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Economic Efficiency of Climate Smart Agriculture Technology: Case of Agrophotovoltaics

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Abstract: Climate change must be the most serious environmental crisis of the present human generation. While corresponding climate-smart agriculture (CSA) practices are emerging, the extent to which CSA is profitable to farmers is unclear. In this paper, we focus on agrophotovoltaics (APV), one of the CSA policies intensively pursued by the Korean government, to analyze the profitability of APV and its implications for rural sustainability. First, we consider the total profit of farms before and after APV installation by a region through generalized least squares (GLS) to verify that APV has overall profitability through the region. Additionally, we estimate farms' productivity by region with a generalized method of moments (GMM) to compare with the results of the profitability. We predict that APV installation will be more profitable than not installing, and the regions with lower productivity will show higher profitability than other regions. The results are in line with the prediction. The profitability of APV is verified in all regions, and the order of profitability by region and productivity by region are opposite to each other. It suggests that regions with lower productivity may have a higher preference for installing APV, implying the installation of APV provides a new incentive to continue farming even in regions with low agricultural productivity. These results have an important policy implication on rural sustainability since the implementation of CSA could generate a sound and sustainable farming environment by addressing the challenges of climate change.

Keywords: climate-smart agriculture; agrophotovoltaics; generalized least square; generalized method of moments; crop productivity; rural sustainability

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1. Introduction

Amidst growing concerns over climate change risks to agriculture, the International Panel on Climate Change (IPCC) forecasts that global agricultural productivity needs to increase by 60% to meet the current food demand. In response, the international agricultural community has emphasized innovative approaches such as climate-smart agriculture (CSA) to achieve food security and agricultural sustainability in the long run [1–3]. In particular, South Korea's food self-sufficiency rate is at 50.2% and could benefit from deploying CSA technology to mitigate the impact of climate change on agricultural productivity, especially in the nation's rural areas [1]. Of the CSA technologies, renewable energy could contribute to achieving all three pillars of CSA—improved productivity, resilient adaptation, and greenhouse gas (GHG) emission mitigation—and improve energy use efficiency and economic competitiveness in the agricultural sector [4].

The most prominent form of renewable energy technology is using solar energy, of which the most compatible with farming are rural solar photovoltaics (PV) and agrophotovoltaics (APV) [5]. Whereas rural solar PV requires a single-use land area solely dedicated to solar power installation, APV allows mixed use of farmland for installing solar panels over cultivated areas [6–8]. Therefore, APV improves land productivity by allowing agricultural production and power generation to occur simultaneously [9–12]. Despite of common concerns that APV impedes plant growth by blocking sunlight with the solar panel, the agricultural output is not significantly affected since any excess sunlight above the photo saturation threshold does not aid the photosynthesis process. APV could allocate such excess sunlight towards energy generation and improve overall agricultural land productivity [13]. Generally, farmers could use the electricity generated by installed solar panels, or they could sell the electricity to earn an extra profit. To take advantage of APV's benefits, several countries began promoting APV installation. For instance, Germany began the APV-RESOLA Project in 2015 to expand APV installation. Since its inception, the project has been operating 194 kW of electricity on a one-third hectare APV facility with crops such as wheat, potato, and celery [14]. France has also developed photovoltaic technology that could be adapted to various crop varieties [15].

In South Korea, APV is one of the policies the government is most focused on. The Ministry of Trade, Industry, and Energy (MOTIE) and the Ministry of Agriculture, Food, and Rural Affairs (MAFRA) set APV as the top-priority dissemination technology among CSA and have begun projects for APV development and distribution [16]. The MOTIE administered the development of a standard system for solar power technology from 2017 to 2020 and led a study on standard models for APV and agricultural productivity by crop type. MAFRA, on the other hand, developed a blueprint for constructing solar power systems by region and by crop type. The national government's recent announcement of the 2030 Policy—a plan to raise the renewable energy mix ratio from 5% to 20% by 2030—further propelled APV distribution [16].

Despite such government efforts, however, APV installation has been exceptionally low in South Korea. In 2018, only 110 million Korean Won (KRW) (0.1 million U.S. dollars (USD)) of the 154 billion KRW (134.6 million USD) budgeted for APV installation-related projects have been used for APV installation. In 2019, only 1.8% of the 40 billion KRW (35.0 million USD) budget for APV installation was executed by the second quarter, indicating a low participate of farmers. The reason for such low adoption may be related to cost barriers, such as farmland conservation fees and high initial installation costs, further complicated by the complex licensing process and uncertain productivity forecast [17,18]. Existing research either highlights the benefit of APV for improving crop productivity [6] or accentuates APV's negative impact on crop productivity [19]. These conflicting results further confound farmers and increase their uncertain outlook toward APV installation. Contrary to existing literature that primarily proposes new solar power modules and crop cultivation methods and empirically assesses their impact, economic analyses of APV could help alleviate farmers' concerns over productivity related to APV installation [20,21].

This study first aims to estimate the agricultural output, production costs, and net profit with and without APV installation of rice cultivating farms in South Korea by using regional data from Seoul Metropolitan Area (SMA), Gangwon province, Chungcheong province, Jeolla province, and Gyeongsang province from 2008 to 2018 (Figure 1). Moreover, we estimate productivity by region to compare and verify the regional productivity order with the regional profitability order. Our prediction is that the order of profitability by region and productivity by region are opposite to each other. This means the installation of APV can generate a new type of profit in regions with low productivity and consequently, an incentive to continue farming could be guaranteed. Furthermore, this implies the dissemination of CSA technology enhances rural sustainability. Ultimately, the study tries to offer implications on regional policies for widely deploying agricultural solar energy technology.

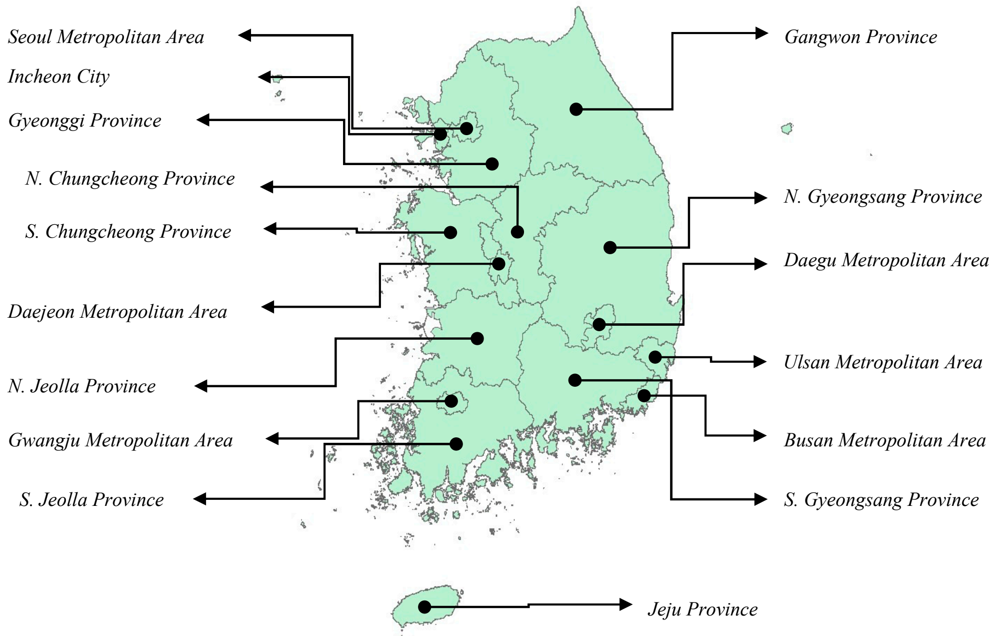

Figure 1. Map of South Korea with regional identification.

In this direction, in Section 2, we highlight the previous papers about general CSA and APV, as well as econometrical studies with estimating profitability and productivity; in Section 3, we identify the methodologies in detail, show the data and explain the limitations of our methodology; Section 4 presents the results of estimation and analysis; finally, Section 5 is for further discussion and the conclusion.

2. Literature Review

CSA aims to increase productivity, reduce greenhouse gas emissions, and build resilient systems. The agricultural sector is largely land-related, and it is important to apply CSA technology to improve the land's carbon sink capacity. As examples of CSA technology development and application, developing countries are actively researching disease control, genetic livestock breed improvement, and conservation agriculture, and developed countries are focusing on the development and introduction of advanced ICT technologies for database construction.

Research on CSA technology can be divided into an inventory application option that considers the agricultural characteristics of each country and an evaluation method according to the case [22–25]. Ref. [26] addressed the application and barriers to the implementation of CSA at a global level, with a case study of the geographical distribution of CSA projects in Europe. Ref. [27] presented applicable CSA technologies and effects by diagnosing the geographical characteristics of Nepal and Ref. [28] emphasized the importance of setting the target area evaluation index in constructing the CSA program. Ref. [29] investigated the reason for adaptation of CSA practices being lower than original expectation despite awareness of their merits, thus emphasizing the social and cultural limitations for adapting a climate change. Notably, the results of the farmer's participatory study in Ref. [30] show that CSA practices could be a better option for attaining higher yields and farm profitability with sustained and improved environmental quality in smallholder rice-wheat production systems of Eastern India and other similar agro-ecologies of South Asia. Ref. [31] also illustrated the opportunity of CSA policies to build climate change resilience of farmers through improving crop yield. Ref. [1] reviewed the technology inventory in consideration of Korea's agricultural characteristics through expert advice. Among numerous practices of CSA, APV improves land-use efficiency by optimally utilizing technology–ecological and technology–economic synergies as a technology of CSA [19]. However, Korea's APV technology is still in the dissemination stage, and it is necessary to verify the effectiveness of the technology through economic analyses to analyze the feasibility of APV technology.

Economic analyses of APV include cost–benefit analysis (CBA), levelized cost of electricity (LCOE), and production cost estimation frameworks [19,20,32]. First, CBA is the method to find alternatives to maximize present value and the analysis method includes internal rate of return (IRR) analysis, payback period (PBP) analysis, return on investment (ROI) analysis, and net present value (NPV) analysis. Ref. [33] analyzed the IRR of photovoltaic installations, while Ref. [21] analyzed the profitability of simulated APV systems in irrigated areas of southwestern Spain using the IRR analysis.

Second, LCOE represents the cost of electricity compared to electrical generation over a complete cycle [5]. In detail, LCOE is the cost of electricity generation per kWh unit per plant, computed as the quotient of the present value of the total cost per plant over the present value of the total electrical generation per plant [34]. Germany's Fraunhofer ISE estimated the LCOE as 0.093 Euro based on data obtained from its APV projects conducted over the past twenty years [35]. Additionally, Ref. [19] calculated crop productivity with and without AV using LCOE and provided an economically beneficial price-to-performance ratio.

Finally, numerous agricultural studies have used the Cobb–Douglas production function to analyze economic efficiency and as well as productivity [34,36–40]. Especially, Ref. [40] used the generalized method of moments (GMM) method and dummy variables for intermediary goods to address endogeneity problems when using the Cobb–Douglas production function to compute productivity. Additionally, Ref. [41] estimated productivity through a transformation of the production function formula after estimating the production function. Also, the authors estimated rice production output using a stochastic frontier Cobb–Douglas production function and analyzed efficiency changes; for this study, cultivation area, labor time, agricultural machinery input, and fertilizer input were used as explanatory variables.

Furthermore, other methods besides the Cobb–Douglas production function are also used, such as the translog production function [42]. Ref. [43] estimated the technical efficiency of rice production farms through translog stochastic frontier production functions and analyzed the factors of technical inefficiency. In this model, the variables used to estimate rice production were labor input, agricultural machinery input, land input, fertilizer input, and pesticide input. As for production costs, Ref. [22] used panel data to estimate the rice production cost function using the two-factor fixed effect and random effect models, concluding that rural regions' scale economy is dependent on the scale of its production output. The estimation process for deriving productivity and efficiency typically generates the production output, as conducted by Ref. [44], which estimated the rice yield under partial shading conditions of farming solar panels and found that shading from APV reduced rice yield.

3. Methodology

3.1. Estimation Model Specification

APV installations reduce the total amount of sunlight that crops can receive, resulting in a decrease in production. At the same time, farmers generate electricity from APV which can be converted into sellable credit. This means APV installation affects the total profit of farmers in two ways, reducing agricultural income and adding new income by selling electricity credits from APV.

In this paper, we will first verify the difference in farmers' profit before and after the installation of APV. To analyze how this differs by region, agricultural income and information about the APV of each region are necessary needed. Information about APV could be found in the data, and we will estimate the production function and the cost function of farms for each region using the generalized least squares (GLS) method verifying the total profit after APV installation by region consequently.

Next, we will also estimate the crop productivity of each region through the generalized method of moments (GMM) method, to confirm our results on the profitability of APV installations and to suggest policy implications for rural sustainability. Our prediction is that the lower the productivity of a region, the higher the profit from the APV installation. Therefore, we expect the order of productivity by region and the order of profitability should be reversed implying that regions with low productivity prefer the installation of APV more.

Therefore, our research hypotheses are as follows. First, comparing before and after installing APV, APV installment is more profitable to farmers in every region. Second, the order of profitability by region and the order of productivity by region is opposite to each other. In other words, the lower productivity region gains more profit by installing APV, resulting in a higher preference for those regions to install APV.

A. Agricultural Output and Costs

This paper uses GLS model for estimation to obtain a production output function with important explanatory variables. In addition, the interaction terms of some explanatory variables and regional dummies are included to analyze the impact of changes in those variables depending on regions of production.

The linear model for estimating the agricultural production output is:

$$Y_{ij} = \alpha + \gamma' V_{ij} + \delta' W_{ij} + \beta' D_j X'_{ij} + \mu D_j + \theta T + \varepsilon_{ij} \tag{1}$$

where Y_{ij} is the farm i's primary agricultural production output and represents rice yield at region j where farm i is located. V_{ij} represents a vector of basic explanatory variables consisting of A_i, L_i, K_i, and M_i, similar to the past study of [41]. A_i is rice cultivation area, L_i is labor input, K_i is capital input, and M_i is a vector of four kinds of intermediary input.

W_{ij} is a vector of additional control variables included at regression to control for the discrepancy in output per farm and per region, containing $\mathrm{Dpay_i}$, $\mathrm{Age_i}$, Machj, $\mathrm{CultRate_j}$, $\mathrm{ElderRate_j}$, non-$\mathrm{CultRate_j}$, and $\mathrm{AgriRate_j}$. $\mathrm{Dpay_i}$ is the amount of farm subsidy received by the farm, Age_i is the age of the farmer surveyed, and $\mathrm{Mach_j}$ is the number of agricultural types of machinery counted at region j. Unlike past studies of Ref. [45] and Ref. [43] that used farm machinery input in form of cost of machines or capital input as the variable values, this study used the number of farm machinery for variable $\mathrm{Mach_j}$. $\mathrm{CultRate_j}$ is the ratio of rice cultivation area used in the current year to that of the previous year, $\mathrm{AgriRate_j}$ is the ratio of agricultural sector population, $\mathrm{ElderRate_j}$ is the ratio of population over 65 years of age to total agricultural sector population, and non-$\mathrm{CultRate_j}$ is the ratio of fallow land to total farmland.

Among W_{ij}, $\mathrm{ElderRate_j}$, and non-$\mathrm{CultRate_j}$ were included to analyze the suitability of utilizing CSA technology for local extinction and rural sustainability. The coefficient of these variables indicates how rice production is associated with the region's proportion of the elderly agriculture sector population and fallow land area. To observe the difference between regions, this study included an interaction term $D_j X'_{ij}$, where X'_{ij} consists of $\mathrm{ElderRate_j}$, non-$\mathrm{CultRate_j}$, and $\mathrm{AgriRate_j}$, and region dummy variable D_j which is from Area 1 to Area 4. Our focus is the difference between regions in $\mathrm{ElderRate_j}$ and non-$\mathrm{CultRate_j}$. Additionally, $\mathrm{AgriRate_j}$ was added with the assumption of a high correlation between rural areas and local extinction and therefore improving the model validity. Finally, T is the year dummy variable and ε_{ij} represents the error term. Every variable is converted in logarithm form prior to putting into vector form unless it is not a dummy variable. Therefore, all coefficients are interpreted as the elasticity that how agricultural output changes with the change of explanatory variables.

For the production cost, we assume that cost function (2) was formulated using the same explanatory variables as (1). C_{ij} represents the production cost for farm i at region j, and other variables are same as defined above.

$$C_{ij} = \alpha + \gamma' V_{ij} + \delta' W_{ij} + \beta' D_j X'_{ij} + \theta T + \mu D_j + \varepsilon_{ij} \tag{2}$$

B. Productivity

The productivity is defined as G_{it} that moves production technology f as in (3) [41]. Assuming the Cobb–Douglas production function, (3) can be converted to the production function of the farm as (4).

$$Q_{it} = G_{it}\, f(R_{it},\, O_{it},\, U_{it},\, H_{it}) \tag{3}$$

$$\ln Q_{it} = \beta_0 + \beta_r \ln R_{it} + \beta_o \ln O_{it} + \beta_u \ln U_{it} + \beta_h \ln H_{it} + v_{it} \tag{4}$$

where Q_{it} is the output of farm i at year t, R_{it} is a capital, O_{it} is a labor, U_{it} is a land, and H_{it} is an intermediary input. Hereafter, output Q and input variables $R,\ O,\ U$, and H represent a log-transformed value. The last term, v_{it}, is a probabilistic error term. The productivity of farms that is not generally observable is included in this term. Therefore, productivity P_{it} can be estimated in the same way as in (5) by OLS of (4) [46].

$$\ln P_{it} = \ln G_{it} = \hat{\beta}_0 + \hat{v}_{it} = Q - \left(\hat{\beta}_r R_{it} + \hat{\beta}_o O_{it} + \hat{\beta}_u U_{it} + \hat{\beta}_h H_{it}\right) \tag{5}$$

The error term v_{it} does not consist only of stochastic components. That is, v_{it} can be decomposed into ϵ_{it}, which is a stochastic element, and s_{it}, which is a non-stochastic element. Here, ϵ_{it} represents a measurement error or a random shock that may occur during the production process. On the other hand, s_{it} represents the characteristics of farm households, the predictable productivity shock of farms, or the ability of farms to respond to them [47]. Reflecting on this point, (4) can be re-expressed as (6) below.

$$Q_{it} = \beta_0 + \beta_r R_{it} + \beta_o O_{it} + \beta_u U_{it} + \beta_h H_{it} + \epsilon_{it} + s_{it} \tag{6}$$

However, farmers can predict s_{it} before defining input O_{it} and H_{it}. This causes bias in estimation since O_{it} and H_{it} are not independent of v_{it} which includes s_{it}. Therefore, the new equation using instrumental variables to use GMM is (7) [48]. Variables that have endogeneity, O_{it} and H_{it}, were replaced with O_{it-1} and H_{it-2}, respectively. Here, D_j represents the regional dummy variable and b is the lagged variable.

$$\begin{aligned} \ln Q_{it} = \beta_0 + \beta_r \ln R_{it} + \beta_o \ln O_{it} + \beta_u \ln U_{it} + \beta_h \ln H_{it} + g[h(\blacksquare)] \\ + \beta_t b + \beta_{tt} b^2 + \beta_{rj} D_j + \phi_{it} \\ where\ g[h(\blacksquare)] = \sum_{s=0}^{3} \sum_{u=0}^{3-s} \sum_{v=0}^{3-s-u} \beta_{suv} R_{t-1}^{s} U_{t-1}^{u} H_{t-1}^{v} \end{aligned} \tag{7}$$

Farm productivity P_{it} is estimated with (8) after estimating (7).

$$\begin{aligned} \ln P_{it} = \ln Q_{it} - \hat{\beta}_r \ln R_{it} - \hat{\beta}_o \ln O_{it} - \hat{\beta}_u \ln U_{it} - \hat{\beta}_h \ln H_{it} \\ = \hat{\beta}_0 + \sum_{s=0}^{3} \sum_{u=0}^{3-s} \sum_{v=0}^{3-s-u} \hat{\beta}_{suv} K_{t-1}^{s} A_{t-1}^{u} M_{t-1}^{v} + \hat{\beta}_t b + \hat{\beta}_{tt} b^2 + \hat{\beta}_{rj} D_j + \hat{\phi}_{it} \end{aligned} \tag{8}$$

3.2. Data Sources

A. Data for Agricultural output and production costs

To estimate output and production costs, this study utilized Agricultural Production Costs Survey (APCS) data provided by Microdata Integrated Service (MDIS) and data from the Korean Statistical Information Service (KOSIS) and the MAFRA. We identified 13,851 farms that indicated rice as their primary crop from 2008 to 2018 from the APCS, which has the largest dataset in Korea with the longest period of data (Table 1). The original monetary unit in data used in estimation was KRW, deflated by Korea's 2018 Consumer Price Index (CPI) to account for price fluctuation. After that, we converted the monetary unit of statistics in tables from KRW to USD according to the annual average exchange rate in 2021 (1 USD=1144.3 KRW). Tables 1 and 2 describe variables and statistics of output and production cost estimation variables.

Table 1. Description of variables used in agricultural output and costs estimation.

Variable	Variable Description	Detailed Description	Sources
Y	Production output	Primary product quantity	Agricultural Production Costs Survey
C	Production cost	The production cost of rice	
A	Land	Area of rice cultivation	
L	Labor	Total labor input	
K	Capital	Sum of agricultural machinery costs, farming facility costs, repair costs, capital costs (fixed), and production maintenance equipment costs	
M	Intermediary input	M1: Seedlings/M2: Fertilizer/ M3: Pesticide/M4: Photothermal energy	
Age	Farmer age	1: Under 30/2: 30–39/3: 40–49/ 4: 50–59/5: 60–67/6: Over 70	
Dpay	Subsidy	Sum of the previous year's fixed subsidy and adjusted subsidy	MAFRA
Mach	Possession of agricultural machinery	Mach1: Number of farming tractors Mach2: Number of farm masters Mach3: Number of motorized rice transplanters Mach4: Number of combine harvesters	KOSIS
CultRate	Cultivated land	Percentage of the previous year's cultivated land from the current year's arable land	
AgriRate	People in the agriculture sector	Percentage of population in the agricultural sector from the total population	
ElderRate	Elderly population	Percentage of population over age 65 from the total agricultural sector population	
non-CultRate	Fallow land	Percentage of fallow land of total cultivated land	
Year	Year dummy	Year dummy for years 2009 to 2018	Agricultural Production Costs Survey
Area	Regional dummy	Reference Area (SMA): Seoul Metropolitan Area, including Gyeonggi and Incheon Area 1 (Gangwon): Gangwon Area 2 (Chungcheong): Chungbuk, Chungnam, Daejeon Area 3 (Jeolla): Jeonbuk, Jeonnam, Gwangju Area 4 (Gyeongsang): Gyeongbuk, Gyeongnam, Daegu, Busan, Ulsan	

Table 2. Summary statistics of agricultural output and costs estimation variables.

Variable	Variable Description	Unit	Average	Std. Dev.	Max.	Min.
Y	Production output	kg	8642	13,714	212,924	450
C	Production cost	1 USD	7459	11,211	175,416	626
A	Land	m^2	12,767	19,788	355,073	1065
L	Labor	Hour	163	236	6054	3
K	Capital	1 USD	62,799	140,703	3,365,506	1
M1	Intermediary input	Count	92	159	3001	1
M2			5036	10,656	457,423	1
M3			10,902	25,137	1,508,290	1
M4			174	872	58,598	1
Age	Farmer age	Categorical	5.020	0.945	6	1
Dpay	Subsidy	1 USD	1891	3078	50,824	123
Mach1	Possession of agricultural machinery	Count	32,365	10,495	48,368	456
Mach2			48,159	28,253	116,593	1048
Mach3			29,045	11,917	56,830	402
Mach4			9574	3358	13,671	162
CultRate	Cultivated land	%	108.3	11.7	133.7	82.9
AgriRate	People in the agriculture sector	%	0.289	0.139	0.580	0.002
ElderRate	Elderly population	%	38.2	5.6	49.2	20.4
non-CultRate	Fallow land	%	0.018	0.009	0.061	0.005

To estimate productivity, this study formed panel data which is necessarily needed due to the lagged variables in the model, of farmers who consecutively indicated rice as their primary crop from 2013 to 2017 in the APCS. With 759 identified farms per year, a total of 3795 farm data were used. The descriptive statistics of the variables associated with estimating productivity are detailed in Tables 3 and 4. Unlike output and production cost estimation, productivity estimation required monetary value data instead of output and input quantity data. To minimize the bias, all data except labor and land, which were measured in acreage instead of monetary values, were adjusted for price fluctuation using the Farm Sales Price Index and Farm Consumption Price Index.

Table 3. Description of variables used in productivity estimation.

Variable	Variable Description	Detailed Description	Sources
Q	Production output	Sum of primary product quantity	Agricultural Production Costs Survey
U	Land	Area of rice cultivation	
O	Labor	Sum of household labor and hired labor	
R	Capital	Sum of agricultural machinery costs, facility usage costs, repair costs, capital costs (fixed), and production maintenance equipment costs	
H	Intermediary input	Sum of seedlings costs, fertilizer costs, pesticide costs, photothermal energy costs	

Table 4. Summary statistics of productivity estimation variables.

Variable	Variable Description	Unit	Average	Std. Dev.	Max.	Min.
Q	Production output	kg	18,224	27,627	361,047	1042
U	Land	m^2	16,878	25,283	283,502	1981
O	Labor	Hour	180	266	3927	9
R	Capital	1 USD	1032	2125	38,772	1
H	Intermediary input	1 USD	1289	2152	31,939	8

B. Costs and Subsidies for APV

A survey by the National Agricultural Cooperative Federation's Fourth Industrial Revolution Research Team conducted in 2018 showed that installing APV that produces 100 kW of electricity (per 1322 m^2) costs 152,466 USD, excluding site maintenance costs (Table 5).

Table 5. APV installation costs breakdown.

<table>
<tr><th colspan="2">Category</th><th>Amount (USD)</th></tr>
<tr><td rowspan="3">Licensing Costs</td><td>Document preparation and approval process facilitation</td><td>6989</td></tr>
<tr><td>Grid connection fee</td><td>7514</td></tr>
<tr><td>Farmland conservation fee</td><td>10,999</td></tr>
<tr><td>Equipment Costs</td><td>Photovoltaic module/Inverter/Connecter box</td><td>63,282</td></tr>
<tr><td>Construction Costs</td><td>Civil engineering/Module installation/Construction/Electrical installation</td><td>63,683</td></tr>
<tr><td colspan="2">Total</td><td>152,467</td></tr>
</table>

Source: National Agricultural Cooperative Federation's Fourth Industrial Revolution Research, 2018.

In addition, the Korea Energy Corporation's Renewable Energy Center offers long-term low-interest loans according to the government's support policy. It is an average interest rate of 1.75% and ten-year installment payments with a five-year grace period financial product to farmers who participate in APV installation projects [49].

3.3. Limitation of the Methodology

At productivity estimation, we used intermediate inputs as an instrument variable of productivity [50] to control the endogeneity problem caused by the correlation between O_{it}, H_{it}, and v_{it} at (4) [50,51]. To use intermediate inputs as an instrument variable, the following three assumptions should be met:

Assumption (1): The demand for intermediate inputs (H_{it}), which is an instrument variable, is determined by the variables that are fixed in shorter (R_{it}, U_{it}) and productivity (s_{it}) of farms as shown in (9).

$$H_{it} = H_{it}(R_{it},\ U_{it},\ s_{it}) \tag{9}$$

Assumption (2): The instrument variable (H_{it}) has a property of strictly monotonic increasing with respect to the productivity (s_{it}). Due to this property, (9) can be substituted with the inverse function of s_{it} as (10).

$$s_{it} = H^{-1}(R_{it},\ U_{it},\ H_{it}) = h(R_{it},\ U_{it},\ H_{it}) \tag{10}$$

Assumption (3): Productivity (s_{it}) has the same relationship as (11) with the productivity of the previous year (s_{it-1}) by the first-order Markov process. ξ_{it} is a random variable meaning the innovation component. (12) can be obtained by substituting (10) into (11).

$$s_{it} = E[s_{it}|s_{it-1}] + \xi_{it} = g(s_{it-1}) + \xi_{it} \tag{11}$$

$$s_{it} = g[h(R_{it-1},\ U_{it-1},\ H_{it-1})] + \xi_{it} \tag{12}$$

When all assumptions are taken into account, (6) is converted to (13), and the error term $\phi_{it} = \xi_{it} + \epsilon_{it}$ satisfies the orthogonal condition of (14). Function $g[h(R_{it-1},\ U_{it-1},\ H_{it-1})]$ is a cubic polynomial that described detailly in (7).

$$Q_{it} = \beta_0 + \beta_r R_{it} + \beta_o O_{it} + \beta_u U_{it} + \beta_h H_{it} + g[h(R_{it-1},\ U_{it-1},\ H_{it-1})] + \phi_{it} \tag{13}$$

$$\begin{gathered} E[\phi_{it}|R_{it},\ U_{it},\ R_{it-1},\ O_{it-1},\ U_{it-1},\ H_{it-1},\ \cdots, R_{i1}, O_{i1}, U_{i1}, H_{i1}] = 0 \\ where\ t = 2, \cdots, T \end{gathered} \tag{14}$$

To use generalized method of moments, we use O_{it-1} and H_{it-2} as an instrument variable for endogenous variable O_{it} and H_{it}, respectively. R_{it} and U_{it} themselves function as an instrument variable, and we used H_{it-2} for intermediary input since H_{it-1} is already included in $g[h(\blacksquare)]$. By adding the regional dummy variable D_j to explain productivity that varies depending on local soil quality and climatic conditions and lagged variable b that also may affect productivity, the final Equation (7) and consequently (8) is obtained.

This methodology can control endogeneity effectively, but the disadvantage is that we cannot use all the data applicable since we took lagged variable as an instrument variable. Moreover, it was impossible to apply the same method to estimate agricultural output and cost because the structure of the data was different from the one used to estimate productivity.

For the other statistical properties, normality may not be a primary concern [52,53]. In addition, heteroscedasticity can cause a type 2 error, in which a coefficient indeed significant is derived as insignificant. However, as we will show in the next chapter, the results are consistent with our initial predictions and hypotheses. Therefore, we conclude that there is no serious problem from heteroscedasticity in our results. Additionally, multicollinearity is another issue that might cause a type 2 error, so it can be considered in the same context as heteroscedasticity. Variance inflation factor (VIF) was a bit high in our regression results, yet this is due to interaction terms with other variables in our model. However, it is not a major problem since the p-value of the interaction term is not affected by multicollinearity and the significance is robust.

4. Results

A. Profitability

The estimation results of rice agricultural output and costs are detailed in Table 6.

Table 6. Results of agricultural output and costs estimation.

Variable	Production Output		Production Costs	
	Estimator	Std. Dev.	Estimator	Std. Dev.
ln Y	0.991 ***	0.008	0.385 ***	0.024
ln L	−0.003	0.002	0.207 ***	0.006
ln K	0.001	0.001	0.241 ***	0.003
ln M_1	−0.004 ***	0.001	0.015 ***	0.004
ln M_2	0.005 ***	0.001	0.057 ***	0.003

Table 6. *Cont.*

Variable	Production Output		Production Costs	
	Estimator	Std. Dev.	Estimator	Std. Dev.
ln M_3	0.006 ***	0.001	0.013 ***	0.002
ln M_4	−0.002 **	0.001	−0.022 ***	0.003
ln Dpay	0.017 **	0.008	−0.097 ***	0.023
ln Age	0.039 ***	0.007	0.189 ***	0.019
ln $Mach_1$	0.133 **	0.053	0.364 **	0.148
ln $Mach_2$	−0.037	0.024	−0.161 **	0.069
ln $Mach_3$	0.156 ***	0.032	0.092	0.090
ln $Mach_4$	−0.196 ***	0.046	−0.239 *	0.130
$Year_{2009}$	0.019 ***	0.008	0.047 **	0.021
$Year_{2010}$	−0.118 ***	0.008	0.031	0.023
$Year_{2011}$	−0.048 ***	0.010	0.192 ***	0.027
$Year_{2012}$	−0.063 ***	0.011	0.39 ***	0.031
$Year_{2013}$	−0.003	0.012	0.453 ***	0.035
$Year_{2014}$	0.086 ***	0.015	0.521 ***	0.042
$Year_{2015}$	0.126 ***	0.016	0.523 ***	0.045
$Year_{2016}$	0.110 ***	0.019	0.529 ***	0.055
$Year_{2017}$	0.106 ***	0.021	0.589 ***	0.061
$Year_{2018}$	0.124 ***	0.023	0.745 ***	0.064
$Area_1$	1.189 **	0.473	2.037	1.335
$Area_2$	1.043 ***	0.279	0.719	0.786
$Area_3$	2.196 ***	0.256	0.305	0.721
$Area_4$	2.454 ***	0.277	0.147	0.783
ln AgriRate	−0.093 ***	0.018	−0.113 **	0.051
ln AgriRate·$Area_1$	−0.176 **	0.083	0.676 ***	0.235
ln AgriRate·$Area_2$	0.054 *	0.028	0.050	0.080
ln AgriRate·$Area_3$	0.066 ***	0.019	0.089 *	0.054
ln AgriRate·$Area_4$	0.101 ***	0.017	0.132 ***	0.048
ln CultRate	−0.213 ***	0.043	−0.247 **	0.121
ln ElderRate	0.164 ***	0.059	−0.331 **	0.168
ln ElderRate·$Area_1$	−0.332 ***	0.105	−0.456	0.296
ln ElderRate·$Area_2$	−0.268 ***	0.062	−0.169	0.175
ln ElderRate·$Area_3$	−0.508 ***	0.056	−0.021	0.159
ln ElderRate·$Area_4$	−0.528 ***	0.062	0.033	0.176
ln nonCultRate	−0.046 ***	0.012	0.053	0.034

Table 6. *Cont.*

Variable	Production Output		Production Costs	
	Estimator	Std. Dev.	Estimator	Std. Dev.
ln nonCultRate·$Area_1$	0.034	0.027	−0.121	0.076
ln nonCultRate·$Area_2$	−0.051 ***	0.015	−0.070	0.044
ln nonCultRate·$Area_3$	0.004	0.015	−0.068	0.043
ln nonCultRate·$Area_4$	0.043 ***	0.014	−0.054	0.039
Constant	−1.635 ***	0.313	8.537 ***	0.883
Observation	13,851		13,851	
Wald Statistics	466,476.7		39,926.4	
Prob > χ^2	0.000		0.000	
Log-likelihood	6026.8		−8342.2	

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

The regional average values of each variable were used in the estimation procedure to calculate the regional rice production and prices (Table 7). Similarly, the regional average rice sales price was used since the sales price of rice varied across regions. When calculating farm revenue, which is comprised of revenue from sales of primary crops (rice) and secondary or by-products (hay, etc.) revenue from secondary products was not included since its proportion to total revenue was minuscule. Instead, the value of secondary product revenue was computed as a product of revenue from rice sales and the ratio of primary crop price to secondary crop price from 2018, which was 3.756% (Table 8).

Table 7. Average estimators in agricultural output and costs by region in 2018.

Variable	SMA	Gangwon	Chungcheong	Jeolla	Gyeongsang
A	13,005	9893	11,167	17,577	10,263
L	141.7	130.2	134.1	192.2	125.7
K	41,031	59,897	51,466	52,028	37,753
M_1	77.2	65.9	79.3	149.9	68.2
M_2	4100	2339	3168	7621	2210
M_3	6722	7938	14,010	15,481	6735
M_4	264.4	229.5	346.1	424.2	253.9
Dpay	2351	1820	2065	3393	1932
Age	4.050	4.097	4.034	4.240	4.286
$Mech_1$	34,885	20,274	28,747	37,212	39,497
$Mech_2$	30,060	19,886	40,486	39,364	78,250
$Mech_3$	19,514	11,352	19,621	21,819	30,261
$Mech_4$	8007	3479	7693	10,680	10,567
AgriRate	0.081	0.306	0.354	0.512	0.249
CultRate	94.1	91.7	95.2	124.4	110.5
ElderRate	38.4	42.2	45.7	47.7	47.1
non-CultRate	0.021	0.031	0.016	0.009	0.025

Table 8. Agricultural profit without APV installation (USD).

	SMA	Gangwon	Chungcheong	Jeolla	Gyeongsang
Rice yield	8801	6282	7952	11,689	6957
Rice price	1.443	1.386	1.409	1.426	1.387
Revenue	12,702	8705	11,206	16,666	9646
Secondary product revenue	477	327	421	626	362
Production Costs	9767	7844	9258	12,746	7889
Agricultural profit	3412	1188	2369	4546	2119

To estimate potential revenue after APV installation, this paper established the following assumptions:

Assumption (1): Farmers will install APV that generates 100 kW per 1322 m^2 of arable land.

Assumption (2): Solar panels generate approximately 3.5 h per day evenly throughout the year and its efficiency declines by 1% per year over twenty years, which is the expected durability of APV.

Assumption (3): The unit price of credit for electricity generated from APV is 0.151 USD per 100 kW, the most recent price as specified by the Korean government in New Renewable Energy Center Notice No. 2019-25.

Assumption (4): 90% of installment cost would be covered with a long-term low-interest loan with a 1.75% interest rate, a ten-year installment payment period, and a five-year grace period.

Assumption (5): About 15% of agricultural output is deducted due to the decreased sunlight by APV installment.

The estimated final profit after the APV installment is detailed in Table 9. There was no change in the crop production costs, and the maintenance cost of APV was not considered.

Table 9. Total profit with APV installation (USD).

	SMA	Gangwon	Chungcheong	Jeolla	Gyeongsang
Rice yield	7481	5340	6759	9936	5913
Rice price	1.443	1.386	1.409	1.426	1.387
Revenue	10,795	7401	9524	14,168	8202
Secondary product revenue	406	278	358	532	308
Production costs	9767	7844	9258	12,746	7889
Agricultural profit	1434	−165	624	1954	621
Profit by APV credit	9545	9545	9545	9545	9545
Total profit	10,979	9380	10,169	11,499	10,166

Comparing the regional total profit and agriculture activity-based profit before installing APV revealed that profit increases by at least about 7000 USD in all regions after APV is installed. The regions with the greatest difference in profit with and without APV were, in order, Gangwon, Gyeongsang, Chungcheong, SMA, and Jeolla (Table 10).

Table 10. Difference in profit between APV installation by region.

	Gangwon	Gyeongsang	Chungcheong	SMA	Jeolla
Difference (USD)	8192	8047	7800	7567	6953

B. Productivity

Assuming that the magnitude of profitability of APV by region and the preference for APV installment is proportional, the study estimated farm productivity using GMM in order to assess the relationship between regional productivity and the preference for APV installation. The average of each regional variable was computed using the 2017 data to estimate the regional productivity values (Tables 11 and 12).

Table 11. Results of the productivity estimation.

Variable	Estimator	Std. Dev
$\ln L_t$	−0.028	0.045
$\ln M_t$	−0.487 ***	0.173
$\ln K_t$	0.218 ***	0.077
$\ln A_t$	1.033 ***	0.031
$\ln K_{t-1}$	1.134 *	0.620
$\ln K^2_{t-1}$	−0.031	0.042
$\ln K^3_{t-1}$	0.002	0.001
$\ln A_{t-1}$	0.546	1.181
$\ln A^2_{t-1}$	0.436 ***	0.159
$\ln A^3_{t-1}$	−0.014 **	0.006
$\ln M_{t-t}$	1.019	0.904
$\ln M^2_{t-1}$	0.087	0.111
$\ln M^2_{t-1}$	0	0.004
$\ln K_{t-1} \cdot \ln A_{t-1}$	−0.165	0.118
$\ln K_{t-1} \cdot \ln A^2_{t-1}$	0.005	0.006
$\ln K_{t-1} \cdot \ln M_{t-1}$	(omitted)	
$\ln K_{t-1} \cdot \ln M^2_{t-1}$	−0.010	0.007
$\ln A_{t-1} \cdot \ln K^2_{t-1}$	−0.009 *	0.005
$\ln A_{t-1} \cdot \ln M_{t-1}$	−0.509 **	0.208
$\ln A_{t-1} \cdot \ln M^2_{t-1}$	0.011	0.010
$\ln M_{t-1} \cdot \ln K^2_{t-1}$	0.002	0.005
$\ln M_{t-1} \cdot \ln A^2_{t-1}$	−0.006	0.010
$\ln K_{t-1} \cdot \ln A_{t-1} \cdot \ln M_{t-1}$	0.022	0.014
time	−0.318 *	0.174
time^2	0.067 *	0.038
Area_1	−0.210 ***	0.035
Area_2	−0.164 ***	0.030

Table 11. *Cont.*

Variable	Estimator	Std. Dev
$Area_3$	−0.071 ***	0.027
$Area_4$	−0.201 ***	0.037
Constant	0	.
Observations	2277	
R-squared	0.847	

Notes: ***$p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 12. Productivity by region.

	Jeolla	SMA	Chungcheong	Gyeongsang	Gangwon
Productivity ($\ln P$)	10.866	10.860	10.664	10.603	10.599

The estimation results reveal the highest productivity in Jeolla, followed by SMA, Chungcheong, Gyeongsang, and Gangwon, which are in exactly the inverse order of regional productivity for APV installment. This finding indicates that regions with low productivity have a high preference for APV installation. It is because although the crop harvest is slightly declined due to the installation of APV, the additional income through credit sales obtained from the APV is more profitable to low-productivity regions. In other words, this implies that even in regions where incentives to continue farming are relatively small, the installation of APV provides a strong economic incentive to continue the farming by providing a new source of income.

C. Rural Sustainability

In terms of local extinction and rural sustainability, Table 13 shows the coefficient and average of ElderRate_j and non-CultRate_j by region, which are variables that represent the feasibility of using CSA technology to address local extinction and rural sustainability. Both the ratio of the aged population and the ratio of fallow land are important factors that affect agricultural profits, especially when considering characteristics of rural areas in Korea, the labor-oriented and aging. Since the reference region was SMA, coefficients of ElderRate_j and non-CultRate_j in Table 6 are same as coefficients of ElderRate_j and non-CultRate_j of SMA. Other regions' coefficients are represented by considering the reference region and the interaction term of reference region and regional dummy variable. For instance, ElderRate_j coefficient of Gangwon was calculated by sum of ElderRate_j and $\ln \text{ElderRate}\cdot\text{Area}_1$ in Table 6.

Table 13. Coefficients of the elderly population and fallow land by region.

	ElderRate		Non-CultRate	
	Coefficient	Average	Coefficient	Average
SMA	0.164	38.4	−0.046	0.021
Gangwon	−0.168	42.2	−0.012	0.031
Chungcheong	−0.104	45.7	−0.097	0.016
Jeolla	−0.344	47.8	−0.042	0.009
Gyeongsang	−0.364	47.1	−0.003	0.025

The coefficients of ElderRate_j suggest that regions with the highest production output loss as the elderly population increases are, in order, Gyeongsang, Jeolla, Gangwon, Chungcheong, and SMA. This result parallels the order of regional preference for APV installation except for Jeolla, which may be due to its existing high input of land, labor, capital, and elderly agricultural sector workforce as shown in its regional average estimates (Table 7). In addition, the positive coefficient of ElderRate_j in SMA could be explained by the relatively small agricultural sector population. The effect of an increase in the elderly population among the agricultural sector workforce is generally negative, but it also contributes to the total increase in the agricultural workforce. In SMA, the positive effect of resultant increase in the agricultural population due to the increase in the elderly farming population is greater than the negative effect.

As for the impact of fallow land area on productivity, the regions with the smallest coefficient of non-CultRate_j were, in order, Chungcheong, SMA, Jeolla, Gangwon, and Gyeongsang. Compared to the order of regional preference for APV installation, the order of Gangwon and Gyeongsang appears relatively low. Such discrepancy might be due to the low preference for rice farming in those regions. In fact, when comparing the average values by region in Gyeongsang and Gangwon with Jeolla and Chungcheong where are the centers of the rice farming in Korea, the percentage of fallow land is much higher in Gyeongsang and Gangwon than in Jeolla and Chungcheong. However, the absolute values of non-CultRate_j coefficient are quite larger in Jeolla and Chungcheong. This finding demonstrates that even small changes in the proportion of fallow land could affect rice productivity in Chungcheong and Jeolla, where rice cultivation is widespread. In contrast, the effect of change in the proportion of fallow land on rice productivity is minuscule in Gangwon and Gyeongsang, where the rice is not commonly cultivated.

5. Discussion and Conclusions

This study estimated regional profitability and productivity with regard to the installment of APV in rice cultivating farms in South Korea. We estimated agricultural production and cost function with GLS and compared the farm income before and after APV installation considering the costs and benefits of APV installation. The results verified that APV installment is profitable in every region and the difference before and after installation is greatest in Gangwon, followed by Gyeongsang, Chungcheong, SMA, and Jeolla, in order.

These results have the same context as studies that show that small farms with low agricultural profitability and productivity are likely to accept new technology [29,30,54]. In order to improve the productivity of small farms, it is necessary to apply the cultivation method according to new environmental factors or technological situations [54,55]. However, small farmers are relatively likely to be unable to cover the initial costs of introducing new technologies. In addition, small-scale rice farms need a government support through incentives because it is difficult to flexibly change cultivation methods or farm management methods in response to changes in external conditions [29,30].

Moreover, we estimated regional productivity to compare and find the relationship with regional profitability. The estimation result shows the highest productivity in Jeolla, followed by SMA, Chungcheong, Gyeongsang, and Gangwon, which are in exactly the inverse order of regional productivity. The opposite order means that regions with lower productivity prefer additional income through credit sales from APV installations. In addition, it implies that economic incentives for continuing agricultural activities could be provided by APV installment though a region has lower productivity that originally has little incentive to continue farming.

Furthermore, this study assessed its potential impact in addressing local extinction and rural sustainability by comparing the regional proportion of the elderly agriculture sector labor, ElderRate_j, and fallow land, non-CultRate_j. Gyeongsang exhibited the highest agricultural output loss per 1% increase in the elder population, followed by Jeolla, Gangwon, Chungcheong, and SMA. In the result of this study, the order of regions most impacted by an increase in the elderly population reflects the inverse order of regions with the highest productivity, except Jeolla. As discussed previously, this exception may be due to Jeolla's exceptionally high labor and land input for agricultural activity compared to that of other regions. On the other hand, Chungcheong exhibited the highest agricultural output loss per 1% increase in the proportion of fallow land, followed by SMA, Jeolla, Gangwon, and Gyeongsang. In particular, Gyeongsang and Gangwon exhibited the least output loss, which may be due to the low prevalence of rice farming in the two regions compared to that of other regions observed.

These results imply that efficiency may decrease if aging continues, which act as a factor that hinders the productivity of rice production [54,56]. Additionally, if the aging of farmers continues, there is a possibility that the productivity of rice production will continue to decrease [54]. Meanwhile, Ref. [56] emphasized that the reason farmers apply for CSA is not because of food security. This implies that policymakers need to educate farmers about the concepts and effects of CSA in order to promote CSA [54].

This study presents several policy implications. First, this study verified that farmers in low-productivity regions are more likely to accept APV installments. This shows the government can consider the direction of promoting and spreading the application of CSA technology focused on farms in those regions, especially smallholder farmers who are more vulnerable to financial matters. Likewise, government policy could help address the smallholder farmer's income problem facing with multiple production and marketing challenges [57]. However, it is difficult for small farmers to apply CSA technology to actual agricultural sites because of initial expenditure and high maintenance costs [1–4]. Therefore, the government needs to support the initial cost of introducing new technologies to small farmers because economic factors are one of the main reasons why it is difficult to apply CSA [26,58]. The government should give farmers information on financial instruments such as sharing information on education and promotion of CSA, microfinance, and incentive support [1,23–25]. Second, this study suggested that aging can be a factor that hinders rice productivity. The issue of aging is also closely related to the issue of food security, and policymakers need to emphasize and educate farmers on the importance of climate change and food security, and the value of CSA as a response to it.

The limitations of this study are as follows. First, in the study, the regional unit of analysis was limited to a metropolitan area or province level due to data availability. If the geographical unit of analysis is subdivided in the future, the regional characteristics of agricultural activities can be better reflected. Second, this study assumed that the conditions related to APV installation were uniform between regions due to data limitations, so the costs and benefits of APV development were the same for all the regions. Additionally, maintenance cost was not considered. However, solar power can cost not only high initial installation costs but also additional costs to repair or replace panels on the APV [59]. On average, a solar panel costs about $225 to $375 for physical reasons such as lightning or hail, or self-defections, which could be able to result in additional costs [60]. Additionally, there is an applicability issue for APV, and a study on the economic evaluation of APV is necessary [19]. Future studies could obtain more precise and meaningful results by including detailed conditions of APV installation and energy generation, such as installation area. Finally, this study showed that even small changes in the proportion of fallow land could affect rice productivity in the regions where rice cultivation is widespread, but the effect of change in the proportion of fallow land on rice productivity could be minuscule in the regions where rice is not commonly cultivated. Therefore, expanding the scope of other primary crop products such as potatoes, radishes, onions, and cabbages in future studies will help you understand the economic effects of APV.

CSA is closely related to the economy in terms of productivity and changes in production cost, and also closely related to environmental aspects such as farm acceptability and convenience, greenhouse gas reduction, soil health, and energy resource minimization [2–4]. For CSA technology to be introduced and expanded to rural areas, it is important to link it with policies considering economic incentives, promotion, and education [1–3], and this study suggested that incentives for introducing CSA are highly needed, focusing on regions with relatively high preference and acceptance. Future research will be able to help extend the application of CSA technologies, including APVs, and further contribute to the ultimate goal of CSA.

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