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Farmers' Adoption of Water Management Practice for Methane Reduction in Rice Paddies: A Spatial Analysis in Shiga, Japan

Shengyi Du [1,*], Katsuya Tanaka [2] and Hironori Yagi [3]

[1] Graduate School of Economics, Doctorate Program, Shiga University, Hikone 520-2192, Japan
[2] Research Center for Sustainability and Environment, Shiga University, Hikone 520-2192, Japan; tanakak@biwako.shiga-u.ac.jp
[3] Department of Agricultural and Resource Economics, The University of Tokyo, Tokyo 113-0033, Japan; ayouken@mail.ecc.u-tokyo.ac.jp
* Correspondence: lidiadu1997@gmail.com

Abstract: As global warming worsens, there is a growing need to reduce emissions of methane, a greenhouse gas. In agriculture, a water management method called alternate wetting and drying (AWD) has proven effective in mitigating methane emissions from paddy fields. It is, therefore, advisable to disseminate it efficiently. This study was conducted in Shiga Prefecture, Japan, to determine what influences AWD adoption behavior and examine the effectiveness of human networks in promoting AWD. Spatial statistical methods, including Moran's I and Global G* and the spatial probit model, were employed for the purpose. The analysis results indicate that the behavior of surrounding farmers, which constitutes a spatial factor, influences that of the individual farmers. Moreover, farmers who acquire and use data, those with large-scale production, and those who mainly sell paddy rice tend to implement AWD, whereas corporate-managed farms do not. Therefore, to more efficiently improve the AWD implementation rate in Shiga Prefecture, this study makes several recommendations. Farmers' active information sharing and technology exchange should be leveraged to strengthen networks and promote best practices for AWD dissemination. Advancing agricultural digitalization and data utilization is crucial, particularly by reducing digital equipment costs and securing technical personnel through public investment. Additionally, the approach toward corporate entities in AWD dissemination should be reconsidered, with market incentives playing a role. Lastly, promoting larger farmland parcels and increasing large-scale management farmers who are motivated to adopt AWD is essential. These strategies constitute this study's original contribution.

Keywords: global warming; paddy agriculture; methane; alternate wetting and drying; spatial probit

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1. Introduction

Methane (CH_4) is the second most emitted greenhouse gas after carbon dioxide (CO_2). On a per-unit basis, it contributes 28 times more than CO_2 to global warming [1]. Therefore, reducing methane emissions has been proposed as an essential measure to mitigate global warming. Notwithstanding, atmospheric methane concentrations have increased significantly since 2007 [2,3]. Methane is a short-lived greenhouse gas. The atmospheric lifetime of methane is approximately 12 years. It means that methane can exert a strong warming effect over short periods. Hence, reducing methane emissions is considered a critical strategy to curb short-term climate change impacts and gain time to achieve long-term climate goals [4].

In agriculture, paddy fields are the second major source of methane emissions after livestock [3,5]. Globally, rice paddies contribute 6–11% of anthropogenic methane emissions [6]. The anaerobic conditions typical of paddy soils facilitate methane production by methanogenic microorganisms [7]. When paddies are submerged for rice cultivation, oxygen levels in the soil decrease further, creating conditions favorable for methane production. Although enteric fermentation and manure management in livestock contribute the highest overall methane emissions, the extensive presence of rice cultivation in East Asia makes controlling methane emissions from rice paddies an urgent task to mitigate global warming. Considering nearly half of the world's population relies on rice as a staple food [8], eliminating rice paddies is not a feasible solution. Instead, adopting sustainable practices to reduce methane emissions from rice paddies is advisable.

In Asia, alternate wetting and drying (AWD), an irrigation management method, has garnered attention. It involves alternating flooding and drying periods during rice cultivation, which effectively curbs methane emissions by increasing soil oxygen levels [9–12]. The method also conserves water, making it an economically viable and environmentally friendly solution. Although AWD has already been implemented in several Asian countries, its widespread adoption remains a challenge due to the variations in geographical and agricultural [13,14].

The AWD offers a distinct advantage in economic feasibility over other methane emission-reducing methods. Many factors, such as soil environment, precipitation, and rice variety, influence methane emissions during rice cultivation. In addition to AWD, using slow-release biochar fertilizers, straw collection and composting, and selecting low-methane-emitting rice varieties are also commonly used to reduce emissions [15–20]. However, these methods often entail additional costs. By contrast, AWD relies on extending or repeating drainage periods already practiced during rice cultivation, which involves minimal additional costs or labor. Therefore, AWD is a practical and highly effective method for alleviating global warming. Expanding its adoption in regions extensively cultivating rice can significantly reduce methane emissions.

Previous studies have identified various factors influencing AWD adoption. Among these, studies have highlighted farmer-specific attributes such as income levels, AWD awareness, and environmental consciousness. Truelove et al. (2015) conducted a case study in Sri Lanka, finding that higher-income farmers were more inclined to adopt AWD [21]. Similarly, farmers' belief in AWD's efficacy significantly impacts its adoption by them. Le (2021) economically evaluated AWD adoption among 250 rice farmers in Vietnam's Mekong Delta, finding that farmers who perceived AWD as easy to implement and those with a strong willingness to undergo technical training were more likely to adopt it [22]. Suwanmaneepong et al. (2023) demonstrate that in Thailand, farmers with a higher AWD awareness and an active participation in environmentally friendly agricultural programs were more willing to adopt AWD [14].

Infrastructural and institutional factors like irrigation technology and government support also influence AWD adoption. Because AWD requires frequent drainage, the state of irrigation systems significantly impacts farmers' AWD adoption. When irrigation systems remain underdeveloped, drainage operations become more difficult, which may discourage farmers from implementing AWD. Le (2021) observes that regions with well-developed irrigation systems exhibit notably high AWD adoption rates [22]. Economic conditions or farmers' limited knowledge may contribute to poor irrigation systems. Support from the government can increase the feasibility of farmers implementing AWD. Enriquez et al. (2021) reviewed AWD practices in the Philippines over the past two decades and highlighted the importance of providing technical support to farmers to increase their willingness to adopt AWD [23].

Furthermore, neighboring farmers' behavior plays a crucial role. Truelove et al. (2015) reported that when farmers learn about others' AWD practices, they become more willing to adopt them [21]. Likewise, Lampayan et al. (2009) observed that introducing AWD and conducting long-term technical training for farmers in several Philippine paddies demonstrated the importance of presenting successful cases to promote AWD adoption [24].

Despite providing valuable insights into the determinants of AWD adoption, previous studies have limitations. Most studies focus on Southeast Asia, and the research on AWD adoption in Japan is scarce. Japan's agriculture is characterized by fragmented small-scale farming, aging farmer populations, and high dependence on agricultural cooperatives [25–27]. These factors pose unique challenges and opportunities for AWD adoption. For example, collective decision-making through cooperatives could accelerate the adoption of AWD if adequately supported. Conversely, aging farmers may be reluctant to adopt new technologies without clear demonstrations and tailored training programs. Considering the substantial differences in agriculture between Japan and Southeast Asia, the findings of previous studies may not directly apply to Japan. Additionally, many prior studies rely on case studies or reviews of past practices, with a limited use of microdata to quantitatively analyze the factors influencing farmers' adoption behavior.

Environmental conservation practices, including AWD, often cluster spatially. Agricultural extension agents and neighboring farmers play a significant role in encouraging these practices [28]. The presence of dense networks can influence individual farmers' behavior, with farmers sharing common networks more likely to adopt similar methods [29,30]. However, despite emphasizing mutual influence among farmers, previous AWD research has not fully utilized spatial models to clarify the impact of spatial factors.

Given the need to promote AWD adoption in Japan, understanding how various factors influence farmers' behavior within the Japanese context is crucial. A spatial econometric analysis, which quantitatively evaluates the effects of spatial factors, is particularly important. The approach focuses on spatial interdependencies and the heterogeneity of data across regions, as detailed in Anselin (2022) [31].

In Japan, farmers implement AWD as an extended form of mid-season drainage. They drain water from paddies to aerate the soil during the rice cultivation period. Normally lasting approximately a week, mid-season drainage can be extended by one to two weeks for AWD implementation. Extending it to 14 days reduces methane emissions by approximately 50% without compromising rice yields [32]. As this study focuses exclusively on Japan, AWD hereafter refers specifically to its implementation within the Japanese context.

This study targets Shiga Prefecture, a region with extensive paddy farming. There are two main reasons for this choice. First, Shiga Prefecture has abundant water resources, with paddy fields accounting for approximately 93% of the total agricultural area [33]. Second, the prefecture leads Japan in adopting environmentally friendly agricultural practices, making it a promising area for promoting AWD. According to the Ministry of Agriculture, Forestry and Fisheries of Japan (2022), the AWD adoption rate in Shiga Prefecture is approximately 21.5%, with a notable spatial concentration of adoption around Lake Biwa and the southeastern region of the prefecture [34]. Considering the significant spatial concentration characteristics of farmers implementing AWD in Shiga Prefecture, there may be strong interactions among farmers. Leveraging farmer interactions as a spatial factor could further improve the AWD implementation rate.

Building on the above, we aim to quantitatively analyze the determinants of AWD adoption and spatial correlations of adoption behavior among farmers in Shiga Prefecture. We use spatial probit modeling to evaluate the effectiveness of interpersonal networks in promoting AWD adoption.

2. Methods

2.1. Study Region

This study targets Shiga Prefecture for the analysis. The prefecture is in central Japan, neighboring Kyoto and Osaka (Figure 1).

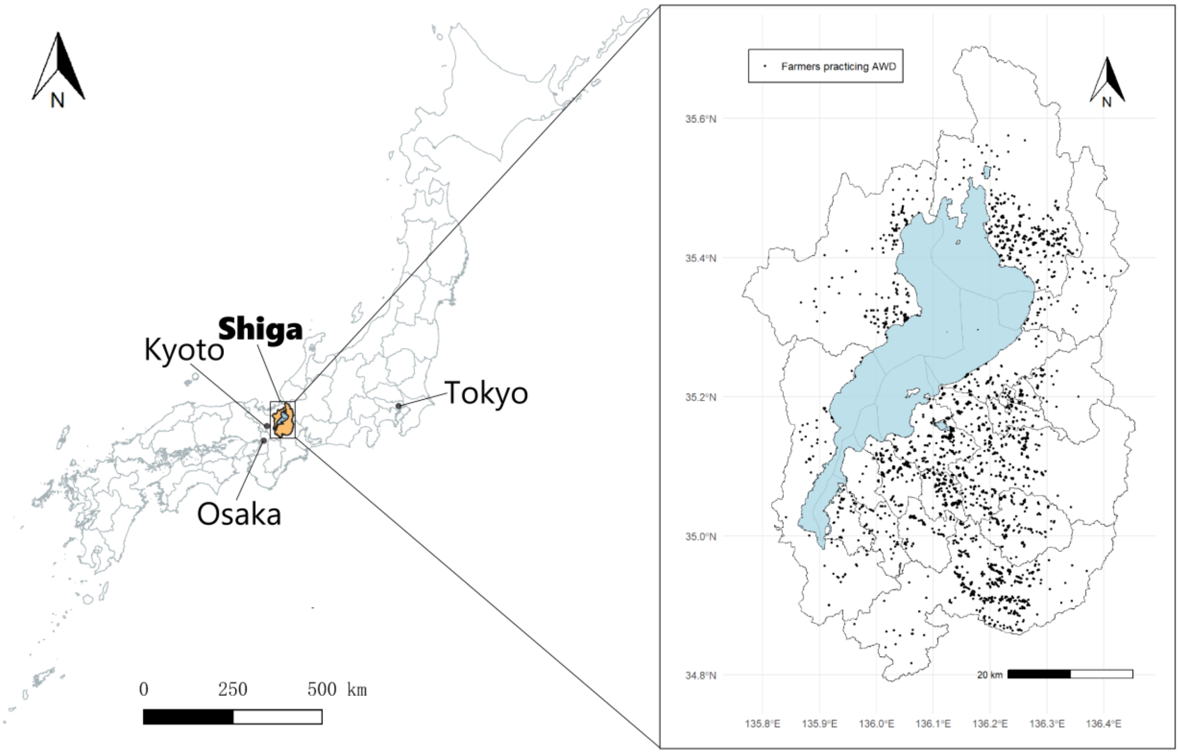

Figure 1. Geographical location of Shiga Prefecture and distribution of farmers implementing AWD.

Shiga Prefecture is known for Lake Biwa, which occupies approximately one-sixth of its total land area. Abundant water resources make rice paddy farming the predominant agricultural activity in the region. The prefecture's agricultural land comprises 46,900 hectares of paddy fields, accounting for approximately 93% of its total farmland as of 2021, the second-highest ratio in Japan [33].

The prefecture's unique geographic characteristics and heavy reliance on water resources for agriculture make farming-related environmental issues particularly prominent. Since 2003, the prefecture has promoted "environmentally friendly agriculture" to achieve sustainable coexistence with natural resources like Lake Biwa and ensure safe and reliable agricultural products. According to the Ministry of Agriculture, Forestry, and Fisheries of Japan (2022), approximately 30% of the farmers in Shiga practice environmentally friendly agriculture, and 21.5% of these farmers implement AWD [34]. However, AWD adoption exhibits spatial concentration, with significant clustering near Lake Biwa and in the southeastern part of the prefecture.

Effectively promoting AWD in Shiga Prefecture requires understanding the potential of leveraging spatial factors such as interpersonal networks to improve adoption rates. This study applies spatial statistical methods, including Moran's I and Global G*, to identify the spatial characteristics of AWD adoption in the region. Moran's I is an indicator that measures how farmers implementing AWD are distributed spatially, particularly the degree of autocorrelation among neighboring farmers. A value of Moran's I close to 0 indicates a random distribution; a positive value indicates that similar implementation situations are adjacent, and a negative value indicates different implementation. Negative values indicate that different implementation situations are adjacent to each other. In contrast, Global G* measures spatial agglomeration and identifies hot spots (high implementation clusters) and cold spots (low implementation clusters). In spatial econometrics, Moran's I and Global G* are often used to determine if a spatial model is needed.

Table 1 summarizes the observed values of Moran's I and Global G* with a neighborhood threshold of 24 (see Section 3.1 for the criteria for setting the nearest neighbor values), both of which are statistically significant. Moran's I value of 0.460 indicates a positive spatial autocorrelation among farmers practicing AWD, while the Global G* value of 0.116 suggests that areas with high adoption rates form identifiable hotspots. These results imply that geographical factors significantly influence AWD adoption.

Table 1. Moran's I and Global G* observables.

	Statistic	**Expectation**	**Variance**	***p*-Value**
Moran's I	0.460	−0.001	1.01×10^{-4}	$<2.2 \times 10^{16}$
Global G*	0.116	0.034	2.96×10^{-6}	$<2.2 \times 10^{16}$

These findings suggest that neighboring farmers' adoption behavior influences that of the individual farmers. As such, encouraging a single farmer to adopt AWD may increase the likelihood of adoption among neighboring farmers.

2.2. Spatial Probit Model

Considering the above spatial characteristics, employing spatial econometric models is necessary to identify the determinants of farmers' adoption behavior. The spatial probit model extends the standard binary probit model and accounts for spatial dependence [35]. Specifically, it acknowledges that farmer i's decision to adopt AWD can be influenced by interactions with neighboring farmer j. Therefore, the adoption behavior y_i of farmer i can be expressed as Equation (1).

$$y_i = \rho W y_j + X\beta + \epsilon \tag{1}$$

Here, the term $\rho W y_j$ captures the influence of spatial factors. Variable y_j represents the adoption behavior of neighboring farmer j, which serves as a factor influencing the decision-making of farmer i. Parameter ρ is the spatial lag coefficient, indicating the extent to which neighboring farmers' behaviors impact farmer i's decision-making. A positive ρ implies that neighboring farmers' adoption behavior positively impacts farmer i's likelihood of adopting AWD. For example, if neighboring farmers implement AWD, farmer i is more likely to follow them. W is the spatial weight matrix, which reflects the proximity of farmers in the region. Various methods exist for constructing W [36]. In this study, we adopt the k-nearest neighbor approach, defining neighboring farmers as the k geographically closest farmers to farmer i.

Term $X\beta$ represents the effects of non-spatial determinants; X denotes a matrix of explanatory variables, representing farmer i's external factors like personal attributes and farming practices. β denotes the parameter vector associated with these explanatory variables, indicating the magnitude of their effects on farmer i's adoption behavior.

Finally, ϵ is the error term, capturing unobservable or omitted factors, and is defined as $\epsilon = (\epsilon_i : i = 1, \ldots, n)'$. It satisfies the following assumptions: it has a mean of zero, implying no systematic bias in unobservable factors, and follows an n-dimensional normal distribution with a variance–covariance matrix equal to the identity matrix I_n, indicating independence and homoscedasticity.

Note that in Equation (1), y is also included on the right side of the equation as y_j and cannot be estimated as is; therefore, transforming the equation is necessary. If y_i on the left side is denoted by $I_n y$, Equation (1) can be transformed into the following inductive form.

Here, it is assumed that $(I_n - \rho W)$ is nonsingular (an inverse matrix exists). If $(I_n - \rho W)$ is denoted by S, the equation can be expressed concisely. Further, $u = S^{-1}\epsilon$ is the error term after the transformation.

$$y_i = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1}\epsilon = S^{-1}X\beta + u \quad (2)$$

Probability P_i that farmer i will voluntarily adopt AWD can then be expressed as follows:

$$P_i = P\left(\left[S^{-1}X\beta\right]_i + u_i > 0\right) = P\left(u_i < \left[S^{-1}X\beta\right]_i\right) \quad (3)$$

Calculating marginal effects is necessary to determine the extent to which each explanatory factor influences farmers' adoption behavior. The spatial probit model is nonlinear, and the parameter estimates themselves do not directly indicate the extent to which each explanatory variable affects the objective variable. In this model, the estimated coefficients are interpreted as changes in probability that follow the cumulative distribution function of a standard normal distribution. Probability P_i that farmer i adopts AWD is expressed using the cumulative distribution function ϕ as follows:

$$P_i = \phi\left(\left[S^{-1}X\beta\right]_i\right) \quad (4)$$

Therefore, we calculate marginal effects to find out how much each explanatory factor changes the probability of adoption. Marginal effects imply the impact of a change in the explanatory variable X on the objective variable y_i. Based on Equation (4), when partially differentiated with respect to P_i, the marginal effects of the explanatory variable X are expressed as follows:

$$\frac{\partial P_i}{\partial X} = \phi\left(\left[S^{-1}X\beta\right]_i\right) \cdot \left[S^{-1}X\beta\right] \quad (5)$$

Because the spatial probit model considers spatial dependence, marginal effects can be divided into direct effects (DE) and indirect effects (IE). The DE refers to the effect on farmer i's own adoption probability y_i and can be calculated as follows:

$$DE = \frac{\partial P_i}{\partial X_i} = \phi\left(\left[S^{-1}X\beta\right]_i\right) \cdot \left[S^{-1}\right]_{ii}\beta \quad (6)$$

By contrast, the IE refers to the impact that occurs through neighboring farmer j and can be calculated as follows:

$$IE = \sum_{j \neq i} \frac{\partial P_i}{\partial X_j} = \phi\left(\left[S^{-1}X\beta\right]_i\right) \cdot \sum_{j \neq i} \left[S^{-1}\right]_{ij}\beta \quad (7)$$

The $\sum_{j \neq i} \left[S^{-1}\right]_{ij}\beta$ on the right side above indicates the effect of a change in the explanatory variable X_j of neighbor farmer j on the adoption probability of farmer i indirectly through the behavior of j.

2.3. Data Development

As mentioned earlier, we used individual questionnaire data from the FY2020 Census of Agriculture and Forestry (census data) and field-by-field direct payment grant application data for Shiga Prefecture for the same year (direct payment data). Part of our data originates from the 2020 Census of Agriculture and Forestry in Japan, conducted every five years. This national census questionnaire is distributed to all farmers in Japan. Farmers complete and return the questionnaire, and responses are collected and aggregated by the Japanese government. The census data contain basic information on farmers throughout Japan, such as cultivated area, management style, and individual attributes, but they do not inform on AWD adoption. Conversely, the direct payment data reflect the implementation status of environmentally friendly agriculture and inform on farmers practicing conventional agriculture but lack other information. While most previous studies use only one of these two types of data, this study combines both. This allows us not only to determine which farmers in Shiga Prefecture are implementing AWD but also to fully understand their characteristics in farming practices and personal attributes. These characteristics can also help specifically analyze what factors influence farmers' adoption of AWD. Moreover, the new data obtained by combining the two datasets retain the characteristics of the census data and constitute farmer microdata.

As the two datasets have different formats, we adjusted the format and integrated the data during preprocessing. We formatted the census data so that each row contains information on a single farmer and each column represents varied information, such as the area under cultivation and management type. We formatted the direct payment data so that each row represents the area of one unit of environmentally friendly agriculture and each column represents attributes of this area, like the implementer name and initiative type. As mentioned earlier, because farmers' AWD adoption behavior is the objective variable in this study, the data used in the final analysis must be per farmer. As this is consistent with the original format of the census data, we did not change the census data format, and only the data on Shiga Prefecture were extracted. We extracted the data with AWD in the Supportive Efforts column from the direct payment data and calculated each farmer's total area under implementation by adding the cumulative total using the Producer Name column. The direct payment data do not distinguish between individual farmers and agricultural corporations; hence, both are included in the Producer Name column. By contrast, the census data make this distinction and therefore include both "name of farmer" and "name of corporation." Therefore, when integrating the two datasets, we checked the Producer Name field in the direct payment data only once against the "farmer name" and "corporation name" fields in the census data. However, some direct payment data could not be matched with the census data due to farmers' writing or data entry errors. A total of 990 data items contained matching errors, and because they could not be checked or corrected one by one, all of them were removed. After merging the two datasets, 13,691 data items were finally available for analysis. All the above processes were performed with R language software (version 4.4.0). Finally, as the spatial probit model analysis requires the coordinate values (latitude and longitude) of each farmhouse, we added them using the CSV matching service of the Center for Spatial Information Science at the University of Tokyo. The latitude and longitude of each farmer were added.

2.4. Study Variables

To investigate the factors influencing AWD adoption, this study incorporates 15 explanatory variables derived from prior research on environmentally friendly farming practices (Table 2) and the integrated dataset [37–49]. The variables are categorized into the following three groups: individual attributes, plot characteristics, and operational factors, reflecting the economic, demographic, and technological dimensions of AWD adoption behavior (Table 3).

Individual attributes include Gender is male, which indicates whether the farmer or corporate representative is male, and Age is over 60, which identifies farmers aged 60 years or older. We also include the variable Has a successor to assess the role of generational continuity in farming. The variables account for the demographic characteristics that may influence farmers' willingness or ability to adopt AWD.

Table 2. Prior research: factors influencing farmers' adoption of environmentally friendly agriculture.

Types of Attributes	Attributes	References
Individual Attributes	gender academic background age concern for environmental issues	Mala and Malý, 2013 [37]; Sodjinou et al., 2015 [38]
Field Attributes	field scale management form	Genius et al., 2006 [39]; Läpple, 2010 [40]; Karki et al., 2011 [41]; Liu et al., 2019 [42]
Others	technological innovation information supply support from the government data use	Serra et al., 2008 [43]; Cranfield et al., 2010 [44]; Khaledi et al., 2010 [45]; Moumouni et al., 2013 [46]; Soltani et al., 2014 [47]; Nalubwama et al., 2019 [48]; Kittipanya-Ngam and Tan, 2020 [49]

Table 3. Objective and explanatory variables.

Variables		Description of Variables
Operational Factors	AWD adoption	adoption of AWD
	Data gathering	whether to obtain data (only)
	Data utilization	whether to obtain and use data
	Agricultural corporation	is it a company-owned business?
	Cultivated area	logarithm of the cultivated area
	Leased land ratio	ratio of leased land to total cultivated area
Plot Characteristics	Rice profitability	is rice the most profitable to sell?
	Direct Sales	are there direct sales to consumers?
	Coop as the main sales channel	is the agricultural cooperative the largest shipping destination for sales?
	Consumers as the main sales channel	is the consumer the largest shipping destination for sales?
Individual Attributes	Gender is male	gender of the farmer (or manager)
	Age is over 60	is the farmer (or manager) over 60 years of age?
	Worked in agriculture $\geq$100 days	did the cumulative days worked in agriculture exceed 100?
	Worked in agriculture-related field $\geq$100 days	did the cumulative days worked in agriculture-related jobs exceed 100?
	Agriculture as the main source of income	is self-employed agriculture the main business?
	Has a successor	whether there is a successor

Plot characteristics encompass variables related to farm size and land management. Cultivated area, a logarithmic transformation of the total cultivated area, represents the scale of operations. In the analyzed data, the minimum value of cultivated area was 2, and the maximum value was 35,719. Because the range of values is broad, the data were converted to the logarithm. Larger farms may benefit from economies of scale, thus facilitating AWD adoption. Variable Leased land ratio, measuring the proportion of leased land to total cultivated area, reflects the extent to which land tenure arrangements may impact farming decisions. Additionally, Rice profitability indicates whether rice constitutes the highest revenue-generating crop for the farmer, highlighting the economic motivation behind rice production.

Operational factors cover technology use and farming practices. Variables Data gathering and Data utilization capture the extent to which farmers use digital tools; Data gathering reflects whether farmers obtain data like weather forecasts or crop growth information, while Data utilization measures whether they actively incorporate such data into decision-making processes. Farmers with greater access to and use of digital tools may be better equipped to implement AWD effectively. Other variables, such as Agriculture as the main source of income, Worked in agriculture ≥100 days, and Worked in agriculture-related field ≥100 days, examine the primary focus and intensity of farming activities. Agriculture as the main source of income indicates whether farming is the primary occupation, while Worked in agriculture ≥100 days and Worked in agriculture-related field ≥100 days measure engagement in farming or related activities, with thresholds set at over 100 days per year.

Table 4 summarizes the descriptive statistics for these variables. The AWD adoption rate in Shiga Prefecture stands at 21.5%, reflecting a moderate diffusion of the practice. Among operational characteristics, only a small proportion of farms are managed as corporate entities, while a significant number of farmers primarily sell rice, consistent with the region's emphasis on paddy cultivation. Moreover, 26% of farmers report direct sales to consumers, although agricultural cooperatives remain the dominant sales channel. Technological engagement is limited; only 8.8% of farmers obtain digital data, and 9.4% use it actively. Demographically, the farming population is predominantly male, and approximately 80% of farmers are aged 60 years or older.

Table 4. Descriptive statistics of objective and explanatory variables.

Variables		Mean	Std. Dev.	Min.	Max.
Operational Factors	AWD adoption	0.22	0.41	0.00	1.00
	Data gathering	0.09	0.28	0.00	1.00
	Data utilization	0.09	0.29	0.00	1.00
	Agricultural corporation	0.03	0.18	0.00	1.00
	Cultivated area	4.73	1.09	0.69	10.48
	Leased land ratio	0.26	0.34	0.00	1.00
Plot Characteristics	Rice profitability	0.84	0.37	0.00	1.00
	Direct Sales	0.26	0.44	0.00	1.00
	Coop as the main sales channel	0.68	0.47	0.00	1.00
	Consumers as the main sales channel	0.08	0.28	0.00	1.00
Individual Attributes	Gender is male	0.96	0.19	0.00	1.00
	Age is over 60	0.78	0.41	0.00	1.00
	Worked in agriculture ≥100 days	0.43	0.49	0.00	1.00
	Worked in agriculture-related field ≥100 days	0.04	0.21	0.00	1.00
	Agriculture as the main source of income	0.47	0.50	0.00	1.00
	Has a successor	0.28	0.45	0.00	1.00

These findings reveal a notable variation in the adoption behavior and highlight the interplay between farm size, technological access, and demographic factors. Farmers operating larger farms or using digital tools may exhibit higher adoption rates, benefiting from enhanced efficiency and information access. However, the low rate of digital tool use among farmers suggests that technological barriers may constrain a broader adoption of AWD. Moreover, the aging of Shiga's farming population poses challenges for long-term sustainability. These observations underscore the need for targeted interventions addressing both economic and technological factors while fostering generational transitions in farming.

3. Results

3.1. Estimation Results

Table 5 summarizes the estimation results of the spatial probit model applied to the integrated dataset. We performed model fitting under several different neighborhood size settings (e.g., k = 8, 16, 24, 32, 40) based on spatial characteristics of farmer distribution. Due to space constraints, we report only the four most representative sets of results, with the neighborhood size k set to 8, 16, 24, and 32, respectively. Although the results across all four models are consistent, the model with k = 24 achieved the lowest AIC value, indicating the best fit. This suggests that setting the neighborhood size to 24 is optimal for this analysis.

Table 5. Estimation results for spatial probit model.

Independent Variable	Model 1 k-Nearest Neighbors = 8			Model 2 k-Nearest Neighbors = 16			Model 3 k-Nearest Neighbors = 24			Model 4 k-Nearest Neighbors = 32		
	Coefficient		Std. Error	Coefficient		Std. Error	Coefficient		Std. Error	Coefficient		Std. Error
(Intercept)	−3.040	***	1.18×10^{-3}	−2.674	***	1.16×10^{-3}	−2.529	***	1.01×10^{-3}	−2.451	***	1.04×10^{-3}
rho (p)	0.688	***	7.52×10^{-5}	0.718	***	8.58×10^{-5}	0.741	***	9.32×10^{-5}	0.763	***	9.48×10^{-5}
Data gathering	0.297	***	3.91×10^{-4}	0.266	***	3.93 × 10−4	0.251	***	4.05 × 10−4	0.246	***	4.06 × 10−4
Data utilization	0.337	***	3.81 × 10−4	0.326	***	3.67 × 10−4	0.318	***	3.80 × 10−4	0.313	***	3.86 × 10−4
Agricultural corporation	−1.610	***	8.23 × 10−4	−1.523	***	8.24 × 10−4	−1.516	***	7.87 × 10−4	−1.465	***	7.58 × 10−4
Cultivated area	0.329	***	1.74 × 10−4	0.288	***	1.69 × 10−4	0.278	***	1.53 × 10−4	0.274	***	1.55 × 10−4
Leased land ratio	0.171	**	4.78 × 10−4	0.186	***	4.35 × 10−4	0.179	***	4.25 × 10−4	0.178	***	4.56 × 10−4
Rice profitability	0.423	***	4.24 × 10−4	0.368	***	4.37 × 10−4	0.354	***	3.94 × 10−4	0.332	***	3.98 × 10−4
Direct sales	0.123	***	3.16 × 10−4	0.133	***	3.08 × 10−4	0.138	***	3.11 × 10−4	0.127	***	3.24 × 10−4
Coop as the main sales channel	0.214	***	3.41 × 10−4	0.179	***	3.21 × 10−4	0.166	***	3.18 × 10−4	0.162	***	3.15 × 10−4
Consumers as the main sales channel	−0.029		5.58 × 10−4	−0.023		5.80 × 10−4	−0.031		5.55 × 10−4	−0.020		5.77 × 10−4
Gender is male	0.324	***	7.29 × 10−4	0.294	***	7.43 × 10−4	0.261	**	7.30 × 10−4	0.258	**	7.09 × 10−4
Age is over 60	0.220	***	3.19 × 10−4	0.220	***	3.25 × 10−4	0.219	***	3.18 × 10−4	0.215	***	3.07 × 10−4
Worked in agriculture ≥100 days	0.084	*	3.49 × 10−4	0.081	*	3.10 × 10−4	0.088	*	3.20 × 10−4	0.091	*	3.15 × 10−4
Worked in agriculture-related field ≥100 days	0.006		6.26 × 10−4	0.009		5.72 × 10−4	−0.015		5.87 × 10−4	−0.029		5.59 × 10−4
Agriculture as the main source of income	−0.038		3.46 × 10−4	−0.032		3.22 × 10−4	−0.037		3.28 × 10−4	−0.035		3.05 × 10−4
Has a successor	−0.015		2.67 × 10−4	−0.009		2.62 × 10−4	−0.006		2.46 × 10−4	−0.008		2.62 × 10−4
# of obs.	13,549			13,549			13,549			13,549		
# of cases	13,549			13,549			13,549			13,549		
Log-Likelihood	−6763			−6524			−6486			−6492		
AIC	13,558			13,079			13,003			13,015		

Note: *, **, and *** indicate statistical significance at 10%, 5%, 1%, and 0.1%, respectively. "#" stands for "Number of".

As mentioned earlier, the data used in this study are farmer microdata characterized by the presence of numerous neighboring farmers in each observation. We calculated the average distance from each farmer to the 24 nearest neighbors to be approximately 750–800 m, which is considered a small radius in rural areas. Accordingly, we use the results of the model with k = 24 to explain the findings of the spatial probit model.

The spatial lag coefficient (p = 0.741) is positive and statistically significant, with a high coefficient value. This indicates a strong spatial autocorrelation in farmers' AWD adoption behavior. In other words, neighboring farmers' decision to adopt AWD significantly influences an individual farmer's decision. Farmers in regions with higher AWD adoption rates are more likely to adopt the practice, whereas those in regions with lower rates are less likely to do so. This result aligns with the spatial distribution patterns of AWD adoption in Shiga Prefecture discussed in Section 2.1.

All explanatory variables except the successor dummy (Has a successor), consumer-priority dummy (Consumers as the main sales channel), days engaged in agriculture-related work (Worked in agriculture-related field ≥100 days), and primary occupation dummy (Agriculture as the main source of income) are statistically significant, indicating that while the other explanatory variables significantly influence AWD adoption behavior, the presence of a successor, prioritizing direct sales to consumers, number of days engaged in agriculture-related work, and farming as a primary occupation do not significantly affect AWD adoption.

Among the significant explanatory variables, several exhibit positive coefficients. These include variables reflecting farming operations, such as the rice-profit dummy (Rice profitability, 0.354), data acquisition dummy (Data gathering, 0.251), data use dummy (Data utilization, 0.318), agricultural cooperative-priority dummy (Coop as the main sales channel, 0.166), and direct sales dummy (Direct sales, 0.138). Variables indicating farm scale, such as cultivated area (Cultivated area, 0.278) and lease rate (Leased land ratio, 0.179), also have positive coefficients. Furthermore, individual attributes, including the gender dummy (Gender is male, 0.261), senior dummy (Age is over 60, 0.219), and years of agricultural work (Worked in agriculture ≥100 days, 0.088), are positively associated with AWD adoption. Thus, farmers who primarily sell rice, acquire and use data, prioritize sales to cooperatives or consumers, have larger cultivated areas or higher lease rates, and are male, older, or have longer agricultural experience are more likely to adopt AWD.

By contrast, the corporate dummy (Agricultural corporation, −1.516) exhibits a negative coefficient, implying that corporate-managed farms are less likely to adopt AWD. Because the spatial probit model is nonlinear, the sign of the coefficients indicates how a variable influences AWD adoption. Nonetheless, the coefficient values themselves do not reflect the precise magnitude of the influence. These specific effects of each explanatory variable are better captured through marginal effects, which we discuss in Section 3.2.

3.2. Marginal Effects

As the spatial probit model is nonlinear and incorporates spatial elements, the estimated coefficients do not directly indicate the magnitude of the influence. To quantify the specific impact of each explanatory variable, we calculated the marginal effects, which include both direct and indirect effects. The direct effect reflects the influence of changes in a farmer's own characteristics on their adoption behavior, whereas the indirect effect captures the influence transmitted through neighboring farmers. The total effect is obtained by adding both effects. Table 6 presents the results of this estimation.

Table 6. Estimation results of the marginal effects.

	Direct Effects	Indirect Effects	Total Effects
Data gathering	0.057	0.161	0.218
Data utilization	0.072	0.203	0.276
Agricultural corporation	−0.345	−0.971	−1.316
Cultivated area	0.063	0.178	0.241
Leased land ratio	0.041	0.115	0.155
Rice profitability	0.080	0.226	0.307
Direct sales	0.031	0.088	0.120
Coop as the main sales channel	0.038	0.106	0.144
Gender is male	0.059	0.167	0.227
Age is over 60	0.050	0.140	0.190
Worked in agriculture ≥100 days	0.020	0.057	0.077

The indirect effects of all variables are larger than their direct effects, suggesting that neighboring farmers' characteristics significantly impact individual farmers' AWD adoption decisions. The indirect effects are particularly large for the corporate dummy (Agricultural corporation, −0.971), rice-profit dummy (Rice profitability, 0.226), and data use (Data utilization, 0.203), suggesting that the management structure of neighboring farms and their rice production levels and data use substantially influence individual farmers through spatial interactions.

The corporate dummy (Agricultural corporation, −1.316) exhibits the largest negative total effect among all variables, indicating that farm management structure most significantly negatively influences AWD adoption. Specifically, corporate-managed farms are far less likely to adopt AWD. Conversely, most variables exhibit positive total effects, suggesting a positive influence on AWD adoption. The rice-profit dummy (Rice profitability, 0.307) has the largest positive total effect, followed by the data use dummy (Data utilization, 0.276), farm scale (Cultivated area, 0.241), and data acquisition dummy (Data gathering, 0.218). These findings demonstrate that prioritizing rice production, acquiring and using data, and larger farm scales strongly and positively impact AWD adoption. In summary, farmers with these attributes are more likely to adopt AWD.

4. Discussion

The analysis provides several important insights into the AWD adoption behavior of farmers in Shiga Prefecture. The positive and statistically significant spatial lag coefficient ($p = 0.741$) implies a strong spatial dependence, underscoring the critical role of neighboring farmers' decisions in individual farmers' adoption behavior. Notably, the magnitude of this coefficient, exceeding 0.5, indicates a robust farmer interdependence. Thus, as neighbors adopt AWD, individual farmers may also substantially increasingly follow suit, which emphasizes the role of localized social networks in driving environmentally friendly agricultural practices.

Implementing environmentally friendly agriculture often involves transitioning away from conventional practices, which can increase perceived risks for farmers. These risks are particularly pronounced when monetary benefits are uncertain or insufficient, as supported by Mills et al. (2018), Dessart et al. (2019), and Pannell and Claasen (2020) [50–52]. Farmers, therefore, tend to mitigate risks by relying on the experiences and insights of neighboring farmers with similar agricultural conditions [29,53]. This social dependence highlights the importance of leveraging existing human networks to promote AWD adoption. Farmers who observe their peers successfully implementing AWD or achieving positive outcomes are more likely to adopt similar practices. This aligns with prior studies showing that peer influence and the dissemination of successful case studies significantly boost adoption rates [54–56].

To capitalize on these findings, strengthening farmer networks and promoting an exchange of experiences are key strategies. Practical measures could include organizing regional workshops and showcasing successful AWD practitioners as "model farmers". Sharing actionable insights and case studies can demystify the perceived risks regarding AWD and provide practical guidance. Such workshops may also serve as platforms for farmers to exchange knowledge, thereby fostering a collaborative environment that accelerates adoption.

The spatial econometric analysis confirmed significant clustering and autocorrelation in AWD adoption. Among the models tested, the one defining neighbors as the 24 geographically closest farmers showed the best fit, as indicated by the lowest AIC value. This finding suggests that the behavior of neighboring farmers within approximately 520 m significantly impacts individual adoption decisions. Läpple and Kelley (2015) in Ireland and Wollni and Andersson (2014) in Honduras used smaller farmer samples [57,58], with sample sizes of 597 and 239, respectively, whereas this study benefits from a higher farmer density in Shiga Prefecture. Thus, a larger number of neighbors influences individual adoption decisions, reflecting the region's unique social and geographical characteristics. The findings highlight the need for spatially targeted policies to promote adoption in clustered farming communities.

Farmers who actively acquire (0.218) and use (0.276) data are more likely to adopt AWD. Data acquisition and analysis enable farmers to make informed decisions on crop management, weather conditions, and financial planning. This reduces uncertainties and enhances production efficiency, creating scope for environmentally sustainable practices [59]. By analyzing their own data, farmers can verify the minimal impact of AWD on rice yields, addressing concerns that academic studies alone may not alleviate.

Digital agriculture is pivotal in promoting AWD adoption. Japan's Agricultural digital transformation initiative exemplifies this by providing environment monitoring systems, digital management platforms, and access to public and private datasets [60]. These measures allow farmers to collect and analyze data more effectively, supporting evidence-based decision-making. Farmers face challenges such as high initial costs and limited technical skills, particularly among elderly farmers [61–63]. Addressing them through subsidies, training programs, and user-friendly technologies is essential for broader adoption. Training younger farmers and providing financial support to small-scale farmers who are less advantaged can be effective in increasing the incentives for farmers to adopt digital technologies [64,65]. At the same time, the government can further accelerate this transition by supporting technology development companies and encouraging them to develop accessible devices for elderly users [66].

The findings also indicate that corporate farms are the least likely to adopt AWD (−1.316). This is likely due to the limited financial incentives under current policies, where subsidies (JPY 800 per 100 m^2, capped at JPY 8000) and market premiums for AWD rice are insufficient to justify adoption. Corporate farms prioritize revenue generation to meet operational demands, making low financial returns from AWD a major deterrent. Given the growing prevalence of corporate farms, tailored policies are needed to increase their willingness to adopt AWD.

One potential strategy is creating market-driven incentives. For example, promoting the environmental benefits of AWD to consumers can increase demand and generate market premiums for AWD-produced rice. Public recognition of corporate farms that implement AWD could enhance their community reputation, indirectly boosting profitability. Furthermore, collaboration with consumers to raise awareness on AWD's role in alleviating climate change could encourage market-oriented adoption among corporate farms.

Farm size (0.241) positively influences AWD adoption, consistent with previous studies in Japan [67,68]. Larger farms benefit from economies of scale, enabling easier adoption of environmentally friendly practices. Unlike other practices that involve significant labor and material costs, AWD requires minimal additional resources, making it suitable for large-scale operations. Moreover, larger farms often have better drainage infrastructure, which facilitates AWD implementation. Considering growing large-scale farming in Japan, promoting AWD therein may yield substantial environmental benefits.

The value of the rice-profit dummy (0.307) highlights the economic advantages of AWD for rice farmers. AWD's compatibility with rice cultivation, when coupled with subsidies and market premiums for environmentally friendly practices, makes it economically attractive. This is particularly important as rice consumption and prices decline, challenging the sustainability of rice farming in Japan. By adopting AWD, farmers can offset these economic pressures while contributing to environmental conservation.

The findings stress the need for multi-faceted strategies to promote AWD adoption. Strengthening farmer networks, expanding digital agriculture, and tailoring policies to corporate farms are crucial. Additionally, raising consumer awareness about AWD's environmental benefits can drive market incentives and encourage adoption. For small-scale farmers, reducing initial investment costs through subsidies and providing technical support can address barriers to adoption. Overall, fostering collaboration among farmers, policymakers, and technology providers is key to expanding AWD adoption in Shiga Prefecture.

5. Conclusions

This study examined factors influencing AWD adoption in Shiga Prefecture and evaluated the role of human networks. A spatial probit model identified significant clustering of AWD adoption, suggesting farmers influence one another's decisions. Many farmers expressed favorable attitudes toward AWD, indicating that leveraging existing human networks can accelerate its diffusion and contribute to mitigating methane emissions.

To enhance AWD adoption efficiently, it is advisable to strengthen information exchange among farmers. Thus, making full use of the extension role of human networks. Data usage emerged as another key driver, highlighting the importance of Japan's agricultural digital transformation in rice farming. However, high initial costs for digital equipment and limited technical expertise remain barriers. Stronger support is needed from the government. As corporate farms expand, policy approaches for these entities must be refined. Current subsidies and modest market premiums do not adequately incentivize corporate farms to adopt AWD. Adjustments to the relevant measures and to the market environment are necessary. Large-scale farming is another facilitator of AWD, underscoring the need for farmland consolidation and drainage improvements.

Because Shiga Prefecture has a high rate of environmentally friendly farming, the effectiveness of human networks may differ elsewhere. Moreover, AWD in Japan primarily involves extended midseason drainage at minimal cost, while other regions might require more elaborate irrigation systems. Japanese extension policy has focused mainly on the use of non-monetary methods, such as the interactions among farmers discussed in this study. For some areas that implement AWD with the use of special irrigation equipment, monetary subsidies may need to be considered more often. Future studies should verify these findings in additional regions and through comparative international research.

Meanwhile, as we mentioned in the introduction, there are various emission-reducing methods other than AWD. For example, using slow-release biochar fertilizers, straw collection and composting, and selecting low-methane-emitting rice varieties. Rice cultivation is affected by many factors such as soil, water quality, and varieties, so the reality is that there are many cases of mixing multiple emission-reducing methods. Discussing the use of multiple emission-reduction methods is also one of the topics that deserve attention in the future.

It is also necessary to combine the data from the field survey to provide further field validation of the findings of this study. Despite these limitations, our results provide quantitative evidence on AWD adoption behavior and inform strategies to promote it more broadly in both policy and practice.

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Institutional Review Board Statement: This study was conducted in compliance with ethical standards for research involving human participants and environmental data. Although formal approval from an ethics committee was not required for this study, the research strictly adhered to ethical guidelines, including obtaining informed consent from all survey participants and anonymizing data to ensure confidentiality. This study also followed the relevant regulations set forth by the Ministry of Agriculture, Forestry, and Fisheries of Japan and the Shiga Prefectural Government.

Informed Consent Statement: Informed consent was obtained from all subjects by the survey agency as part of their panel recruitment and survey participation process.

Data Availability Statement: This study utilized confidential data provided by the Ministry of Agriculture, Forestry, and Fisheries of Japan and the Shiga Prefectural Government. The data contain sensitive and proprietary information and are not publicly available due to confidentiality agreements. Access to the data was granted under special permission from the Japanese government and is strictly limited to the purposes of this study. For readers interested in these data, the authors are willing to share the details of the application process.

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