if other crops are included or if different combinations of crops are selected.

For open-field vegetable production, we assumed medium- to large-scale cultivation systems based on national smart farming demonstration projects of 10, 30–50, and 20–30 ha for green onion, cabbage, and Japanese radish, respectively. The cultivation systems for conventional and smart farming of each vegetable crop are listed in Tables A3–A5. For green onion, the cultivation systems were defined based on data from smart farming demonstration projects [21,22], along with information on conventional-farming mechanization systems [23]. For cabbage, data on mechanization under conventional farming [24,25] were used as the basis, supplemented by findings from national smart farming demonstration projects [21,22,26]. Similarly, cultivation systems for Japanese radish were defined based on conventional mechanization data [27] and data from smart farming demonstration projects [21,22]. We assumed that an autonomous tractor, agricultural drones, and farm management system were used to cultivate each vegetable crop. In addition, a variable-rate fertilizer broadcaster was used to cultivate green onion and cabbage. We assumed that an autonomous harvester was present for cabbage cultivation. The assumed technological level of autonomous machinery and agricultural drones used for pesticide spraying was the same as that assumed for paddy rice cultivation. However, the variable-rate fertilization

system differs from that used in paddy rice cultivation. In open-field vegetable cultivation, crop-growth conditions and soil fertility are monitored using agricultural drones and satellite imagery. Based on these data, the farm management system generates prescription maps. Basal fertilization was then conducted using a variable-rate fertilizer broadcaster according to the prescription maps.

The expected effects of SAT introduction on the agricultural inputs and crop yields of open-field vegetable cultivation and the influencing factors are summarized in Table 2. Using the same approach as applied to paddy rice cultivation, the rates of change in agricultural input and crop yield associated with SAT adoption were estimated for each vegetable crop. The crop-specific change rates were aggregated using a weighted average based on the production value of each vegetable in 2015 (the reference year of the IO table; see Section 2.2). The data sources used to model the changes in each agricultural input and crop yield associated with SAT adoption are provided in Table A6, while details of the demonstration fields from which the data were collected are provided in Table S1b of the Supplementary Materials.

Table 2. Changes in direct inputs and outputs associated with SAT adoption in open-field vegetable cultivation and influencing factors.

Direct Input/ Output Items	Change Rate	Factors
Fertilizers	−13%	• Optimization of chemical fertilizer inputs through variable-rate fertilization
Diesel (agricultural fuel)	−14%	• Improved efficiency of agricultural operations through autonomous technologies
Information and telecommunications services	231%	• Increased costs associated with the introduction of farm management systems and the use of internet and GNSS communication services
Machinery capital and related services	54%	• Increased costs associated with the adoption and maintenance of SATs
Labor	−22%	• Improved efficiency of agricultural operations due to SATs
Yield	13%	• Increased operational precision through autonomous technologies • Reduced yield variability within fields due to variable-rate fertilization

2.2. Construction of the Smart Farming Extended Input–Output (SFEIO) Table

The SFEIO table was constructed by adding four new industrial sectors (smart rice, smart open-field vegetables, smart agricultural machinery, and agricultural drones) to the 2015 Japanese IO table, comprising 391 sectors. Consequently, the extended table consists of 395 sectors and represents the production structure of smart farming systems within a conventional IO framework.

2.2.1. Construction of Technical Coefficient Vectors and Estimation of Output Structures for the Smart Rice and Smart Open-Field Vegetable Sectors

The technical coefficient vector for the smart rice sector was constructed by incorporating the changes in agricultural inputs and crop yields listed in Table 1 into the corresponding sectors of the existing technical coefficient vector of the rice sector. In this study, rice produced under a smart farming system was assumed to be equivalent to that produced under a conventional-farming system. Therefore, the rice sector's output structure was considered applicable to the smart rice sector.

The smart open-field vegetable sector was constructed using the same procedure as that used for the smart rice sector. The technical coefficient vector for the smart open-field vegetable sector was created by incorporating the changes in the agricultural inputs and crop yields shown in Table 2 into the technical coefficient vector of the existing open-field veg-

etable sector from the 2015 IO table. The output structure of the smart open-field vegetable sector was assumed to be identical to that of the existing open-field vegetable sector.

The constructed technical coefficient vectors of the smart rice and smart open-field vegetable sectors are provided in Table S2 of the Supplementary Materials.

2.2.2. Construction of the Technical Coefficient Vector and Estimation of the Output Structure for the Smart Agricultural Machinery Sector

The smart agricultural machinery sector includes the production activities of autonomous agricultural machinery, such as tractors, rice transplanters, combine harvesters, and cabbage-harvesting machines. The technical coefficient vector for this sector was constructed by incorporating the unit input costs of additional equipment required for SATs, such as information and communication hardware and software, into the technical coefficient vector of the existing agricultural machinery sector in the 2015 IO table. First, the additional equipment required for SAT-enabled machinery was identified based on product specifications for conventional and autonomous agricultural machinery [28,29] and a previous study [15]. Next, the corresponding sectors in the IO table were identified for each equipment component. The additional equipment costs were estimated based on the price differences between conventional and autonomous agricultural machinery and allocated to the corresponding sectors. These costs were then added to the respective inputs in the technical coefficient vector of the existing agricultural machinery sector to construct the technical coefficient vector for the smart agricultural machinery sector.

The constructed technical coefficient vector of the smart agricultural machinery sector is provided in Table S2 of the Supplementary Materials.

2.2.3. Construction of the Technical Coefficient Vector and Estimation of the Output Structure for the Agricultural Drone Sector

The agricultural drone sector does not correspond directly to any of the existing sectors in the 2015 Japanese IO table. Therefore, the technical coefficient vector and output structure of the agricultural drone sector were constructed based on the estimated manufacturing cost structure of agricultural drones. Manufacturing costs were estimated using product specifications, cost information, and statistical data, whereas value-added and output structures were determined with reference to related existing sectors in the 2015 IO table. The constructed technical coefficient vector of the agricultural drone sector is provided in Table S2 of the Supplementary Materials. Further details of the modeling procedure, estimations, and data sources are provided in Appendix C.

2.3. Estimation of LC-GHG Emissions Using the IO Approach

2.3.1. Analytical Conditions and Methods

In this study, carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) were the target GHGs, and their emissions were estimated using an IO approach. The system boundary was defined as cradle-to-farm gate for crop production (paddy rice and open-field vegetables), and both the direct and indirect GHG emissions associated with these production activities were analyzed. The GHG emissions originating from the production of capital goods used directly in farming activities were included in the analysis. In contrast, emissions associated with the construction and production of capital goods not exclusively used for farming activities, such as GNSS communication satellites, were excluded from the system boundary.

First, the LC-GHG emissions were estimated for paddy rice and open-field vegetable cultivation under conventional and smart farming systems. Subsequently, emissions were

compared between the two systems for each crop to quantitatively assess the impact of SAT adoption on GHG emissions from open-field crop production in Japan.

The LC-GHG emissions (E), estimated using the IO approach, were calculated using Equation (1):

$$E = \mathbf{e}^T(\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} \quad (1)$$

where $\mathbf{e}$ is the vector of direct GHG emission coefficients by sector, T denotes the transpose, $(\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse matrix, and $\mathbf{f}$ is the final demand vector. In this study, GHG emissions were calculated per 1 million Japanese Yen (JPY) of crop production; accordingly, the final demand vector was set to represent crop production with a value of JPY 1 million. In addition, the capital inputs required to produce one unit of crop are included in the final demand. The capital inputs per unit of crop production were determined using official statistics [17,30].

2.3.2. Construction of Direct GHG Emission Coefficients for the Extended Sectors

To estimate LC-GHG emissions using the IO approach, we constructed a direct GHG emission coefficient vector corresponding to the SFEIO table. In Japan, the National Institute for Environmental Studies developed a database of direct GHG emission coefficients corresponding to the 2015 IO table, known as the 3EID [31]. In this study, this database was used to construct direct GHG emission coefficients for the extended sectors. Because the 3EID provides emission coefficients by emission source for each sector, the coefficients for the extended sectors were derived from those of the corresponding existing sectors while accounting for changes in input structures. The direct GHG emission coefficient vector for the SFEIO table is provided in Table S3 of the Supplementary Materials.

For the smart rice and smart open-field vegetable sectors, the direct GHG emission coefficients were constructed by reflecting changes in GHG emissions associated with changes in agricultural inputs and crop yields, including changes in N_2O and CO_2 emissions from fertilization and fuel consumption, based on differences in the technical coefficient vectors between the smart and conventional sectors. By contrast, the direct GHG emission coefficients for the smart agricultural machinery sector were constructed under the assumption that the inputs of goods and services that directly generate GHG emissions are identical to those of the existing agricultural machinery sector. For the agricultural drone sector, the emission coefficients were constructed based on the toy sector, while reflecting differences in the direct inputs of fossil fuels such as petroleum products and city gas.

3. Results and Discussion

3.1. LC-GHG Emissions from Paddy Rice Cultivation

3.1.1. LC-GHG Emission Reduction Potential and Its Determinants in Paddy Rice Cultivation

Table 3 shows the LC-GHG emissions from paddy rice cultivation under conventional and smart farming systems for each GHG separately, including direct emissions from agricultural operations and indirect emissions from the supply chain. LC-GHG emissions were estimated at 15.23 and 13.93 t CO_2-eq./million JPY under conventional and smart farming systems, respectively (LC-GHG emissions per unit weight of crop are provided in Table S4a of the Supplementary Materials). In terms of the composition of LC-GHG emissions, CH_4 accounted for the largest share (62%) under both conventional and smart farming systems. CO_2 accounted for 33% under conventional and 32% under smart farming systems, whereas N_2O accounted for 5% under conventional and 4% under smart farming systems. These results indicate that the transition from conventional to smart farming systems can potentially reduce LC-GHG emissions from paddy rice cultivation by approximately 9%. Among

the individual GHGs, the reduction rate was highest for CO_2 at 11% (with reductions of 11% and 13% for energy- and non-energy-related CO_2, respectively), followed by N_2O at 10%. CH_4 exhibited the smallest reduction rate (7%).

Table 3. LC-GHG emissions from paddy rice cultivation under conventional and smart farming systems.

GHGs	GHG Emissions (t CO_2-eq./Million JPY)						Change in LC-GHG Emissions Due to the Transition to Smart Farming Systems [(f) − (c)]/(c) × 100
	Conventional Farming			Smart Farming			
	(a) Direct	(b) Indirect	(c) Life Cycle (a) + (b)	(d) Direct	(e) Indirect	(f) Life Cycle (d) + (e)	
CO_2 (energy-related)	1.05	3.27	4.33	0.91	2.96	3.87	−11%
CO_2 (non-energy-related)	0.07	0.64	0.71	0.06	0.56	0.62	−13%
CH_4	9.01	0.37	9.37	8.38	0.32	8.70	−7%
N_2O	0.74	0.07	0.82	0.67	0.07	0.74	−10%
Total	10.87	4.36	15.23	10.02	3.91	13.93	−9%

Several factors contributed to the reduction in the LC-GHG emissions associated with SAT adoption. First, SATs enable more precise agricultural operations, resulting in an increased yield per unit area. Consequently, the amount of agricultural input required per unit of paddy rice production is reduced, leading to lower LC-GHG emissions. The results indicate that 81% of the LC-GHG emission reduction potential can be attributed to yield improvement. Second, SATs reduce several agricultural inputs per unit area, including fertilizers, fuel, and pesticides. For example, variable-rate fertilization reduces chemical fertilizer application per unit area, thereby decreasing direct N_2O and CO_2 emissions from soils. Autonomous agricultural machinery also improves the fuel efficiency during agricultural operations, resulting in additional reductions in CO_2 emissions from fuel combustion. The remaining 19% of the LC-GHG emission reduction potential was attributed to reductions in agricultural inputs per unit area.

Although the transition to smart farming systems results in a reduction in LC-GHG emissions, direct CH_4 emissions account for the largest share of total LC-GHG emissions. As shown in Table 3, direct CH_4 emissions were estimated at 9.01 and 8.38 t CO_2-eq./million JPY, accounting for 59% and 60% of the total LC-GHG emissions under conventional and smart farming systems, respectively. Paddy rice is cultivated in flooded fields; therefore, CH_4 is generated by anaerobic methanogenic microorganisms in the soil. Direct CH_4 emissions from paddy fields are unlikely to be substantially reduced through SAT adoption alone. Although the increase in crop yield per unit area contributes to some reduction in CH_4 emissions per unit of production, as discussed above, the reduction rate of CH_4 remains the smallest among the emitted GHGs. These findings suggest that, in addition to SAT adoption, implementing CH_4 mitigation practices, such as extended mid-season drainage, is essential for achieving further reductions in GHG emissions from paddy rice cultivation.

3.1.2. Contribution of Individual SATs to LC-GHG Emission Reduction in Paddy Rice Cultivation

Figure 2 shows the contributions of individual SATs to the estimated LC-GHG emission reduction potential. The contribution of each SAT was estimated independently by comparing the LC-GHG emissions with and without the respective technology. All changes in agricultural inputs and crop yields associated with the adoption of each technology, including their direct and indirect effects, were attributed to the respective SAT. This approach does not explicitly account for interactions among different SATs.

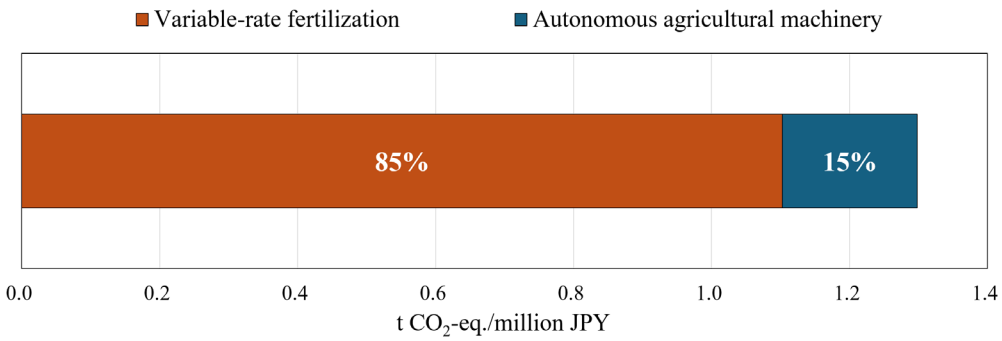


Figure 2. Contributions of individual SATs to LC-GHG emission reduction in paddy rice cultivation.

The results indicate that 85% of the total reduction potential is attributable to the adoption of variable-rate fertilization, whereas the remaining 15% is attributable to the adoption of autonomous agricultural machinery. The latter includes the effects of agricultural drone use. Variable-rate fertilization optimizes fertilizer application rates according to the crop growth conditions, thereby contributing to both an increased yield per unit area and reduced fertilizer application per unit area. Consequently, this contributed significantly to the reduction in LC-GHG emissions. In contrast, the introduction of autonomous driving technology in agricultural machinery improves the efficiency of various agricultural operations, thereby reducing the use of agricultural inputs such as fuel per unit area. However, paddy rice cultivation is already highly mechanized in conventional systems, and agricultural operations are relatively efficient. Therefore, the LC-GHG emissions reduction potential associated with the introduction of autonomous driving technologies is relatively limited.

3.2. LC-GHG Emissions from Open-Field Vegetable Cultivation

3.2.1. LC-GHG Emission Reduction Potential and Its Determinants in Open-Field Vegetable Cultivation

Table 4 shows the LC-GHG emissions from open-field vegetable cultivation under conventional and smart farming systems for each GHG, separately showing direct and indirect emissions. LC-GHG emissions were estimated at 4.13 and 3.66 t CO_2-eq./million JPY under conventional and smart farming systems, respectively (LC-GHG emissions per unit weight of crop are provided in Table S4b of the Supplementary Materials). In terms of the composition of LC-GHG emissions, CO_2 accounted for the largest share in both systems, representing 79% of the total LC-GHG emissions under conventional farming and 80% under smart farming systems. N_2O accounted for 16% and 15% of total LC-GHG emissions under conventional and smart farming systems, respectively, whereas CH_4 accounted for the smallest share, at 5% in both systems. These results indicate that the transition to smart farming has the potential to reduce LC-GHG emissions from open-field vegetable cultivation by approximately 11%. Among the four GHG emission categories, N_2O exhibited the largest reduction rate (17%), followed by non-energy-related CO_2 (16%), CH_4 (10%), and energy-related CO_2 (9%).

As in paddy rice cultivation, the primary factors contributing to the reduction in LC-GHG emissions are improvements in crop yield and reductions in agricultural inputs per unit area resulting from SAT adoption. The LC-GHG emission reduction potential for open-field vegetable cultivation was 11%, which is greater than the 9% reduction estimated for paddy rice cultivation. This difference can be attributed to greater improvements in yield and agricultural input-use efficiency associated with SAT adoption in open-field vegetable cultivation than in paddy rice cultivation (Tables 1 and 2). One reason for this difference is the lower spatial uniformity of growing conditions in open-field vegetable fields than in paddy fields. Because paddy rice is cultivated under flooded conditions, the soil properties

and growing conditions tend to remain relatively uniform. In contrast, vegetables are cultivated in upland fields, where the spatial variability in soil nutrients and moisture is greater, even within the same field. Consequently, technologies such as autonomous agricultural machinery, which improve the precision of agricultural operations such as ridge formation, and variable-rate fertilization, which optimizes fertilizer application, may provide greater opportunities to improve yield in open-field vegetable cultivation than in paddy rice cultivation. In addition, in open-field vegetable cultivation, the direct GHG emissions from agricultural fields, which are difficult to reduce through SAT adoption alone, are lower than those in paddy rice cultivation. Therefore, the emission reduction effects of reduced fertilizer application through variable-rate fertilization and reduced fuel consumption through autonomous agricultural machinery were greater than those observed in paddy rice cultivation. As a result of these factors, the reduction rate of LC-GHG emissions is greater for open-field vegetable cultivation than for paddy rice cultivation.

Table 4. LC-GHG emissions from open-field vegetable cultivation under conventional and smart farming systems.

GHGs	GHG Emissions (t CO_2-eq./Million JPY)						Change in LC-GHG Emissions Due to the Transition to Smart Farming Systems [(f) − (c)]/(c) × 100
	Conventional Farming			Smart Farming			
	(a) Direct	(b) Indirect	(c) Life Cycle (a) + (b)	(d) Direct	(e) Indirect	(f) Life Cycle (d) + (e)	
CO_2 (energy-related)	0.22	2.46	2.68	0.19	2.26	2.45	−9%
CO_2 (non-energy-related)	0.06	0.51	0.57	0.05	0.43	0.48	−16%
CH_4	0.01	0.19	0.20	0.01	0.17	0.18	−10%
N_2O	0.63	0.05	0.67	0.51	0.04	0.56	−17%
Total	0.91	3.22	4.13	0.76	2.90	3.66	−11%

The emission structure in terms of direct and indirect emissions also differed from that of paddy rice cultivation. As shown in Table 4, direct GHG emissions were estimated at 0.91 t CO_2-eq./million JPY under conventional cultivation and 0.76 t CO_2-eq./million JPY under the smart farming system, accounting for 22% and 21% of the total LC-GHG emissions, respectively. Thus, indirect emissions accounted for nearly 80% of total LC-GHG emissions in both systems. Indirect energy-related CO_2 emissions accounted for 60% of the total LC-GHG emissions under conventional farming and 62% under the smart farming system. These emissions are primarily associated with the production of various agricultural inputs required for agricultural production. Therefore, in addition to improving crop yield and reducing agricultural input use with SAT adoption, the decarbonization of upstream supply chains, such as using renewable energy, may have greater potential to reduce LC-GHG emissions from open-field vegetable cultivation.

3.2.2. Contribution of Individual SATs to LC-GHG Emission Reduction in Open-Field Vegetable Cultivation

Based on the same analytical conditions as those used for paddy rice cultivation (Figure 2), Figure 3 shows the contributions of individual technologies to the estimated LC-GHG emission reduction potential of open-field vegetable cultivation. The results indicate that 56% of the total reduction potential is attributable to the adoption of variable-rate fertilization, whereas the remaining 44% is attributable to the adoption of autonomous agricultural machinery. As described above, upland crop production, including open-field vegetable cultivation, is characterized by less homogeneous field conditions than paddy rice cultivation, in which fields are maintained under flooded conditions. Therefore, the potential to improve yield per unit area through more precise agricultural operations associated with the adoption of autonomous agricultural machinery is greater in open-

field vegetable cultivation than in paddy rice cultivation. In addition, because the level of mechanization in open-field vegetable cultivation is generally lower than that in paddy rice cultivation, the use of autonomous driving technology can contribute substantially to reducing agricultural input use per unit area. These factors explain why the contribution of autonomous agricultural machinery to LC-GHG emission reduction is relatively large in open-field vegetable cultivation, accounting for 44% of the total reduction potential, compared with 15% in paddy rice cultivation.

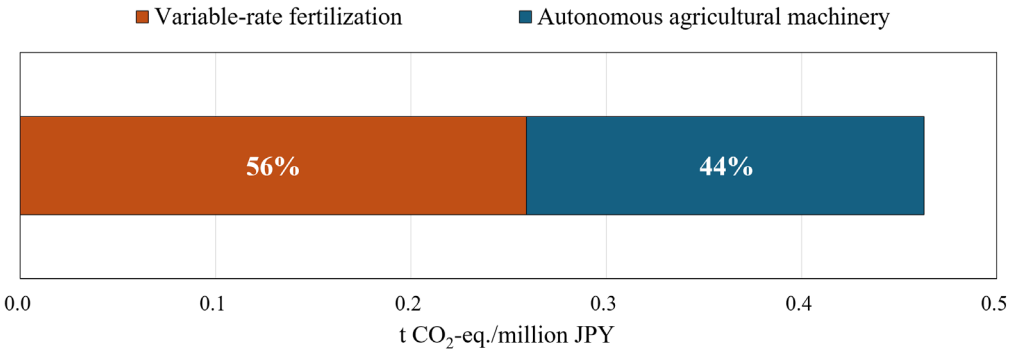


Figure 3. Contributions of individual SATs to LC-GHG emission reduction in open-field vegetable cultivation.

3.3. Changes in Supply Chain GHG Emissions Associated with Agricultural Machinery Manufacturing

As described in Sections 3.1 and 3.2, the adoption of SATs in paddy rice and open-field vegetable cultivation has the potential to reduce LC-GHG emissions. However, as described below, the adoption of SATs also induces additional demand to produce smart agricultural machinery, including sensors and electronic components. Thus, GHG emissions associated with agricultural machinery manufacturing activities may increase in upstream industries within the supply chain.

For paddy rice cultivation, GHG emissions associated with agricultural machinery manufacturing were estimated at 0.90 t CO_2-eq./million JPY under conventional cultivation and 0.89 t CO_2-eq./million JPY under the smart farming system. These emissions accounted for approximately 6% of the total LC-GHG emissions of both systems. Table 5 compares sectoral GHG emissions at the agricultural machinery manufacturing stage between conventional and smart farming systems for paddy rice cultivation and identifies the industrial sectors in which emissions increase under the smart farming system. The results indicate increased emissions from sectors such as ceramic products, liquid crystal display (LCD) panels, semiconductor devices, other glass products, and electronic components. These sectors primarily supply components for information and communication devices and sensors newly introduced through SAT adoption. In addition, upstream sectors supplying raw materials, energy, and transport services to produce these components also experience increased GHG emissions owing to the increased demand. Thus, although GHG emissions associated with agricultural machinery manufacturing per unit of crop production remained nearly unchanged between conventional and smart farming systems, the industrial sectors responsible for these emissions may differ.

In contrast, for open-field vegetable cultivation, GHG emissions associated with agricultural machinery manufacturing were estimated at 0.39 and 0.48 t CO_2-eq./million JPY under conventional and smart farming systems, respectively. These emissions accounted for 9% and 13% of the total LC-GHG emissions under conventional and smart farming systems, respectively. This result indicates a potential increase in GHG emissions associated with

agricultural machinery manufacturing of 23% under the smart farming system. Table 6 presents the results of the same analysis as in Table 5 for open-field vegetable cultivation. A major feature is the increase in emissions from the pig iron sector, which supplies raw materials for steel products used in agricultural machinery manufacturing. Additionally, emissions from sectors such as coal, crude oil, and natural gas are induced by the increased demand associated with iron and steel production processes.

Table 5. Sectors with the largest increases in GHG emissions associated with agricultural machinery manufacturing during the transition from conventional to smart paddy rice cultivation.

Sector	Change in GHG Emissions (Smart-Conventional) [t CO_2-eq./Millions JPY]
Electricity (for business use)	0.013
Road freight transport (excluding in-house transport)	0.002
Ceramic products	0.002
Coal, crude oil, and natural gas	0.001
Other mineral products	0.001
In-house transport (by cars)	0.001
Liquid crystal display (LCD) panels	0.001
Semiconductor devices	0.001
Other glass products	0.001
Basic petrochemical products	0.001
Petroleum products	0.001
Self-generated electricity	0.001
In-house transport (by trucks)	<0.001
Cyclic intermediates, synthetic dyes, and organic pigments	<0.001
Other electronic components	<0.001

Table 6. Sectors with the largest increases in GHG emissions associated with agricultural machinery manufacturing during the transition from conventional to smart open-field vegetable cultivation.

Sector	Change in GHG Emissions (Smart-Conventional) [t CO_2-eq./Million JPY]
Electricity (for business use)	0.029
Pig iron	0.011
Coal, crude oil, and natural gas	0.006
Self-generated electricity	0.006
Road freight transport (excluding in-house transport)	0.004
Other mineral products	0.003
In-house transport (by trucks)	0.003
In-house transport (by cars)	0.002
Coal products	0.002
Petroleum products	0.002
Basic petrochemical products	0.001
Coastal and inland water transport	0.001
Hot-rolled steel products	0.001
Lead and zinc (including recycled)	0.001
Ceramic products	0.001

The differences between paddy rice and open-field vegetable cultivation in terms of changes in GHG emissions and emission structures can be attributed to their different levels of mechanization, as discussed above. In paddy rice cultivation, where agricultural mechanization is already well established, SAT adoption primarily induces the additional

production of equipment such as sensors and communication devices. In contrast, in open-field vegetable cultivation, where the level of mechanization is relatively low, SAT adoption induces not only additional production of such equipment but also increases the production of agricultural machinery itself. As a result, in open-field vegetable production, despite the higher productivity of the smart farming system compared with the conventional farming system, GHG emissions associated with agricultural machinery manufacturing per unit of crop production are higher under the smart farming system.

Few studies have examined changes in GHG emissions associated with agricultural machinery manufacturing resulting from SAT adoption. However, the results of this study demonstrate that SAT adoption can lead to increased GHG emissions in upstream industries and that the extent and structure of these increases differ depending on the existing level of mechanization in agricultural production systems. These findings highlight the importance of considering not only the direct effects of SAT adoption on agricultural production, but also the associated changes in GHG emissions throughout the supply chain of agricultural machinery and equipment when evaluating the GHG emission reduction potential of SAT adoption.

3.4. Impact of SAT Adoption on LC-GHG Emissions from Japan's Crop Production Sector

This section quantifies the impact of the transition to smart farming in open-field production systems on GHG emissions from Japan's crop production sector, based on the results obtained for paddy rice and open-field vegetable production. It also discusses the implications of these findings for policymaking.

Assuming a full transition of these cultivation systems to smart farming, annual LC-GHG emissions from Japan's crop production sector would decrease by approximately 5%, from 46.72 to 44.54 Mt CO_2-eq., based on the LC-GHG reduction potentials estimated in Sections 3.1 and 3.2 (9% for paddy rice and 11% for open-field vegetables). For this analysis, the same average changes in agricultural inputs and crop yields estimated for leafy and stem vegetables and root vegetables were assumed to apply to fruit vegetables as well. These results are shown in Figure 4.

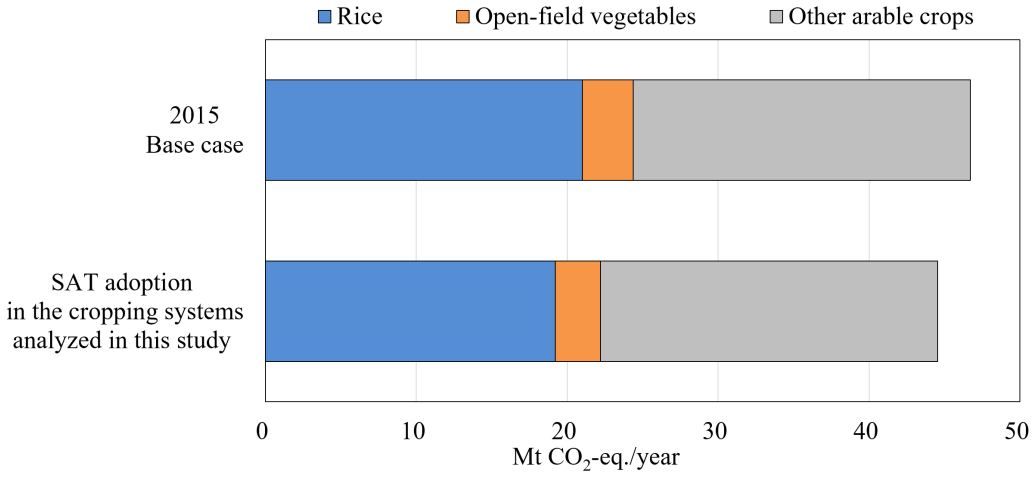


Figure 4. Annual LC-GHG emissions from Japan's crop production sector under the 2015 base case and a case with SAT adoption in analyzed cropping systems (paddy rice and open-field vegetables). "Other arable crops" represents the remaining crop categories included in the crop production sector.

These results indicate that the adoption of SATs in open-field agriculture has the potential to contribute to GHG emission reduction in Japan's crop production sector. However, the reduction alone is unlikely to be sufficient to achieve national targets such as carbon

neutrality by 2050 or net-zero CO_2 emissions in the agriculture, forestry, and fisheries sector. Notably, the primary objectives of SAT adoption are to improve labor productivity, reduce labor requirements, and enhance agricultural productivity, rather than mitigate GHG emissions. As these technologies are expected to be increasingly adopted worldwide, the associated reduction in GHG emissions can be regarded as an important co-benefit of smart farming.

Therefore, these findings suggest that SATs should be regarded as a component of an integrated decarbonization strategy rather than as a standalone mitigation measure. Additional measures, including intermittent irrigation in paddy rice cultivation for methane mitigation and the deployment of renewable energy and energy-efficient technologies across both the supply chain and on-farm operations, should be implemented simultaneously through appropriate policy instruments to achieve deeper emission reductions.

In Japanese agricultural policy, SATs have been recognized as one of the measures contributing to GHG emission reductions; however, their contribution has not previously been quantified at the national level. The present analysis provides a quantitative estimate of the contribution of SAT adoption to LC-GHG emission reductions in Japan's crop production sector using the SFEIO framework developed in this study. These findings provide useful evidence for evaluating the role of smart farming in agricultural climate policy in Japan, while the SFEIO framework provides a basis for similar assessments in other countries promoting agricultural decarbonization.

The analysis in this section has several limitations. The estimates are based on simplified assumptions and therefore do not fully capture the diversity and complexity of agricultural production systems in Japan. In addition, the national-level estimates account only for the potential reductions associated with paddy rice and open-field vegetable production. Therefore, the potential contributions of SAT adoption in other crop production systems are not included.

3.5. Sensitivity Analysis

To examine the sensitivity of the estimated LC-GHG emission reduction potential, a sensitivity analysis was conducted focusing on changes in crop yield, which is considered one of the most important factors influencing LC-GHG emissions. The yield change rate associated with SAT adoption was varied while keeping the other analytical conditions unchanged. The sensitivity analysis was conducted for three cases: paddy rice cultivation, open-field vegetable cultivation, and the national-level analysis presented in Section 3.4. The results are presented in the following sections.

3.5.1. Sensitivity Analysis for Paddy Rice Cultivation

As shown in Table 1, the yield change rate associated with the transition to smart farming in paddy rice cultivation was estimated to be 8%. However, the actual yield response to SAT adoption does not necessarily converge on a single, definitive value, as it may be influenced by various factors, including field conditions, differences in specific cultivation practices, and farmers' proficiency in using new technologies. Therefore, a sensitivity analysis was conducted to examine how LC-GHG emissions change when the yield change rate is varied by ±15 percentage points from the reference case of 8%.

Figure 5 shows the results of the sensitivity analysis. The dashed line represents LC-GHG emissions under conventional farming. Overall, LC-GHG emissions decrease as crop yield increases, whereas they increase as crop yield decreases. For example, at the maximum yield increase (23%), LC-GHG emissions are estimated to be 12.17 t CO_2-eq./million JPY, representing a 20% reduction compared with conventional farming. In contrast, when the yield change rate is −3%, indicating a yield decrease relative to conventional farming,

LC-GHG emissions increase to 15.44 t CO_2-eq./million JPY, approximately 1% higher than under conventional farming. These results indicate that when crop yield falls below the conventional farming level, LC-GHG emissions may also increase.

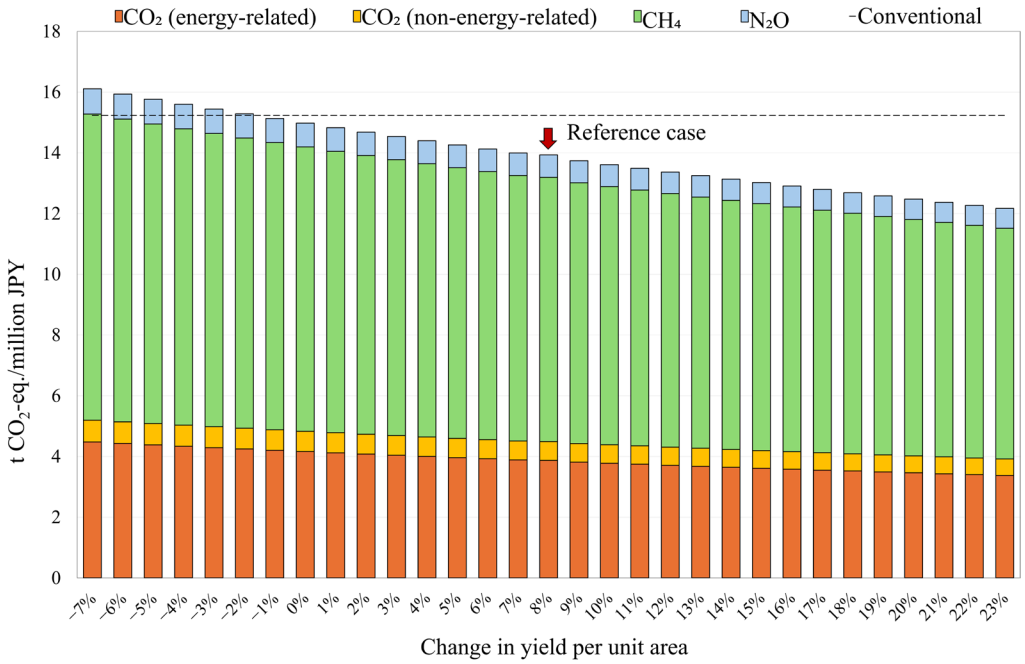


Figure 5. LC-GHG emissions under different assumed yield change rates (−7% to 23%) in smart paddy rice cultivation.

In one of the field demonstration cases, although a 13% yield increase was initially targeted, the actual increases were limited to 7% in the first year and 8% in the second year of the SAT adoption [32]. This suggests that the expected yield improvements may not necessarily be achieved in practice. Although crop yield is influenced by various complex factors, including climatic conditions, it is important to establish suitable cultivation systems through the selection of technologies that account for geographical conditions and to promote farmers' acquisition of the necessary technical skills. Policy support is important to facilitate these efforts and achieve stable and sustained improvements in crop yield.

3.5.2. Sensitivity Analysis for Open-Field Vegetable Cultivation

As shown in Table 2, the yield change rate associated with the transition to smart farming in open-field vegetable cultivation was estimated to be 13%. However, cultivation practices may vary to some extent among vegetable crops, and the actual yield response to SAT adoption may not always be consistent with this estimated value. Accordingly, following the same approach as for paddy rice cultivation, a sensitivity analysis was conducted to examine changes in LC-GHG emissions by varying the reference case of 13% by ±15 percentage points.

Figure 6 shows the results of the sensitivity analysis. As in Figure 5 for paddy rice cultivation, the dashed line represents LC-GHG emissions under conventional farming. Overall, the results show a similar trend to those for paddy rice cultivation: LC-GHG emissions decrease as crop yield increases and increase as crop yield decreases. For example, when crop yield increases by 28% relative to conventional farming, LC-GHG emissions decrease by 22%. When the crop yield increase rate is 1%, the LC-GHG emission reduction effect becomes zero. In contrast, when crop yield remains at the same level as under conventional farming (i.e., a 0% yield change), LC-GHG emissions increase by 1%. These

results suggest that, as with paddy rice cultivation, if SAT adoption does not result in sufficient yield improvements relative to conventional farming, LC-GHG emissions may increase despite improvements in fertilizer and fuel use efficiency, partly reflecting emissions associated with additional capital inputs.

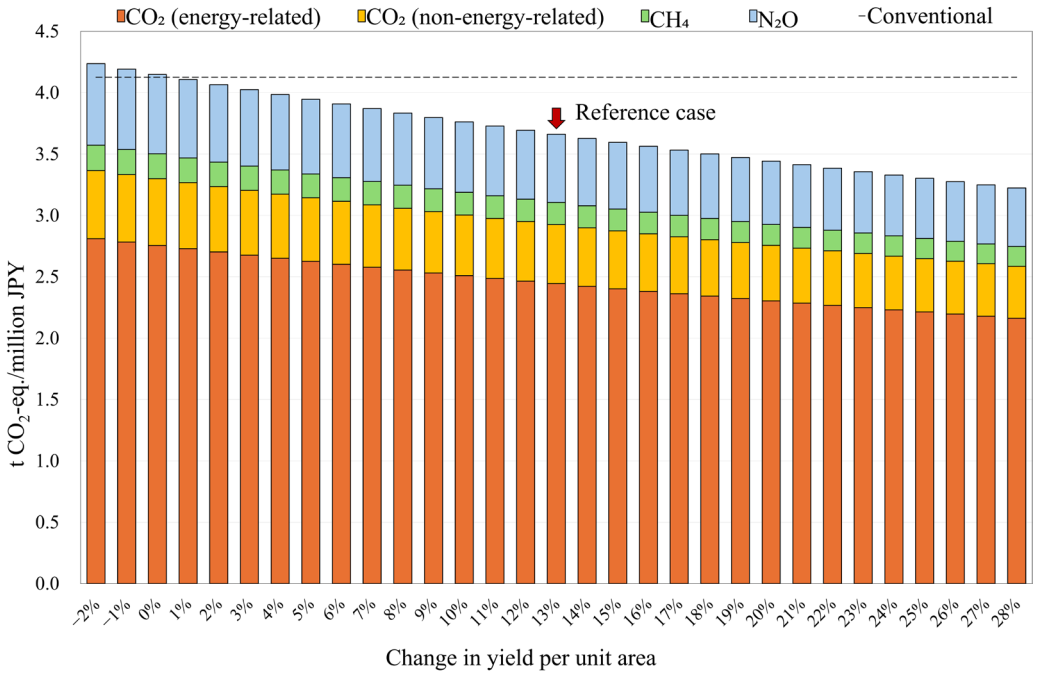


Figure 6. LC-GHG emissions under different assumed yield change rates (−2% to 28%) in smart open-field vegetable cultivation.

In this regard, an interim report from a field demonstration of SAT adoption in open-field vegetable production documented a case involving a crop not examined in this study, in which crop yield declined relative to conventional farming because cultivation under the newly introduced system, including fertilizer management and other cultivation practices, did not proceed as planned [33]. Although multiple factors may have contributed to the yield decline, this example suggests that changes in cultivation systems associated with SAT adoption may sometimes lead to lower crop yields. Therefore, as with paddy rice cultivation, policy support to facilitate the appropriate introduction and implementation of SATs is important not only from the perspective of farm management but also for reducing LC-GHG emissions.

3.5.3. Sensitivity Analysis of the Impact of SAT Adoption on LC-GHG Emissions from Japan's Crop Production Sector

As shown in Section 3.4, the full transition to smart farming in paddy rice and open-field vegetable production was estimated to have the potential to reduce GHG emissions from Japan's entire crop production sector by 5%. However, as discussed in Sections 3.5.1 and 3.5.2, the actual yield changes associated with SAT adoption may differ from the estimated values. Therefore, a sensitivity analysis was conducted to examine how variations in yield change rates for paddy rice and open-field vegetable production affect LC-GHG emissions from Japan's crop production sector at the national level. Using the SAT adoption case presented in Section 3.4 as the reference case, the yield change rates were set at 8% for paddy rice and 13% for open-field vegetables, and both rates were varied by ±15 percentage points. As in the analysis presented in Section 3.4, it was assumed that SATs would not be introduced into cropping systems other than paddy rice and open-field vegetable production.

Figure 7 shows the results of the sensitivity analysis. The dashed line represents annual LC-GHG emissions from Japan's crop production sector under the conventional farming scenario for all crops (2015 base case). When the yield increase rates for both smart paddy rice and open-field vegetable cultivation are 15 percentage points higher than their respective reference case—that is, 23% for paddy rice and 28% for open-field vegetables—annual LC-GHG emissions from the entire crop production sector are estimated to decrease to 41.76 Mt CO_2-eq./year, representing an 11% reduction compared with conventional farming. In contrast, when the yield increase rates are 10 percentage points lower than their reference case, the potential for GHG emission reductions at the national level becomes virtually zero. These results suggest that, although the analysis considers SAT adoption only in paddy rice and open-field vegetable production, yield changes in these two cropping systems have some influence on LC-GHG emissions from Japan's entire crop production sector.

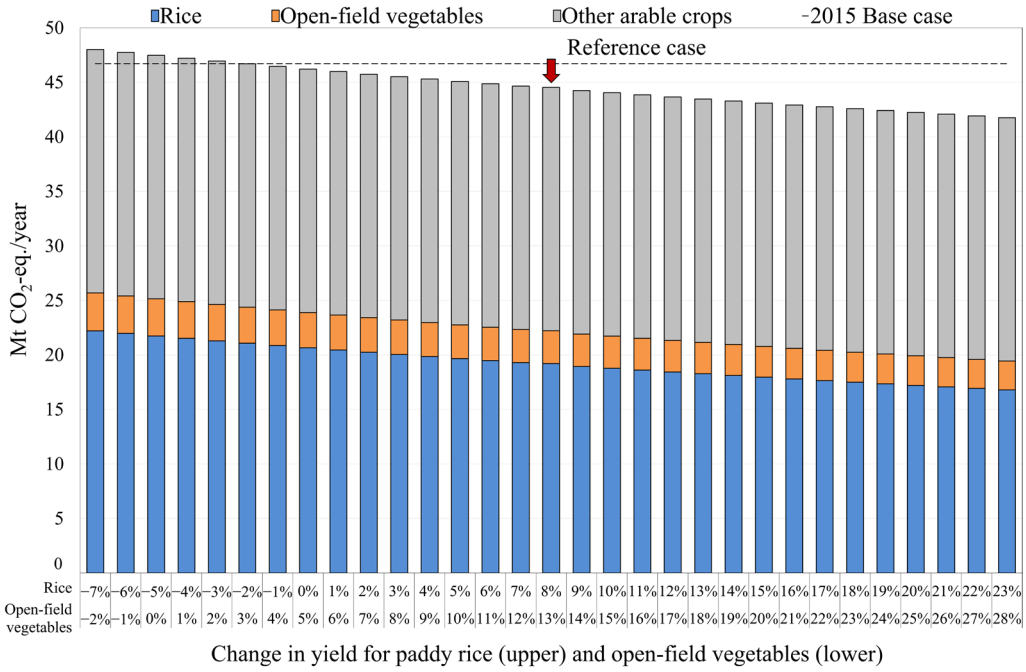


Figure 7. Annual LC-GHG emissions from Japan's crop production sector under different assumed yield change rates in a case with SAT adoption in paddy rice and open-field vegetable cropping systems.

The sensitivity analysis indicates that if the transition to smart farming systems does not result in sufficient yield improvements, it may fail to contribute sufficiently to reducing LC-GHG emissions from the crop production sector, or may even lead to an increase. Conversely, successful yield improvements can contribute to further reductions in the sector-wide emissions. These findings also highlight the importance of maintaining and improving crop yields through the selection of technologies suited to local field conditions and the development of appropriate cultivation systems. Policy support to facilitate these efforts is therefore important for realizing the GHG reduction potential of SAT adoption.

Finally, several common limitations of the sensitivity analyses presented in Section 3.5 should be noted. First, the purpose of these analyses was to examine the sensitivity of the estimated LC-GHG emission reduction potential to variations in yield change rates around the reference case, rather than to estimate the likelihood or probability of specific yield outcomes in practice. Second, the analyses do not consider potential market effects associated with changes in crop yields, such as changes in crop prices and adjustments in harvested quantities.

3.6. Comparison with Previous Studies

To further examine the results of this study, this section compares the LC-GHG emission reduction potentials reported in previous studies examining the effects of adopting multiple SATs in open-field cropping systems. Although the analytical conditions, including functional units and system boundaries, differ among studies, the comparison focuses on relative emission reductions rather than absolute emission levels.

Medel-Jiménez et al. [3] conducted an LCA of arable cropping systems in Austria and reported reductions in LC-GHG emissions of 2.4% with the introduction of autonomous tractors, 6.5% when autonomous tractors were combined with automatic section control, 17.0% when proximal sensors were used for variable-rate fertilization, and 9.0% when prescription maps from remote sensing were applied for variable-rate fertilization. Karagkounis et al. [4] evaluated the effects of introducing an integrated precision agriculture system incorporating multiple SATs across various open-field cropping systems in Greece and reported average LC-GHG emission reductions of 9.5% (for the 2020 scenario) and 4.8% (for the 2021 scenario). Sanches et al. [5] examined sugarcane production systems in Brazil and found that the combined use of autonomous steering, automatic section control, and variable-rate fertilization could reduce LC-GHG emissions by approximately 13%.

Overall, despite the differences in regions, crops, and analytical conditions, the estimated reduction potentials associated with the adoption of multiple SATs in open-field cultivation showed consistent trends across this and previous studies. This consistency likely reflects the common mechanisms of SAT adoption, including improved input-use efficiency and reduced fuel consumption, regardless of the crop type or production region. Although the quantitative results presented in this study are specific to Japan, the analytical framework and findings regarding the role of SATs in agricultural decarbonization may be applicable to other countries promoting smart farming. Future studies should examine a wider range of crops and production systems to improve the robustness of estimates.

4. Conclusions

This study proposed a Smart Farming Extended Input–Output (SFEIO) framework to quantitatively evaluate the effects of SAT adoption on LC-GHG emissions from agricultural production. The framework was applied to paddy rice and open-field vegetable cultivation in Japan to quantify the effects of adopting multiple SATs on LC-GHG emission reduction.

The transition to smart farming could reduce LC-GHG emissions by 9% for paddy rice and 11% for open-field vegetables, primarily through improved agricultural input-use efficiency and crop yields. Variable-rate fertilization accounted for 85% and 56% of the reduction potential, respectively, while autonomous agricultural machinery accounted for 15% and 44%, respectively. These differences reflect variations in mechanization levels and field conditions between the two cropping systems. The SFEIO analysis also indicated the potential for increased upstream GHG emissions associated with agricultural machinery manufacturing. Although emissions per unit of crop production remained unchanged for paddy rice, they increased for open-field vegetables, where the conventional level of mechanization was relatively low. These findings suggest that the GHG emission reduction potential of SAT adoption may be partially offset when the existing level of mechanization is low.

Assuming the adoption of SATs in the analyzed paddy rice and open-field vegetable cropping systems across Japan, annual GHG emissions from the crop production sector were estimated to decrease by approximately 5%. Although this represents a meaningful contribution to agricultural decarbonization, SAT adoption alone is unlikely to achieve the level of emission reductions required to meet Japan's carbon neutrality target. Therefore,

SAT adoption could be promoted as part of an integrated mitigation strategy rather than as a standalone solution.

The sensitivity analyses further showed that changes in crop yield per unit area are an important factor influencing the LC-GHG reduction potential of SAT adoption. Greater yield improvements relative to conventional farming can enhance the LC-GHG emission reduction potential of SAT adoption. Conversely, if crop yields decrease relative to conventional farming, LC-GHG emissions may increase. These results highlight the importance of policy support for farming practices and technological development so that SATs are implemented appropriately and can deliver sufficient yield improvements.

Further GHG emission reductions in smart farming systems may be achieved through measures such as the use of renewable energy in upstream supply chains and the electrification of smart agricultural machinery [34]. Evaluating the effects of such mitigation measures requires an approach that considers the entire life cycle. The proposed SFEIO framework can be applied to evaluate the effects of such mitigation measures from a life-cycle perspective.

Although the quantitative estimates presented in this study are specific to Japan, the framework accounts for both agricultural production systems and the upstream supply chains associated with SAT manufacturing and could therefore be adapted to different cropping systems and regional contexts. For example, in regions where agricultural mechanization is generally less advanced, GHG emissions from upstream supply chains associated with the manufacture of agricultural machinery introduced together with SATs could be greater. Therefore, applying the proposed SFEIO framework to agricultural production systems in such regions could help evaluate the LC-GHG mitigation potential of SAT adoption.

Several issues remain to be addressed in future research. First, although the SFEIO framework accounts for capital goods directly used in agricultural production, such as agricultural machinery, it does not include infrastructure that supports SATs but is not exclusively dedicated to agricultural use, such as satellites and telecommunications networks. Second, further research should examine how differences in farm size and cultivation conditions affect the costs and GHG mitigation potential of SAT adoption, because the present analysis was based on demonstration projects conducted on medium- to large-scale farms. Third, technological and structural changes in the economy since 2015, such as developments in production technologies and changes in the electricity mix, are not fully reflected in the estimates. Finally, integrating economic and social indicators, including production costs, labor productivity, and employment, would enable a more comprehensive assessment of smart farming transitions.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su182211796/s1: Table S1a: Reference field data for paddy rice cultivation; Table S1b: Reference field data for open-field vegetable cultivation; Table S2: Technical coefficient vectors of the extended sectors in the SFEIO table; Table S3: Sectoral direct GHG emission coefficients for the SFEIO table; Table S4a: LC-GHG emissions per unit weight of paddy rice; Table S4b: LC-GHG emissions per unit weight of open-field vegetables. References [17,19–22,26,35–43] are cited in the Supplementary Materials.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Agricultural machinery and services for conventional and smart farming in paddy rice production.

Field Operations	Agricultural Machinery and Services	
	Conventional Farming	**Smart Farming**
General field operations	Tractor (73.6 kW)	[1] Autonomous tractor (73.6 kW)
Land leveling and bund formation	Stubble cultivator Laser leveler Plow Vertical harrow Bund former	Stubble cultivator Laser leveler Plow Vertical harrow Bund former
Sowing and seedling raising	Dehydrator Seeder Seedling tray washer	Dehydrator Seeder Seedling tray washer
Transplanting and basal fertilization	Rice transplanter	[1] Autonomous rice transplanter
Pest control and topdressing	Power sprayer	[1] Agricultural drone
Harvesting	Combine harvester (six-row)	[1] Autonomous combine harvester (six-row)
	Grain transport vehicle	Grain transport vehicle
Drying and processing	Dryer Rice huller Color sorter Flexible container hopper Forklift	Dryer Rice huller Color sorter Flexible container hopper Forklift
Bund weeding	Brush cutter	Brush cutter
Farm management	Paper-based maps and notes	[1] Farm management system

[1] Machinery and services incorporating smart agricultural technologies (SATs).

Table A2. Data sources for estimating changes in agricultural inputs and crop yields associated with SAT adoption in paddy rice cultivation.

Input and Output Items	Data Sources
Fertilizers	• Smart farming demonstration projects [19,36,44]
Pesticides	• Smart farming demonstration projects [37]
Diesel (agricultural fuel)	• Smart farming demonstration projects [20]
Information and telecommunications services	• Input values from existing sectors in the IO table [17] • Market prices of farm management systems [45,46]

Table A2. *Cont.*

Input and Output Items	Data Sources
Machinery capital and related services	• Prices of conventional agricultural machinery from manufacturers [29,47–58] • Estimated prices of smart agricultural machinery from smart farming demonstration projects [36] • Input values from existing sectors in the IO table [17]
Labor	• Smart farming demonstration projects [19,36] • Actual smart farming cases [38]
Yield	• Smart farming demonstration projects [19,36]

Appendix B

Table A3. Agricultural machinery and services for conventional and smart farming in green onion cultivation.

Field Operations	Agricultural Machinery and Services	
	Conventional Farming	**Smart Farming**
General field operations	Tractor (36.8 kW)	[1] Autonomous tractor (36.8 kW)
	Riding tiller	Riding tiller
Tillage and land preparation	Rotary tiller	Rotary tiller
Fertilization	Broadcaster	[1] Variable-rate fertilizer broadcaster
	Lime spreader	Lime spreader
	Manure loader	Manure loader
	Manure spreader	Manure spreader
Transplanting and seedling raising	Bed former for transplanting	Bed former for transplanting
	Automatic transplanter	Automatic transplanter
Pest control and weeding	Boom sprayer	[1] Agricultural drone
	Rotary cultivator	Rotary cultivator
Harvesting	Harvester	Harvester
	Back carrier	Back carrier
Post-harvest handling	Semi-automatic processing machine	Semi-automatic processing machine
	Sorter	Sorter
Sensing	—	[1] Agricultural drone
Farm management	Paper-based maps and notes	[1] Farm management system

[1] Machinery and services incorporating SATs.

Table A4. Agricultural machinery and services for conventional and smart farming in cabbage production.

Field Operations	Agricultural Machinery and Services	
	Conventional Farming	**Smart Farming**
General field operations	Tractor (22.1 kW)	[1] Autonomous tractor (22.1 kW)
	Tractor (51.5 kW)	[1] Autonomous tractor (51.5 kW)
	Tractor (73.6 kW)	[1] Autonomous tractor (73.6 kW)
	Riding tiller	Riding tiller

Table A4. *Cont.*

Field Operations	Agricultural Machinery and Services	
	Conventional Farming	**Smart Farming**
Tillage and land preparation	Rotary tiller	Rotary tiller
	Moldboard plow	Moldboard plow
Fertilization	Broadcaster	[1] Variable-rate fertilizer broadcaster
	Lime spreader	Lime spreader
	Manure loader	Manure loader
	Manure spreader	Manure spreader
Transplanting and seedling raising	Ridger	Ridger
	Transplanter	Transplanter
Pest control and weeding	Boom sprayer	[1] Agricultural drone
	Rotary cultivator	Rotary cultivator
Harvesting	— (Manual labor)	[1] Autonomous harvester
	Back carrier	Back carrier
Sensing	—	[1] Agricultural drone
Farm management	Paper-based maps and notes	[1] Farm management system

[1] Machinery and services incorporating SATs.

Table A5. Agricultural machinery and services for conventional and smart farming in Japanese radish production.

Field Operations	Agricultural Machinery and Services	
	Conventional Farming	**Smart Farming**
General field operations	Tractor (22.1 kW)	[1] Autonomous tractor (22.1 kW)
	Tractor (51.5 kW)	[1] Autonomous tractor (51.5 kW)
	Riding tiller	Riding tiller
Tillage and land preparation	Rotary tiller	Rotary tiller
Fertilization	Broadcaster	[1] Variable-rate fertilizer broadcaster
	Lime spreader	Lime spreader
	Manure loader	Manure loader
	Manure spreader	Manure spreader
Seeding	Seeder	Seeder
Pest control and weeding	Boom sprayer	[1] Agricultural drone
	Rotary cultivator	Rotary cultivator
Harvesting	Harvester	Harvester
	Cart	Cart
Post-harvest handling	Washer	Washer
Sensing	—	[1] Agricultural drone
Farm management	Paper-based maps and notes	[1] Farm management system

[1] Machinery and services incorporating SATs.

Table A6. Data sources for estimating changes in agricultural inputs and crop yields associated with SAT adoption in open-field vegetable cultivation.

Direct Input/Output Items	Data Sources
Fertilizers	• Smart farming demonstration projects [26,39]
Diesel (agricultural fuel)	• Smart farming demonstration projects [21,22,26,40,59]
Information and telecommunications services	• Input values from existing sectors in the IO table [17] • Market prices of farm management systems [45,46]
Machinery capital and related services	• Prices of conventional agricultural machinery from manufacturers [29,51,52,54,58,60–64] • Estimated prices of smart agricultural machinery from smart farming demonstration projects [36] • Input values from existing sectors in the IO table [17]
Labor	• Smart farming demonstration projects [21,22,26,40–42]
Yield	• Smart farming demonstration projects [21,26,43]

Appendix C

In this section, the procedures and data sources used to construct the technical coefficient vector and estimate the output structure of the agricultural drone sector are described.

First, the costs of the individual components (material costs) of agricultural drones were identified using cost information on agricultural drones and related equipment [36,65], as well as cost data for general-purpose drones [66]. Next, the overhead costs associated with drone manufacturing (e.g., utilities and consumables) were estimated using statistical data on the average ratio of material costs to overhead expenses in the Japanese manufacturing sector [67]. The breakdown of overhead costs was determined with reference to the "other manufacturing" sector in the Survey on Input–Output Structure 2015 [68]. For gross value-added components, including labor costs, depreciation, operating surplus, and indirect taxes, both the total amount and internal composition were assumed based on the existing toy sector in the IO table. The toy sector includes the production of general-purpose drones and radio-controlled products.

In this study, the inputs from the agricultural drone sector to the intermediate sectors were assumed to occur only in the machinery repair sector and within the drone sector. The input of the machinery repair sector was set with reference to the self-input ratio of the smart agricultural machinery sector. The self-input ratio of the agricultural drone sector was assumed to be based on that of the toy sector.

References

1. Ministry of Agriculture, Forestry and Fisheries. Overview of Smart Farming in Japan. 2026. Available online: https://www.maff.go.jp/j/kanbo/smart/smart_meguji.pdf (accessed on 1 October 2026). (In Japanese)
2. Ministry of Agriculture, Forestry and Fisheries. Toward the Realization of the MIDORI Strategy for Sustainable Food Systems. 2025. Available online: https://www.maff.go.jp/j/kanbo/kankyo/seisaku/midori/attach/pdf/index-343.pdf (accessed on 1 October 2026). (In Japanese)
3. Medel-Jiménez, F.; Krexner, T.; Gronauer, A.; Kral, I. Life cycle assessment of four different precision agriculture technologies and comparison with a conventional scheme. *J. Clean. Prod.* **2024**, *434*, 140198. [CrossRef]
4. Karagkounis, A.; Fragkou, E.; Tsegas, G.; Barmpas, F.; Moussiopoulos, N. Assessing the environmental efficiency of smart farming via life cycle assessment: A case study in Greece. *Euro-Mediterr. J. Environ. Integr.* **2024**, *9*, 2009–2021. [CrossRef]
5. Sanches, G.M.; Bordonal, R.O.; Magalhães, P.S.G.; Otto, R.; Chagas, M.F.; Cardoso, T.F.; Luciano, A.C.S. Towards greater sustainability of sugarcane production by precision agriculture to meet ethanol demands in south-central Brazil based on a life cycle assessment. *Biosyst. Eng.* **2023**, *229*, 57–68. [CrossRef]

6. Tascione, V.; Raggi, A.; Petti, L.; Manca, G. Evaluating the environmental impacts of smart vineyards through the Life Cycle Assessment. *Sci. Total Environ.* **2024**, *922*, 171240. [CrossRef] [PubMed]
7. Bacenetti, J.; Paleari, L.; Tartarini, S.; Vesely, F.M.; Foi, M.; Movedi, E.; Ravasi, R.A.; Bellopede, V.; Durello, S.; Ceravolo, C.; et al. May smart technologies reduce the environmental impact of nitrogen fertilization? A case study for paddy rice. *Sci. Total Environ.* **2020**, *715*, 136956. [CrossRef] [PubMed]
8. Paleari, L.; Zoli, M.; Bacenetti, J.; Confalonieri, R. Can PocketNNI, a new smart app for Nitrogen Nutrition Index estimation, reduce the environmental impact of rice? In Proceedings of the 2021 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), Trento-Bolzano, Italy, 3–5 November 2021; pp. 476–480. [CrossRef]
9. Vatsanidou, A.; Fountas, S.; Liakos, V.; Nanos, G.; Katsoulas, N.; Gemtos, T. Life cycle assessment of variable rate fertilizer application in a pear orchard. *Sustainability* **2020**, *12*, 6893. [CrossRef]
10. Núñez-Cárdenas, P.; Diezma, B.; San Miguel, G.S.; Valero, C.; Correa, E.C. Environmental LCA of precision agriculture for stone fruit production. *Agronomy* **2022**, *12*, 1545. [CrossRef]
11. Jovarauskas, D.; Steponavičius, D.; Kemzūraitė, A.; Zinkevičius, R.; Venslauskas, K. Comparative analysis of the environmental impact of conventional and precision spring wheat fertilization under various meteorological conditions. *J. Environ. Manag.* **2021**, *296*, 113150. [CrossRef] [PubMed]
12. Medel-Jiménez, F.; Piringer, G.; Gronauer, A.; Barta, N.; Neugschwandtner, R.W.; Krexner, T.; Kral, I. Modelling soil emissions and precision agriculture in fertilization life cycle assessment-A case study of wheat production in Austria. *J. Clean. Prod.* **2022**, *380*, 134841. [CrossRef]
13. Sponagel, C.; Weik, J.; Witte, F.; Back, H.; Wagner, M.; Ruser, R.; Bahrs, E. Climate change mitigation potential and economic evaluation of selected technical adaptation measures and innovations in conventional arable farming in Germany. *J. Environ. Manag.* **2025**, *374*, 123884. [CrossRef] [PubMed]
14. Seo, Y.; Umeda, S.; Yoshikawa, N. Environmental impact of agricultural sprayers used in Japanese rice farming. *Int. J. Agric. Sustain.* **2023**, *21*, 2247803. [CrossRef]
15. Choi, S.W.; Shin, Y.J. Role of smart farm as a tool for sustainable economic growth of Korean agriculture: Using input–output analysis. *Sustainability* **2023**, *15*, 3450. [CrossRef]
16. Bahmutsky, S.; Grassauer, F.; Arulnathan, V.; Pelletier, N. A review of life cycle impacts and costs of precision agriculture for cultivation of field crops. *Sustain. Prod. Consum.* **2024**, *52*, 347–362. [CrossRef]
17. Ministry of Internal Affairs and Communications. Input–Output Tables for Japan 2015. 2020. Available online: https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00200603&tstat=000001130583&cycle=0&year=2015&month=0 (accessed on 1 October 2026). (In Japanese)
18. Ministry of Agriculture, Forestry and Fisheries. Composition ratio of total agricultural output, agricultural income produced statistics for 2023. 2025. Available online: https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00500206&tstat=000001015617&cycle=7&tclass1=000001019794&tclass2=000001227383&stat_infid=000040262910&tclass3val=0 (accessed on 1 October 2026). (In Japanese)
19. Agriculture, Forestry and Fisheries Research Council; National Agriculture and Food Research Organization. Results of the Smart Farming Demonstration Project (Paddy Rice), FY2019. 2022. Available online: https://www.affrc.maff.go.jp/docs/smart_agri_pro/jissho_data/file3R1suiden_2year.pdf (accessed on 1 October 2026). (In Japanese)
20. Ibaraki Agricultural Center. *Guide for the Introduction of Smart Farming for Field Crops*, 4th ed.; 2024. Available online: https://www.pref.ibaraki.jp/nourinsuisan/nosose/cont/img/smart_hutuusaku.pdf (accessed on 1 October 2026). (In Japanese)
21. Agriculture, Forestry and Fisheries Research Council; National Agriculture and Food Research Organization. Results of the Smart Farming Demonstration Project (Non-Paddy Crops), FY2019. 2022. Available online: https://www.affrc.maff.go.jp/docs/smart_agri_pro/jissho_data/file5R1excsuiden_2year.pdf (accessed on 1 October 2026). (In Japanese)
22. National Agriculture and Food Research Organization. Smart Farming Demonstration Project. FY2019: Open-Field Vegetables and Floriculture. 2020. Available online: https://www.naro.go.jp/smart-nogyo/r1/subject/rojiyasai-kaki/index.html (accessed on 1 October 2026). (In Japanese)
23. Japan Agricultural Development and Extension Association; Kubota Corporation. Mechanized Systems for Green Onion Production by Scale. 2009. Available online: https://www.jeinou.com/kaiteki/vegetable/2009/05/151215.html (accessed on 1 October 2026). (In Japanese)
24. Gunma Prefecture. Guide for Appropriate Introduction of Agricultural Machinery. 2022. Available online: https://www.pref.gunma.jp/uploaded/attachment/134939.pdf (accessed on 1 October 2026). (In Japanese)
25. Ministry of Agriculture, Forestry and Fisheries. Overview of Vegetable Production. 2026. Available online: https://www.maff.go.jp/j/seisan/ryutu/yasai/attach/pdf/index-102.pdf (accessed on 1 October 2026). (In Japanese)
26. National Agriculture and Food Research Organization. Smart Farming Demonstration Project. FY2020: Open-Field Vegetables and Floriculture. 2021. Available online: https://www.naro.go.jp/smart-nogyo/r2/subject/rojiyasai-kaki/index.html (accessed on 1 October 2026). (In Japanese)

27. National Agriculture and Food Research Organization. Mechanized Integrated Cultivation System for Japanese Radish, FY1998 Tohoku Agricultural Research Results, No. 13. 1999. Available online: https://www.pref.aomori.lg.jp/soshiki/nourin/nosui/files/H11-52.pdf (accessed on 1 October 2026). (In Japanese)
28. Kubota Corporation. Product Catalogue of Agri Robo Tractor MR1000AH. 2022. Available online: https://agriculture.kubota.co.jp/img_sys/catalog/2-30-2-0035-01.pdf (accessed on 1 October 2026). (In Japanese)
29. Kubota Corporation. Products and Solutions. 2025. Available online: https://www.kubota.co.jp/product/index.html (accessed on 1 October 2026). (In Japanese)
30. Ministry of Agriculture, Forestry and Fisheries. Statistical Survey on Farm Management and Economy 2015. 2017. Available online: https://www.e-stat.go.jp/stat-search/database?page=1&layout=datalist&toukei=00500201&bunya_l=04&tstat=000001013460&cycle=7&tclass1=000001013651&tclass2=000001019774&tclass3=000001101175&tclass4val=0 (accessed on 1 October 2026). (In Japanese)
31. Nansai, K. Embodied Energy and Emission Intensity Data for Japan Using Input–Output Tables (3EID). National Institute for Environmental Studies, Japan. 2025. Available online: https://3eid.nies.go.jp/ (accessed on 1 October 2026).
32. National Agriculture and Food Research Organization. Smart Farming Demonstration Project. FY2019: Paddy Rice. 2020. Available online: https://www.naro.go.jp/smart-nogyo/r1/subject/suidensaku/index.html (accessed on 4 November 2026). (In Japanese)
33. Ministry of Agriculture, Forestry and Fisheries; National Agriculture and Food Research Organization. Demonstration Results of the Smart Farming Demonstration Project (Interim Report): Upland Field Crops, Open-Field Vegetables, Greenhouse Horticulture, Fruit Trees, and Regional Crops. 2021. Available online: https://www.affrc.maff.go.jp/docs/smart_agri_pro/pdf/jissho_data/r1/chukan_hokoku_suidensakuigai.pdf (accessed on 4 November 2026). (In Japanese)
34. Lagnelöv, O.; Larsson, G.; Larsolle, A.; Hansson, P.A. Life cycle assessment of autonomous electric field tractors in Swedish agriculture. *Sustainability* **2021**, *13*, 11285. [CrossRef]
35. Ministry of Agriculture, Forestry and Fisheries. Agricultural Price Statistics 2017 (2015 Base Year). 2018. Available online: https://www.e-stat.go.jp/dbview?sid=0003272503 (accessed on 4 November 2026). (In Japanese)
36. Aomori Prefecture Northwest-Type Paddy Agriculture Promotion Council. Smart Agricultural Technology Introduction Manual for Northwest-Type Paddy Farming. 2023. Available online: https://www.pref.aomori.lg.jp/soshiki/nourin/ni-nosui/files/smart.pdf (accessed on 1 October 2026). (In Japanese)
37. Ministry of Agriculture, Forestry and Fisheries. Status of Drone Utilization in Agriculture for 2021. 2021. Available online: https://www.maff.go.jp/j/kanbo/smart/attach/pdf/drone-176.pdf (accessed on 1 October 2026). (In Japanese)
38. Kii Minpo Co., Ltd. Pesticide Spraying by Drone for Paddy Rice Cultivation in Wakayama Prefecture: Significant Reduction in Work Time. 2024. Available online: https://www.agara.co.jp/article/394088 (accessed on 1 October 2026). (In Japanese)
39. National Agriculture and Food Research Organization. Smart Farming Demonstration Project for Addressing Labor Shortages: Open-Field Vegetables and Floriculture. 2021. Available online: https://www.naro.go.jp/smart-nogyo/kaisho/subject/rojiyasai-kaki/index.html (accessed on 4 November 2026). (In Japanese)
40. Saitama Prefecture. Smart Farming Introduction Navi: Case Study of Green Onion Production Using Assisted Steering Tractors. 2024. Available online: https://smartagri-navi.pref.saitama.lg.jp/case-study/485/ (accessed on 1 October 2026). (In Japanese)
41. NTT e-Drone Technology Corporation. Demonstration of Pesticide Spraying by Agricultural Drone for Green Onion in Ibaraki Prefecture. 2022. Available online: https://www.nttedt.co.jp/post/20221109-negi-ibaragi (accessed on 1 October 2026). (In Japanese)
42. NTT e-Drone Technology Corporation. Demonstration of Pesticide Spraying by Agricultural Drone for Cabbage in Ibaraki Prefecture. 2023. Available online: https://www.nttedt.co.jp/post/ac101-furukawa-20231009 (accessed on 1 October 2026). (In Japanese)
43. Hashimoto, H. Demonstration of a Paddy-Based Integrated Farming Model in Hilly and Mountainous Areas Centered on Rice and Green Onion for Next-Generation Sustainability. 2022. Available online: https://www.pref.tottori.lg.jp/secure/1270599/104_1_hukunari.pdf (accessed on 1 October 2026). (In Japanese)
44. Ministry of Agriculture, Forestry and Fisheries. Collection of New Agricultural Technologies, Products and Services. 2025. Available online: https://www.maff.go.jp/j/kanbo/smart/attach/pdf/products-347.pdf (accessed on 1 October 2026). (In Japanese)
45. FJDynamics Pte. Ltd. Retrofit Automatic Steering System. 2023. Available online: https://agri.mynavi.jp/file/tomitamotors/pdf/230307_fjdynamics.pdf (accessed on 1 October 2026). (In Japanese)
46. Kubota Corporation. KSAS: Kubota Smart Agri System. 2025. Available online: https://agriculture.kubota.co.jp/ksas/ (accessed on 1 October 2026). (In Japanese)
47. Agri-ya Co., Ltd. Estimated Prices of New Forklifts by Manufacturer. 2024. Available online: https://www.agri-ya.jp/column/2024/04/30/investigate-new-and-used-forklift-prices/ (accessed on 1 October 2026). (In Japanese)
48. FORT Co., Ltd. Rice Milling Machine Catalogue List. 2025. Available online: https://seimaiki-fort.com/catalog-list/ (accessed on 1 October 2026). (In Japanese)
49. Ishii Manufacturing Co., Ltd. Product List. 2025. Available online: https://isi-mfg.com/items (accessed on 1 October 2026). (In Japanese)

50. Katou AM Co., Ltd. Genki Agricultural Equipment Online Store. 2025. Available online: https://www.genkinougyou.com/ (accessed on 1 October 2026). (In Japanese)
51. Kobashi Kogyo Co., Ltd. *Agricultural Machinery Price List 2025*; Kobashi Kogyo Co., Ltd.: Okayama, Japan, 2025. (In Japanese)
52. Ministry of Agriculture, Forestry and Fisheries. Overview of Agricultural Machinery. 2026. Available online: https://www.maff.go.jp/j/seisan/sien/sizai/s_kikaika/attach/pdf/index-31.pdf (accessed on 1 October 2026). (In Japanese)
53. Satake Corporation. Products and Services. 2025. Available online: https://www.satake-japan.co.jp/products/index.html (accessed on 1 October 2026). (In Japanese)
54. Sugano Farm Machinery MFG Co., Ltd. *General Catalogue 2025*; Sugano Farm Machinery MFG Co., Ltd.: Ibaraki, Japan, 2025. (In Japanese)
55. Tiger Kawashima Co., Ltd. Product Information. 2025. Available online: https://www.tiger-k.co.jp/info (accessed on 1 October 2026). (In Japanese)
56. Wataden Co., Ltd. Kikaiya Agricultural Equipment Online Store. 2025. Available online: https://www.e-kikaiya.jp/ (accessed on 1 October 2026). (In Japanese)
57. Yamabiko Corporation. Product information: KIORITZ. 2025. Available online: https://www.yamabiko-corp.co.jp/kioritz/ (accessed on 1 October 2026). (In Japanese)
58. Yanmar Holdings Co., Ltd. Agricultural Products and Services. 2025. Available online: https://www.yanmar.com/jp/agri/ (accessed on 1 October 2026). (In Japanese)
59. Japan Association for Techno-innovation in Agriculture; Forestry and Fisheries. Commissioned research results (FY2019) for Kyoto Prefectural Agriculture, Forestry and Fisheries Technology Center Tango Agriculture Research Division. 2020. Available online: https://www.jataff.or.jp/project/inasaku/pdf/R1_2_07-2.pdf (accessed on 1 October 2026). (In Japanese)
60. Hokuetsu Co., Ltd. Product Information. 2025. Available online: https://www.hokuetsu.jp/product.html (accessed on 1 October 2026). (In Japanese)
61. IHI Agri-Tech Corporation. General Catalogue (Hokkaido Edition). 2023. Available online: https://www.ihi.co.jp/iat/products/agricultural_machinery/pdf/2023_catalog_hokkaido.pdf (accessed on 1 October 2026). (In Japanese)
62. Karasawa Agricultural Machinery Service Co., Ltd. Noukinavi Agricultural Equipment Online Store. 2025. Available online: https://shop.noukinavi.com/view/page/guide (accessed on 1 October 2026). (In Japanese)
63. Maruyama Mfg. Co., Inc. Product Catalogue BSM301. 2018. Available online: https://www.maruyama.co.jp/books/catalog20180601/FLASH/data/80.html (accessed on 1 October 2026). (In Japanese)
64. Matsuyama Co., Ltd. Product Information. 2025. Available online: https://www.niplo.co.jp/products/list.php (accessed on 1 October 2026). (In Japanese)
65. Iwate Agricultural Research Center. Low-Cost RTK-GNSS Implementation Manual for Agricultural Application. *Easy Smart Farming Series*. 2023, No. 1. Available online: https://www.pref.iwate.jp/agri/_res/projects/project_agri/_page_/002/006/815/01_rtk-gnss_manual.pdf (accessed on 1 October 2026). (In Japanese)
66. Drone Navigator. How to Build a Drone: Required Parts, Costs, and Relevant Regulations. 2023. Available online: https://drone-navigator.com/drone-self-made#necessary-parts-and-points-to-select (accessed on 1 October 2026). (In Japanese)
67. Ministry of Economy, Trade and Industry. Basic Survey of Small and Medium Enterprises: FY2015 Financial Results. 2017. Available online: https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00553010&tstat=000001019842&cycle=7&tclass1=000001104315&tclass2=000001104316&tclass3val=0 (accessed on 1 October 2026). (In Japanese)
68. Ministry of Internal Affairs and Communications. Survey on Input-Output Structure 2015. 2017. Available online: https://www.e-stat.go.jp/stat-search?page=1&query=%E7%94%A3%E6%A5%AD%E9%80%A3%E9%96%A2%E6%A7%8B%E9%80%A0%E8%AA%BF%E6%9F%BB (accessed on 1 October 2026). (In Japanese)

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