sustainability

MDPI

Article

Evaluating Farm Management Performance by the Choice of Pest-Control Sprayers in Rice Farming in Japan

Yuna Seo * and Shotaro Umeda

Faculty of Science and Technology, Tokyo University of Science, Noda 278-8510, Japan; 7416021@ed.tus.ac.jp
* Correspondence: yuna.s@rs.tus.ac.jp

Abstract: With rapidly advancing technologies such as IoT, AI, robotics, and others, smart agriculture in Japan has been introduced and tested throughout the country. The validity of the implementation of smart agriculture could be measured by using cost analysis, working capacity assessment, and management efficiency analysis. In this study, we focused on pest-control management, wherein unmanned aerial vehicles (UAVs) for crop spraying have been recently introduced. In order to clarify the validity of UAVs for rice fields in Japan regarding costs and performance, we conducted a comparative study of pest-control sprayers, specifically: (1) tractor- mounted boom sprayers, (2) remote-control spraying helicopters (RC helicopters), and (3) UAVs. We estimated pest-control costs and the working capacity of each method. We also evaluated the management efficiency of 21 case scenarios of different pest-control sprayers and field areas ranging from 0.5 to 30 ha using data envelopment analysis (DEA) based on an input-oriented model. We used the input of pest-control cost and the output of gross farm income and surplus working capacity. Pest-control costs per unit area of boom sprayers, RC helicopters, and UAVs were approximately 925,597 yen/ha (US $8819/ha), 6,924,455 yen/ha (US $65,975/ha), and 791,724 yen/ha (US $7543/ha), respectively. The working capacity during pest-control scheduled days was 120, 195, and 135 ha, respectively. DEA results suggested that UAVs would be more efficient than boom sprayers and RC helicopters for the analyzed cases. UAVs for crop spraying showed relatively low cost and high management efficiency compared to the boom sprayers and RC helicopters; hence UAVs could be a suitable replacement to save cost and time.

Keywords: pest-control sprayer; UAVs; cost; DEA; rice farming

Citation: Seo, Y.; Umeda, S. Evaluating Farm Management Performance by the Choice of Pest-Control Sprayers in Rice Farming in Japan. *Sustainability* **2021**, *13*, 2618. https://doi.org/10.3390/su13052618

Academic Editor: Imre J. Holb

Received: 7 January 2021
Accepted: 24 February 2021
Published: 1 March 2021

1. Introduction

Smart agriculture promotes the utilization of cutting-edge technologies such as robotics, AI, and IoT. In the agricultural sector, labor shortages are a serious problem due to the decrease in the number of workers and the aging of the population. Therefore, the average cultivation area per worker is expanding [1]. Technological innovation is indispensable as a solution to the shortage of workers and in transferring the farmers' skills to the next generations [1]. Within the next decade, self-driving tractors and robots may perform time-consuming tasks currently performed by humans, becoming more common in the agriculture sector. To accelerate this trend, the Ministry of Agriculture, Forestry and Fisheries of Japan (MAFF) has promoted the introduction and demonstration of smart agricultural technology to farming sites in the "Smart Agriculture Acceleration Implementation Project" since 2019. For example, self-driving tractors, self-driving transplanting machines, auto watering management systems, remote sensing, and pest-control using agricultural drones, i.e., unmanned aerial vehicles (UAVs), for rice production are under field demonstration [2].

Among these, the use of UAVs for crop spraying is an expanding market in Japan. UAVs sprayed 684 ha in 2016 and 31,020 ha in 2018, an approximately 45-fold increase. The number of registered aircraft rose from 227 in 2016 to 1552 in 2018 [3,4]. Although there still are a few regulatory hurdles, which strictly limit the number of operators per unit, the flight level, the payload, the types of pesticides to use, and so on, UAVs are becoming one option to complement the use of boom sprayers and RC helicopters. Seemingly, this method would be more easily promoted with government support. The MAFF has established a numerical target to expand the field area sprayed by UAVs to up to 1 million hectares by 2022, and some regulations are under revision concerning user-friendliness [4].

Following the technological verification at field sites, there is an increasing need for farm management research including cost analysis and management efficiency of smart agricultural technology in order to realize its implementation at farms. At the farm level, it is recommended to formulate machinery utilization plans according to types of crop, cultivation methods, field areas, etc., to ensure effective and efficient machinery utilization and further the efficient farm management. As to building a machinery investment strategy, the working capacity and the cost are estimated and applied to the farm management evaluation. The working capacity is the indicator of the machinery performance assessed by the amount of field area that the machinery can be applied to in the cultivation process, for tasks such as plowing, planting, weeding, and harvesting, within scheduled working days or hours. It is often measured in field tests, or estimated based on operation width, speed, and the actual field-working rate. The pest-control cost is analyzed by fixed costs and variable costs [5–8].

Some reports have suggested the optimized usage of machinery by using linear programming [9–11]. They evaluated the effectiveness of the machinery according to the contribution to the improvement of the farm income and profits. This approach is useful to optimize farm management by maximizing farm income or profits based on the existing machinery, but it is hard to compare between farms at once. These studies also only targeted self-driving tractors, combines, and rice transplanters.

In order to clarify the validity of UAVs for crop spraying regarding costs and performance, we performed a comparative study of pest-control sprayers, namely tractor-mounted boom sprayers (boom sprayers), remote-control spraying helicopters (RC helicopters), and UAVs in rice production and estimated the costs, the working capacity, and the management efficiency at the farm level for rice production in Japan. We targeted the preventive control method, which involves applying pesticides in advance of pest and disease breakouts regularly twice a year. For management efficiency, we built 21 scenario cases of different pest-control sprayers (boom sprayers, RC helicopters, and UAVs) and farm area, ranging from 0.5 to 30 ha, and applied data envelopment analysis (DEA) to distinguish the efficient farms.

2. Methodology

2.1. Cost Analysis of Pest-Control Sprayers

Pest-control cost (Pc) per unit area (ha) was estimated by fixed cost (Cf) and variable costs (Cv) (Equation (1)), where S refers to field area (ha).

$$Pc \text{ (yen/ha)} = Cv \text{ (yen/ha)} + Cf \text{ (yen/unit)}/S \text{ (ha)} \quad (1)$$

Cf per unit was calculated by summing up depreciation expenses, repair and maintenance costs, and capital interest. Depreciation expenses were calculated by dividing purchase price by service life. Purchase prices were collected from the statistics of agriculture, forestry, and fisheries and manufacturers [12]. Service life was assumed to be 7 years for all machinery [13]. Repair and maintenance costs were calculated by multiplying purchase price and repair and maintenance cost rate. Repair and maintenance cost rates were assumed to be 3.8% for boom sprayers, 4.0% for tractors, 40% for RC helicopters, and 30% for UAVs [14]. Capital interest was assumed to be 3.5% for all [14]. Depreciation expenses, repair and maintenance costs, and capital interest were allocated by working rate: 100% for boom sprayers, RC helicopters, and UAVs and 58% for tractors [6,15]. Working rate (%) refers to a rate of the amount of time taken for pest control to the total working time. That is, all sprayers but the tractor were used only for pest control, but the tractor was used for other processes such as plowing and fertilizing.

Cv per unit area (ha) was estimated by summing up pesticide costs, fuel costs, and labor costs [6]. Data were collected from previous reports [16–18]. Pesticide costs were collected from the preliminary implementation test data and interviews with farmers [2,17]. Fuel costs were estimated by multiplying fuel efficiency (l/h), fuel price (yen/l), and operating hours (h/ha). Labor costs were estimated by multiplying operating hours (h/ha), the number of operators, and wages (1700 yen/h).

2.2. Working Capacity

Working capacity (*Wc*, ha) is the indicator of machinery performance assessed by the amount of field area that the machinery can be applied to within scheduled working days or hours [15,19–22]. *Wc* was estimated using working time (*Wt*, h) and working efficiency (*We*, ha/h) (Equation (2)). *Wt* was calculated by using scheduled working days (*sWd*, 14 days for pest control), actual working day rate (*Wd*, 77%), and daily working time (*dWt*, 8 h per day) according to Equation (3) [9]. *We* was calculated using working width (*Ww*, m), speed (*Ws*, km/h), and actual field-working rate (*Wr*, %) of each pest-control sprayer (Equation (4)). *Wr* refers to the ratio of actual field-working time to the total working time, including preparation, transferring, etc. Data were provided under the assumption of a standard sector of leveled soil and that they could vary by skills of operators, farm location, road conditions, etc. [15,19–22].

$$Wc = sOt \times Wl \tag{2}$$

$$Wt = sWd \times Wd \times dWt \tag{3}$$

$$We = Ww \times Ws \times Wr \tag{4}$$

2.3. Management Efficiency

Management efficiency of three different sprayers applicable to different farm areas ranging from 0.5 to 30 ha paddy fields was measured using DEA based on an input-oriented model [23,24]. Efficiency score was calculated using the Chames, Cooper, and Rhodes (CCR) model of 1 input (pest-control cost) and 2 outputs (gross farm income and surplus working capacity) [25–27].

We built 21 scenarios of decision-making units (DMUs; rice farms) resulting from the permutations of three pest-control sprayers (boom sprayers, RC helicopters, and UAVs) and seven paddy field areas with 0.5, 1, 3, 5, 10, 15, and 30 ha per field. Pest-control costs were estimated as described in Section 2.1. Surplus working capacity was assessed by subtracting the field area of DMUs from the working capacity (ha) of each sprayer, which represents the potential working area after application in the field area and possibly offering pest-control service to other farms. Farm gross incomes were collected from the Agriculture and Forestry Census [28]. We assumed 1 unit of sprayers per farm through areas, and operators as 1, 3, and 2 persons for boom sprayers, RC helicopters, and UAVs, respectively [29].

2.3.1. Data Envelopment Analysis

DEA is a mathematical linear programming method used to construct a non-parametric piecewise surface (or frontier) over the data, which is able to calculate efficiencies relative to this surface. Management efficiency can be evaluated by measuring how far each decision-making unit (DMU) deviates from the efficient frontier based on the DMU that shows the best management efficiency obtained from actual data. In addition, there are two types of DEA—input-oriented and output-oriented models—depending on the concept of efficiency. The input-oriented model evaluates a DMU that can produce a given production with a smaller input as a more efficient DMU. On the other hand, the output-oriented model evaluates a DMU that can produce more output from a given input as a more efficient DMU. Hence, there are two models for the scale-related returns law: the model assuming a constant return to scale (CRS) and the model assuming a variable return to scale (VRS). Two models were chosen or applied in parallel according to the study scope, i.e., whether it was appropriate to use a constant or a variable return to scale model [30,31]. DEA can make relative comparisons between business entities with a small number of samples, and an approach different from production function analysis is possible. Another strength of DEA is that it can simultaneously consider multiple input elements with different units [24]. DEA is widely used by researchers to analyze the performance of the agricultural sector. There are studies at regional level that analyze management efficiency, production efficiency, land use, irrigation use, etc [27,32,33].

2.3.2. Estimation of Management Efficiency

Management efficiency was estimated based on the CCR input-oriented model [25]. DEAP version 2.1 was used [23]. Briefly, based on the CCR model, the efficiency score (θ) of DMU$_k$ (k = 1, . . . , n) was calculated by maximizing its virtual output subject to virtual input equalling 1, the efficiency of all DMU being below 1, and weights of inputs and outputs not being zero, using linear programming Equation (5). We used 1 input of pest-control cost (x_1) and 2 outputs of farm gross income (y_1) and surplus working capacity (y_2). Input weight was v_1, and output weights were u_1 and u_2.

$$\begin{gathered} \mathrm{Max}\theta_o: = u_1 y_{1o} + u_2 y_{2o} \\ \text{s.t. } v_1 x_{1o} = 1 \\ u_1 y_{1k} + u_2 y_{2k} \leqq v_1 x_{1k}\ (k = 1, \ldots, n) \\ v_1, u_1, u_2 \geqq 0 \end{gathered} \tag{5}$$

3. Results

3.1. Pest-Control Cost

Fixed costs per unit for the tractor mounted boom sprayers, RC helicopters, and UAVs were 878,064, 6,876,500, and 744,132 yen, respectively (Table 1). Variable costs per unit area were 47,532 yen for boom sprayers, 47,955 yen for RC helicopters, and 47,592 yen for UAVs (Table 2). Therefore, pest-control cost per unit area was estimated to be 925,597, 6,924,455, and 791,724 yen, respectively.

Table 1. Fixed costs of pest-control sprayers.

Pest-Control Machine	Purchase Price (Yen)	Service Life (Year)	Farm Work Rate (%)	Fixed Expenses (yen)			
				Depreciation	Repair	Capital Interest	Sum
Boom sprayer							878,064
Sprayer	2,464,000	7	100	352,000	93,139	86,240	531,379
Tractor	2,782,200	7	58	230,509	59,702	56,475	346,685
RC helicopter	11,900,000	7	100	1,700,000	4,760,000	416,500	6,876,500
UAVs (incl.battery)	1,557,227	7	100	222,461	467,168	54,503	744,132

Table 2. Variable costs of pest-control operation (yen/ha).

Pest-Control Sprayer	Pesticides Cost	Fuel Cost	Labor Cost	Sum
Boom sprayer	46,369	265	898	47,532
RC helicopter	46,369	96	1490	47,955
UAVs	46,369	9	1214	47,592

Table 3 shows pest-control costs according to field area. Changes according to area were mostly driven by fixed costs, which are dependent on purchase price. Overall, UAVs had the lowest cost, followed by the boom sprayers and RC helicopters. This was due to the low purchase price of the UAVs and fuel cost, although labor cost for two operators was higher than that for boom sprayers. Specifically, UAV cost was maximized at 0.5 and minimized at 3 ha.

Table 3. Pest-control costs of boom sprayers, RC helicopters, and unmanned aerial vehicles (UAVs).

Area (ha)	Boom Sprayers (yen)	RC Helicopters (yen)	UAVs (yen)
0.5	1,780,826	13,777,909	1,512,992
1	925,597	6,924,455	791,724
3	412,558	2,413,306	368,094
5	397,855	1,599,658	371,369
10	447,934	1,052,008	435,141
15	618,120	1,024,362	610,091
30	1,196,254	1,408,894	1,193,590

3.2. Working Capacity

Working capacity for 14 days of pest control was estimated using working time and working efficiency. The results for boom sprayers, RC helicopters, and UAVs were 120, 195, and 135 ha, respectively. Working efficiency was estimated by using working speed, width, and actual field-working rate of each sprayer. The working speed of boom sprayers, RC helicopters, and UAVs was 2.4, 17.5, and 13.0 km/h. The working width was 15, 7.5, and 3.5 m, respectively. Actual field-working rate was 56%, 25%, and 50%, respectively. Pest-control operation included spraying, supplying pesticides and water, and washing tanks and nozzles. Since RC helicopters and UAVs spray a small amount of pesticide at a high concentration, it takes less time to transport water for diluting pesticides, supplying pesticides, and washing the tank [8]. However, both require frequent battery changes, which means that their operation is more time-consuming than that of boom sprayers [15]. According to interviews, UAV users are saving time by keeping charged replacement batteries from a generator loaded in a light truck to use for transfer. However, for RC helicopters, the battery replacement is more time-consuming than for the UAV due to the additional assembly and adjustment time [34]. Therefore, the working efficiency for the three sprayers was determined to be 2.0, 3.3, and 2.3 ha/h, respectively. The speed and the coverage of RC helicopters seemed to overwhelm the relatively lower field-working rate and represented the highest working efficiency, which led to the highest working capacity.

3.3. Management Efficiency

This study used an input-oriented DEA model with a constant return-to-scale for evaluating efficiency [25]. An input-orientated model is aimed to minimize the inputs at a given output level. This study employed input orientation considering the specificity of the agriculture sector, which relies on limited inputs, under the presumption that a DMU can produce the same amount of output by using a smaller quantity of inputs [27,32,33]. Regarding the scales, the constant return-to-scale assumption was employed to compare each DMU in terms of efficiency because they use varying quantities of inputs to produce different levels of outputs. Management efficiency was estimated using DEA based on pest-control costs, surplus working capacity, and gross farm income. We compared 21 DMUs of three pest-control sprayers for different field areas ranging from 0.5 to 30 ha (Figure 1). This showed that the overall efficiencies increased along with the farm size. The efficiency of UAVs for fields of 3 to 30 ha was 1. The efficiency of UAVs was slightly higher than that of boom sprayers, representing the same tendency across the farms. The boom sprayer marked 1 for a 30 ha field. The efficiency of RC helicopters on fields ranging from 0.5 to 30 ha was the lowest among the three sprayers.

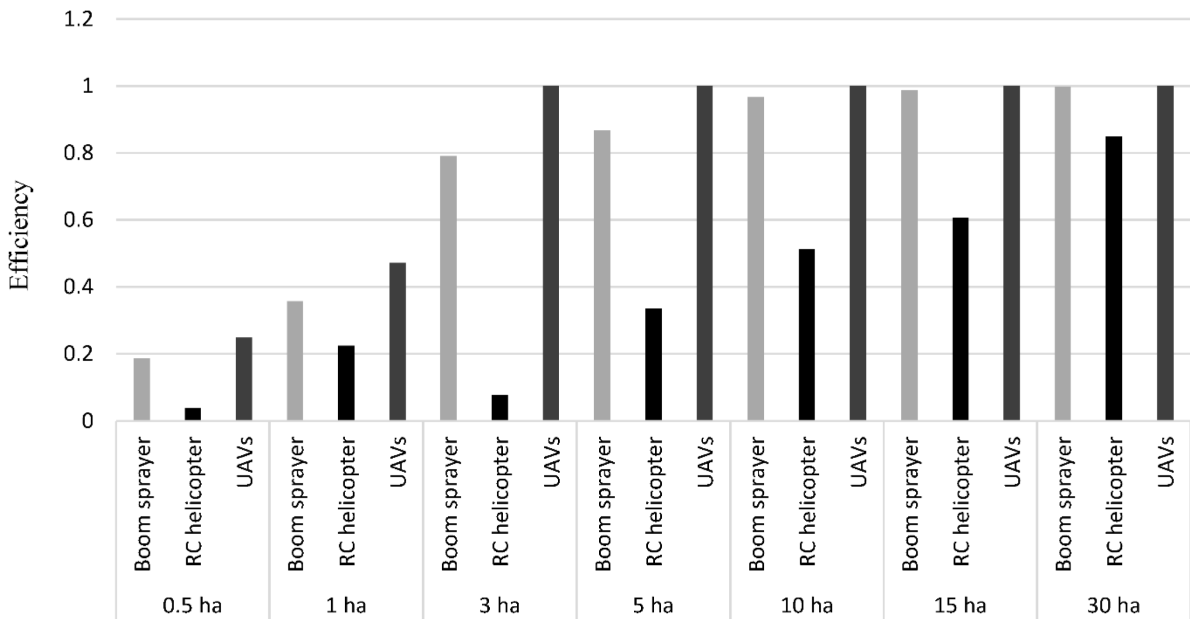

Figure 1. Efficiency for pest-control calculated using the data envelopment analysis (DEA), for rice farms ranging in size from 0.5 to 30 ha, and using either a boom sprayer (light gray bars), an RC helicopter (black bars) or a UAV (dark gray).

4. Discussion

4.1. Validity of UAVs in Rice Production

In the agricultural sector in Japan, which has a labor shortage problem, there is a need for work efficiency and labor saving. Recently, the UAV market has been established with a continuous deregulation from the Japanese government. We explored the validity of UAVs in rice production in Japan by assessing the cost and the performance at varying scales of farms through comparison with boom sprayers and RC helicopters. Pest-control costs were mostly driven by fixed costs, estimated by adding depreciation expenses, repair and maintenance costs, and capital interest. Costs along the farm scales of UAVs and boom sprayers were similar, and both were minimized at 3 to 5 ha (Table 3). These costs were estimated with the assumption of one unit of sprayers regardless of the field area. The results suggest that one unit would be cost efficient for 3 to 5 ha farms. Although the purchase cost of the boom sprayers was almost double that of UAVs, the fixed costs of both were similar due to high maintenance and repair cost of UAVs. Seemingly, this is because UAVs are in their introductory phase in the Japanese agriculture sector. Although it is expected that the cost would possibly decrease with technological improvement, the initial and maintenance and repair costs remain obstacles to UAV introduction and adoption [35]. On the other hand, RC helicopters showed the highest cost throughout, approximately nine times that of UAVs, due to the expensive purchase price and labor cost of three operators. Thus, individual farms are reluctant to purchase them. RC helicopters are often used by the pest-control service of Japan Agricultural Cooperatives (JA) or private service companies, at a cost of around 18,000 yen/ha [36–38].

Variable costs did not change significantly among the sprayers, which were highly dependent on pesticides cost, making up approximately 97% of the total variable costs. As described above, pest control in this study represents preventive control, applied regularly twice a year before the breakout of pests. Hence, the pesticide amount was assumed consistent among the three sprayers according to the labels and laws [18]. We also referred to the preliminary implementation test and interviews with farmers [2,17]. In certain field tests, relatively lower quantities and costs of pesticides have been reported due to lower liquid pesticide prices according to grain type [4,39]. Since Japan is located in the East Asian monsoon region, which brings warm and long rainy seasons, pests are likely to occur, generally leading to more extensive preventive control than in other countries in order to manage the decrease in yield and quality due to pests [16,40]. The ratio of pesticide cost to the total production cost in Japan reached approximately 8% for rice production in 2015 [41].

Management efficiency, dealing with the cost, the gross income, and the performance, showed that the overall efficiencies increased along with the scale of the fields (Figure 1). UAVs and boom sprayers represented similar efficiency from 10 to 30 ha, reaching 1, although the efficiency of UAVs was slightly higher than that of boom sprayers over 0.5 to 5 ha. This suggests that these methods would be recommendable for farms bigger than 10 ha. In other words, at present, UAVs do not have a significant advantage over boom sprayers. The spread of UAVs in agriculture, in addition to deregulation and technological advances, should reduce costs and improve usability [4,35].

4.2. Challenges to Implementing UAVs in the Agriculture Sector

Our results showed that the total cost of UAVs would be almost comparable to that of boom sprayers, which does not tend to be a strong motivation for switching to UAVs as a first choice at present. They also revealed that initial costs and maintenance costs account for a large percentage of the total cost. Therefore, it is required that these costs are reduced as technology progresses in order for UAVs to be widely used in the near future.

Besides the cost, according to interviews and survey data, farmers are especially concerned about the number of operators, the limited number of applicable pesticides, operability, etc., of UAVs. A UAV unit needs two operators, one flying the drone and the other watching, which raises the operational cost. Moreover, under the current regulations, it is necessary to apply for approval from the Ministry of Land, Infrastructure, Transport and Tourism (MLIT), take a course at a driving school designated by the Agriculture, Forestry and Fisheries Aviation Association, and obtain a certificate for flying UAVs [35,42,43].

UAVs mostly use liquid pesticides, which do not cover all types of pests; moreover, these liquid applications are more limited for fruits and vegetables. Pesticide payload is regulated by aviation law at up to 10 kg per UAV unit, which limits an area for working capacity during one flight, subsequently increasing costs. Currently, the government are testing the group flight approach using two UAVs to save time. Spray uniformity is also being tested for UAVs, assessing optimal flight parameters, drift, downwash effects, etc [44,45].

As for the aircraft, only the manual control type is approved, and automatic navigation for UAVs is not permitted. Automatic navigation technologies and deregulation should be conducted while maintaining safety measures. The MAFF intends to revise the guidelines to promote the utilization of drones in the agricultural field. Regulations on safety measures for autonomous flight, a review of approvals that need to be obtained for each model, etc., are being considered. It is also necessary to work with MLIT to improve operation regulations to meet the demands of farmers [2,4,35].

4.3. Future Application of UAVs in Agriculture

The goal of this research and the utilization of UAVs in the agriculture sector is to showcase the autonomous growth-management of crops and vegetables by monitoring growth and autonomously applying pesticide injection to targeted plants [42,46]. With technology innovation and the development of pesticide formulations, precision farming using UAVs is attracting attention for its potential mitigation of the broadscale use of pesticides and reduction of labor. It would be possible to increase yields and reduce pesticides by utilizing image analysis and remote sensing to digitize farm condition information using UAVs and spraying pesticides to the targeted area [47,48].

Current accomplishments demonstrate that UAVs observe crops with different indices [48–50] and cover hectares of fields in a single flight using thermal and multispectral cameras to record reflectance of vegetation canopy [51–54]. The data observed from the multispectral camera through telemetry could be analyzed using the normalized difference vegetation index (NDVI) [55,56]. The information–communication infrastructure in rural areas is indispensable to the monitoring and autonomous flight of UAVs. Currently, wireless base stations are being tested, such as broadband wireless access (BWA) for forwarding mass picture/video data and low power wide area (LPWA) networks for measuring the weather, water level, and other parameters [57].

Together with this research and development, it would be important to strengthen the training of farmers to familiarize them with technologies and give them the ability to operate such equipment [4]. It has been reported that awareness of farmers may be one of the major factors determining the introduction of these new technologies [58,59]. To enable easy access, it would be necessary to educate the communicators between the technical personnel and farmers.

5. Conclusions

We compared the costs, the working capacity, and the management efficiency among boom sprayers, RC helicopters, and UAVs for crop spraying in rice production in Japan. It was revealed that UAVs are comparable to boom sprayers, showing similar pest-control costs and management efficiency at a scale ranging from 0.5 to 30 ha fields. Technological advances and deregulation are necessary to expand the use of UAVs while meeting the safety measures and ensuring usability. Although the estimation assumed regional characteristics in Japan, it could be helpful for the strategic planning scheme of preliminary decision making to introduce new technologies to rice production.

Author Contributions: Conceptualization, Y.S.; methodology, Y.S.; software, Y.S.; validation, Y.S., and S.U.; formal analysis, S.U.; investigation, S.U.; resources, S.U.; data curation, S.U.; writing—original draft preparation, Y.S.; writing—review and editing, Y.S.; visualization, Y.S.; supervision, Y.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study [12,13,28].

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

References

1. MAFF. Development of Smart Agriculture. 2018. Available online: https://www.affrc.maff.go.jp/docs/smart_agri_pro/attach/pdf/smart_agri_pro-11.pdf (accessed on 19 September 2020).
2. MAFF. Smart Agriculture Demonstration Project. 2018. Available online: https://www.affrc.maff.go.jp/docs/smart_agri_pro/attach/pdf/smart_agri_pro-20.pdf (accessed on 19 September 2020).
3. MAFF. The Implementation Status of Aerial Spraying of Pesticides. 2016. Available online: https://www.maff.go.jp/j/syouan/syokubo/gaicyu/g_kouku_zigyo/attach/pdf/index-46.pdf (accessed on 25 September 2020).
4. MAFF. The Implementation Status of Aerial Spraying of Pesticides. 2019. Available online: https://www.maff.go.jp/j/syouan/syokubo/gaicyu/g_kouku_zigyo/attach/pdf/index-49.pdf (accessed on 25 September 2020).
5. Tsuruta, M.; Takahashi, M. Simulations of field capacity and coverage of agricultural machines. *Tohoku Agric. Res.* **1993**, *46*, 107–108.
6. Matsuoto, K.; Miyaoto, T.; Yonetani, T. Management evaluation of new mechanized technology centered on paddy rice pest control method. *Bull. Hyogo Prefect. Agric. Inst.* **1998**, *46*, 27–32.
7. MAFF. Formulation of a Plan for the Introduction of Specified High-Performance Agricultural Machinery and Its Handling-Guideline. 2013. Available online: https://www.maff.go.jp/j/seisan/sien/sizai/s_kikaika/hosin/pdf/guide_line.pdf (accessed on 23 October 2020).
8. Sun, W. Labor-saving control technology using multicopters in mountainous areas. *NARO Tech. Rep.* **2020**, *5*, 30–33.
9. Matsumoto, K.; Umemoto, M. Effect of introducing agricultural operating robots in large-scale paddy field management. *Kanto Tokai J. Farm Manag.* **2013**, *103*, 65–71.
10. Matsukura, S.; Nanseki, T.; Fujii, Y.; Sato, M.; Chomei, Y.; Miyazumi, M. Effect of farming skill and farm size on production costs on large rice farms: A simulation analysis by FAPS-DB. *Agric. Inf. Res.* **2015**, *24*, 35–45.
11. Matsumoto, K. Evaluation and prospect of management evaluation method of smart agricultural technology. *Bull. NARO* **2019**, *1*, 33–37.

12. MAFF. Statistics of Agriculture, Forestry, and Fisheries. 2020. Available online: https://www.maff.go.jp/j/tokei/kouhyou/noubukka/attach/pdf/index-81.pdf (accessed on 23 August 2020).
13. National Tax Agency (NTA). Service Lives (Machinery, Instrument). Available online: https://www.keisan.nta.go.jp/h30yokuaru/aoiroshinkoku/hitsuyokeihi/genkashokyakuhi/taiyonensukikai.html (accessed on 30 September 2020).
14. Japan Agricultural Mechanization Association (JAMA). *Basic Policy Reference Materials for Test Research, Promotion and Introduction of High-Performance Agricultural Machinery, etc.*; Japan Agricultural Mechanization Association (JAMA): Tokyo, Japan, 2008.
15. Yamaguchi Prefecture. Guidelines for the Introduction of High-Performance Agricultural Machinery. 2019. Available online: https://www.pref.yamaguchi.lg.jp/cmsdata/7/f/8/7f8b98f9e6953171a99e0ce74b989db6.pdf (accessed on 25 September 2020).
16. FAO. Pesticides Average Use Per Area of Cropland. Available online: http://www.fao.org/faostat/en/#data/EP/visualize (accessed on 14 October 2020).
17. MAFF. Survey on the Supply of Agricultural Materials in Japan and Overseas. 2019. Available online: https://www.maff.go.jp/j/press/seisan/sizai/attach/pdf/190802-2.pdf (accessed on 23 August 2020).
18. Japan Crop Protection Association (JCPA). Laws Related to Pesticides. 2020. Available online: https://www.jcpa.or.jp/qa/a6_24.html (accessed on 2 August 2020).
19. Aichi Prefecture. Basic Policy on Test Research, Promotion and Introduction of High-Performance Agricultural Machinery. 2013. Available online: https://www.pref.aichi.jp/engei/daizu-mugi/up-h250708/01sagyou.pdf (accessed on 3 August 2020).
20. Hiroshima Prefecture. Concept of Machine Selection, Guide for Fostering Village Corporations. 2012. Available online: https://www.pref.hiroshima.lg.jp/soshiki/81/syuurakuhoujinnikuseinotebiki.html (accessed on 4 October 2020).
21. Ibaraki Prefectural Agricultural Revitalization Council. Concept of Farm Area Related to Machine Introduction. 2013. Available online: http://www.ibaraki-suiden.jp/data/jyosei/sn2_28.pdf (accessed on 4 October 2020).
22. Hokkaido Prefecture. Agricultural Machinery Introduction Plan Formulation Guide. 2014. Available online: http://www.pref.hokkaido.lg.jp/ns/gjf/kankyo/tokuteikouseinou_keikaku.pdf (accessed on 3 October 2020).
23. Coelli, T. *A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program*; Centre for Efficiency and Productivity Analysis; University of New England: Armidale, Australia, 1996.
24. Cooper, W.W.; Seifbrd, L.M.; Tone, K. *Introduction to Data Envelopment Analysis and Its Uses; with DEA-Solver Software and References*; Springer Sciences & Business Media. LLC: Berlin/Heidelberg, Germany, 2006. [CrossRef]
25. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision-making units. *EJOR* **1978**, *2*, 429–444. [CrossRef]
26. Fukuda, A.; Nakamura, E.; Morisugi, M.; Imura, H. Research on eco-efficiency seen from land use and agricultural production. *Environ. Syst. Res.* **2003**, *31*, 91–99. [CrossRef]
27. Toma, E.; Dobre, C.; Dona, I.; Cofas, E. DEA applicability in assessment of agriculture efficiency on areas with similar geographically patterns. *Agric. Agric. Sci. Procedia* **2015**, *6*, 704–711. [CrossRef]
28. MAFF. Agriculture and Forestry Census. 2015. Available online: https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00500209&tstat=000001032920&cycle=7&year=20150&month=0&tclass1=000001077437&tclass2=000001077396&tclass3=000001085297 (accessed on 17 September 2020).
29. Ministry of Land, Infrastructure, Transport and Tourism (MLIT). Guidelines for Safe Flight of Unmanned Aerial Vehicles (Drones, Radio-Controlled Aircraft, etc.). 2019. Available online: https://www.mlit.go.jp/common/001303818.pdf (accessed on 25 August 2020).
30. Basso, A.; Funari, S. Constant and variable returns to scale DEA models for socially responsible investment funds. *Eur. J. Oper. Res.* **2014**, *235*, 775–783. [CrossRef]
31. Oyerinde, Y.; Bankole, F. Influence of Constant Returns to Scale and Variable Returns to Scale Data Envelopment Analysis Models in ICT Infrastructure Efficiency Utilization. In Proceedings of the 11th Annual Pre-ICIS SIG GlobDev Workshop, San Francisco, CA, USA, 13 December 2018.
32. Aldaz, N.; Millan, J.A. Regional productivity of Spanish agriculture in a panel DEA framework. *Appl. Econ. Lett.* **2003**, *10*, 87–90. [CrossRef]
33. Diaz, J.A.; Poyato, E.C.; Luque, R.L. Applying benchmarking and data envelopment analysis (DEA) techniques to irrigation districts in Spain. *Irrig. Drain.* **2004**, *53*, 135–143. [CrossRef]
34. Sakai, H.; Tanaka, R.; Endo, G. Operation sequence in direct sowing rice cultivation by radio controlled helicopter. *Tohoku Agric. Res.* **1997**, *50*, 23–24.
35. Fuji Keizai. *Agribusiness Status and Future Prospects 2018*; Fuji Keizai: Tokyo, Japan, 2018.
36. Azumino City. Agricultural Work Standard Labor Wage/Machine Work Fee Agreement Table 2020. 2020. Available online: https://www.city.azumino.nagano.jp/soshiki/49/1589.html (accessed on 2 August 2020).
37. JA Utsunomiya. The Implementation of Pesticide Spraying Control of Paddy Fields by Radio-Controlled Helicopter 2020. 2020. Available online: https://www.jau.or.jp/info/1204/ (accessed on 2 August 2020).
38. JA Chichibu. Pest-Control with a Radio-Controlled Helicopter. Available online: https://www.ja-chichibu.jp/news/%E3%83%A9%E3%82%B8%E3%82%B3%E3%83%B3%E3%83%98%E3%83%AA%E3%81%A7%E7%97%85%E5%AE%B3%E8%99%AB%E9%98%B2%E9%99%A4.html (accessed on 2 August 2020).
39. Meng, Y.; Lan, Y.; Mei, G.; Guo, Y.; Song, J.; Wang, Z. Effect of aerial spray adjuvant applying on the efficiency of small unmanned aerial vehicle for wheat aphids control. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 46–53. [CrossRef]

40. MAFF. Current Situation over Pesticides. 2016. Available online: https://www.maff.go.jp/j/seisan/sien/sizai/noyaku/attach/pdf/index-1.pdf (accessed on 23 August 2020).
41. MAFF. Agricultural Management Statistics Survey. 2015. Available online: https://www.e-stat.go.jp/dbview?sid=0003190950 (accessed on 30 September 2020).
42. MAFF. Agricultural Drones. Available online: https://www.maff.go.jp/j/kanbo/smart/pdf/hukyuukeikaku.pdf (accessed on 19 September 2020).
43. Agriculture, Forestry and Fisheries Aviation Association (AFFA). Introduction of AFFA. Available online: http://www.j3a.or.jp/intro_201709.pdf (accessed on 24 February 2021).
44. Hokkaido Prefecture. Utilization of Drones in the Primary Industry Field. 2019. Available online: http://www.pref.hokkaido.lg.jp/ss/ssa/siryo2.pdf (accessed on 25 August 2020).
45. Bamon, N.; Oomura, K.; Tameike, Y.; Uemuro, K. *Differences between Downwash of Agricultural Drones and Unmanned Helicopters and Liquid Spraying Characteristics*; Kyushu Okinawa Agricultural Experiment Research Results Information; Kyushu Okinawa Agricultural Research Center, NARO: Koshi, Japan, 2019.
46. Mogili, U.R.; Deepak, B.B.V.L. Review on application of drone systems in precision agriculture. *Procedia Comput. Sci.* **2018**, *133*, 502–509. [CrossRef]
47. Freeman, P.K.; Freeland, R.S. Agricultural UAVs in the US: Potential, policy, and hype. *RSASE* **2015**, *2*, 35–43.
48. Sugiura, R. High-throughput field phenotyping using aerial imagery from drone. *J. Robot. Soc. Jpn.* **2019**, *35*, 369–371. [CrossRef]
49. Simelli, I.; Tsagaris, A. The Use of Unmanned Aerial Systems (UAS) in Agriculture. In Proceedings of the 7th International Conference on Information and Communication Technologies in Agriculture, Food and Environment (HAICTA) 2015, Kavala, Greece, 17–20 September 2015; pp. 730–1498. Available online: http://ceur-ws.org/Vol-1498/HAICTA_2015_Proceedings.pdf (accessed on 19 September 2020).
50. Veroustraete, F. The rise of the drones in agriculture. *ECAG* **2015**, *2*, 325–327.
51. Bendig, J.; Bolten, A.; Bareth, G. Introducing a low-cost mini-UAV for thermal-and multispectral-imaging. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2012**, *39*, 345–349. [CrossRef]
52. Colomina, I.; Molina, P. Unmanned aerial systems for photogrammetry and remote sensing: A review. *ISPRS J. Photogramm. Remote Sens.* **2014**, *92*, 79–97. [CrossRef]
53. Nonami, K. Global drone development trends and challenges and prospects from agricultural applications. *J. Soc. Instrum. Control Eng.* **2016**, *55*, 780–787.
54. Hama, A.; Tanaka, K.; Den, H.; Kondoh, A. Comparison and consideration of near-infrared cameras for drones: RedEdge and Yubaflex. *J. Remote Sens. Soc. Jpn.* **2018**, *38*, 451–457.
55. Reinecke, M.; Prinsloo, T. The influence of drone monitoring on crop health and harvest size. In Proceedings of the 2017 1st International Conference on Next Generation Computing Applications (NextComp), Mauritius, 19–21 July 2017; pp. 5–10. [CrossRef]
56. Bhandari, A.K.; Kumar, A.; Singh, G.K. Feature extraction using Normalized Difference Vegetation Index (NDVI): A case study of Jabalpur city. *Procedia Technol.* **2012**, *6*, 612–621. [CrossRef]
57. MAFF. Land Improvement Facility Information Infrastructure Maintenance Promotion Survey. 2020. Available online: https://www.maff.go.jp/j/nousin/soumu/yosan/R1hojyo/attach/pdf/index-23.pdf (accessed on 3 September 2020).
58. Matsumoto, K.; Yamamoto, J.; Sekino, K. The factor in introducing the new technology that involve capital investment. *Jpn. J. Farm Manag.* **2004**, *42*, 35–40.
59. Ogata, Y.; Nanseki, T.; Chomei, Y. Factor analysis of agricultural corporation managers' consciousness of ICT cost-effectiveness. *Agric. Inf. Res.* **2019**, *28*, 1–12. [CrossRef]