

## Article

# Technology Acceptance among Farmers: Examples of Agricultural Unmanned Aerial Vehicles

Osman Parmaksiz<sup>†</sup> and Gokhan Cinar<sup>\*ID</sup>

Department of Agricultural Economics, Faculty of Agriculture, Adnan Menderes University, 09970 Aydin, Türkiye

\* Correspondence: gokhan.cinar@adu.edu.tr

† This study is part of the master's thesis of the first author.

**Abstract:** Agricultural drones (AUAVs) contribute greatly to sustainable agriculture by reducing input use. The literature on this topic is scarce, so there is little information on the adoption of agricultural drones by farmers. The purpose of this paper is to investigate the factors affecting farmers' intention to adopt drones for agricultural tasks. Within the scope of this study, face-to-face surveys with 384 farmers were conducted. The obtained data were analyzed using different statistical, econometric, and decision techniques, including the conditional valuation method, lower payment bound estimation, probit model regression, fuzzy pairwise comparison, and the Vise Kriterijumska Optimizacija I Kompromisno Resenje-multi-criteria optimization and compromise (VIKOR) technique. The results showed that government support had a positive impact on AUAV purchasing decisions. Farmers' primary borrowing channel preference was interest-free loans. The willingness to rent AUAV technology was higher than the willingness to purchase it, with farmers agreeing to pay TRY 287.54 for one hectare. They preferred cooperatives for the provision of rental services. In general, young farmers who were interested in technology and who had a high agricultural income made up the profile of AUAV adoption. The information obtained from this research not only provides new insights for decision-makers regarding the adoption of AUAV technology but also contributes to the preparation of the promotion process for potential market actors.

**Keywords:** agricultural innovation; digitalization in agriculture; farmer decision; precision agriculture; smart farming technologies



**Citation:** Parmaksiz, O.; Cinar, G. Technology Acceptance among Farmers: Examples of Agricultural Unmanned Aerial Vehicles. *Agronomy* **2023**, *13*, 2077. <https://doi.org/10.3390/agronomy13082077>

Academic Editors: Andreas Stylianou, George Adamides, Damianos Neocleous and Christopher Brewster

Received: 4 July 2023  
Revised: 3 August 2023  
Accepted: 3 August 2023  
Published: 7 August 2023



**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

The agricultural sector is crucial for every country, both in terms of feeding people and accounting for a significant share of national income. The ability of agriculture to provide for human needs now and in the future is, however, threatened by a number of issues. They include growing production costs, a decline in the number of farms, declining biodiversity, depletion and contamination of water resources, and soil pollution [1,2].

By 2050, agricultural water use is expected to increase by 13%. Excessive salinization of irrigated lands causes about 1.5 million hectares of arable land to be lost worldwide each year [1]. According to UNEP (2009) [3], agricultural production may decrease by 25% after 2050 if no action is taken.

Agriculture, through the way it is practiced, is also the main cause of these problems. In particular, the extensive use of chemical inputs and the prolonged time chemicals remain in water and soil are among the reasons for the emergence of environmental problems [4].

The agricultural sector needs new approaches to growing that are more efficient, environmentally friendly, sustainable, and based on knowledge, innovation, and technology. Numerous scientists believe that precision (smart) agriculture practices, in particular, may hold the key to enhancing the performance and sustainability of agricultural production systems [5–8].

The International Society for Precision Agriculture [9] defines precision agriculture as “a management concept based on intensive data collection and data processing to guide targeted actions that improve the efficiency, productivity, and sustainability of agricultural activities”. Data collection and processing technologies [10] consist of a range of operators, such as remote sensing technologies [11], mapping [12], and geographic information systems [13].

These practices have very significant benefits for sustainable agriculture. For example, they reduce farm expenditures by controlling agricultural inputs [14] and increase production by increasing yield [15]. Moreover, they contribute to the protection of the environment and human health through the controlled use of fertilizers and pesticides [16]. Therefore, adopting precision agriculture practices offers public benefits by improving soil, water, and air quality [17].

Agricultural drones (AUAVs) represent a new branch of technological developments in precision agriculture. AUAVs can carry out a wide variety of agricultural operations in support of precision agriculture, including soil health screening, irrigation program planning, seed planting, fertilizer application, and weather analysis. With agricultural unmanned aerial vehicles (AUAVs), agricultural lands can be sprayed faster in a more effective, efficient, and cost-effective manner [18,19]. With their autonomous and spraying capabilities, drones—which are employed to eradicate pests in agriculture—optimize input consumption by using the quantity of fertilizer and pesticide that the plant requires.

Pesticides cause many diseases in humans, from respiratory disorders to cancer [20]. According to reports, farmers frequently have severe health issues as a result of excessive exposure to pesticides [21,22]. In the traditional method, farmers are in the field while spraying pesticides. Therefore, there is a high probability of drug exposure. The farmer can continue to spray from an area outside the field with AUAVs. Thus, the side effects of pesticides on farmers’ health are minimized [23].

AUAVs reduce pesticide consumption by reducing the rate of water utilization when compared to conventional spraying techniques [24]. Therefore, they reduce the impact of chemical residues on nature and people compared to traditional spraying methods.

Overall, more widespread use of AUAVs by farmers will save time and costs by reducing labor intensity and input use. Thus, water use is better managed, product quality is improved, soil fertility is maintained, environmental sustainability is promoted, and human health is not harmed [25–29].

In addition, cameras mounted on AUAVs can collect instant information on plant health and water stress levels [30]. Moreover, they can create new job opportunities for young people.

Despite all the advantages, studies show that the adoption rate of technological applications in agriculture is quite slow [31–35].

AUAV technology is still a very new concept in Türkiye. In Türkiye, a cooperative project has recently been launched involving TARNET, a technology company affiliated with the Agricultural Credit Cooperatives, and the General Directorate of Agricultural Research and Policies, a state institution. Within the scope of this protocol, different types of orchards and a small area under paddy cultivation were sprayed using AUAVs. Despite these small developments, there is a lack of information on how to ensure the widespread use of AUAVs in Türkiye. The vast majority of farmers have little or no knowledge about AUAVs. As an emerging technology, AUAVs represent a new method for farm spraying. There are also many unknowns regarding technology adoption and use. Moreover, the attitudes of farmers toward agricultural drone spraying are not well known.

The purpose of this article is to investigate the factors affecting the intentions of farmers to adopt agricultural drones. The AUAV types under consideration in this study are with a spraying feature. This study focuses on identifying the factors affecting the acceptance of crop spraying with AUAVs, which is a precision agriculture practice, by Turkish farmers. Thus, it makes important contributions to the literature. The information obtained from this research not only provides new insights for decision-makers regarding

the adoption of AUAV technology but also contributes to the preparation of the promotion process for potential market actors.

## 2. The Literature Review

The literature is generally focused on the adoption of precision agriculture practices. In general, research can be grouped as the effect of socio-demographic characteristics on technology adoption, the effect of economic reasons on adoption, and the facilitating factors that enable adoption. It can be stated that socio-demographic characteristics play a role in the adoption of precision agriculture practices by farmers. Accordingly, a high level of education [36–39], farm size [40], high labor intensity [41], and interest in technology [42–44] positively contribute to the adoption of precision agriculture practices. On the other hand, the age of farmers [45–47], experience [48], and small farm size [49,50] negatively contribute to the adoption of precision agriculture practices.

Another important issue in the adoption of technology by farmers is economic considerations. Accordingly, high investment cost [15,51–54] and perceived profitability [16] can be significant barriers to adoption. AUAV technology has an initial cost of ownership of around USD 15–25,000, according to the dealers selling AUAVs in Türkiye [55]. AUAVs have the ability to spray. This can be a significant barrier to adoption by farmers. Therefore, the farmers' attitudes toward the factors that facilitate adoption should be monitored.

Previous studies show that facilitating factors play an important role in the adoption of precision agriculture practices [7]. Studies suggest that financial subsidies can encourage farmers to adopt a new technology [56]. Access to financial support, such as government subsidies and loans on the condition of purchasing an AUAV, can be listed as a facilitating factor. In addition, another facilitating factor is infrastructural and organizational support in access to technology [57]. In this context, the issue of renting an AUAV can be considered as another facilitating factor. In such a case, how much the rental fee should be, who will provide this service, and what the farmer's expectations are may affect adoption.

While the issue of farmers' adoption of precision agriculture practices covers a large body of literature, there is a limited number of studies on farmers' intentions to adopt AUAVs. A group of studies emphasized the importance of sensory characteristics. Michels et al. (2021) [58] investigated the factors influencing the intention of German farmers to use agricultural UAVs utilizing the technology acceptance model. He found that confidence in using drones increases acceptance. Several studies in China found that perceived ease of use, perceived utility [22], leadership [59], and cooperative membership [60] were positively associated with farmers' willingness to adopt agricultural UAVs. Skevas and Kalaitzandonakes (2020) [61] emphasized future prospects for farmers, arguing that specific information on environmental and economic benefits plays an important role in encouraging American farmers to adopt agricultural UAVs.

Another group of researchers emphasized socioeconomic variables. Michels et al. (2020) [62] analyzed a sample of German farmers. While farm size positively influenced the adoption process, age had a negative effect. Another study conducted in Hungary reached similar conclusions. Farm size, age, and education affect the acceptance process [63]. Another study conducted for Australian farmers found that higher education, a greater need for water, farm capital, and a holistic farm structure positively contributed to the adoption of AUAVs [64]. The consensus in some studies is that access to borrowing channels positively affects the adoption of AUAVs [24,59,61].

In summary, the literature shows that the access that farmers have to the borrowing channels, their interest in technology, and positive perceptions of the advantages of equipment for their farm will have a positive impact on adoption.

To the best of our knowledge, there is no literature report that explores the factors that influence Turkish farmers' adoption of AUAV technology in the application of pesticides. It is important to empirically analyze farmers' sentiments and aspirations in support of paying for AUAV technology, given its environmental and economic contributions to agriculture.

This study was designed to answer the following research questions:

- Do farmers want to buy an AUAV?
- Do financial incentives influence the purchase decision?
- Are farmers willing to lease the AUAV?
- If so, how much are they willing to pay?
- Are there variables that influence the leasing decision?

### 3. Material and Methods

#### 3.1. Sample Selection

The sampling location of the survey was Aydin province in Türkiye. The basis of economic life in this province is agriculture and agriculture-dependent industry. The area is suitable for polyculture agriculture as a result of its soil, climate, tomographic structure, and ecological characteristics. Aydin has an area of 368,336 hectares, of which 238,416 (64.7%) hectares are used for irrigated agriculture. Aydin ranks first in fig, olive, and chestnut production, second in cotton and artichoke production, and third in strawberry and okra production in Türkiye. It contains 93% of the floral diversity in Türkiye [65].

In addition, the first smart village project to be developed by Vodafone (an international communication company) is being carried out in a village in this region. In a Vodafone Smart Village, sustainable production is realized by spreading digitalization via Internet of Things applications, such as irrigation automation, greenhouse automation, fertilizer management automation, poultry house automation, frost automation, milk automation, beekeeping automation, pedometers, and early warning systems.

As a result of these features, this province was selected for this study.

According to the information from the Chambers of Agriculture Information System, at the time of this study, there were 130,686 registered farmers in the region. The proportional sample volume formula was used to determine the number of farmers in the survey.

This formula is as follows [66]:

$$n = \frac{Np(1-p)}{(N-1)\sigma_p^2 + p(1-p)} \quad (1)$$

where  $n$  denotes the sample volume;  $N$  denotes the population volume (130,686), and  $P$  denotes the prediction rate, referring to the probability level confidence interval ( $\sigma_p$ : 0.02552 from the equation,  $1.96 \sigma_p$ : 0.05 for a 95% confidence interval, and a 0.05 margin of error). In the Formula (1), 1.96 is taken for the  $Z_{0.05}$  statistic in the normal distribution table. For the 95% confidence interval, the error is 0.05. The variance ( $\sigma_p$ ) is obtained by the properties of the error to the z-statistic.

In this study, we aimed to reach the maximum sample size. The sample volume was determined using a 95% confidence interval and a 5% margin of error.

As a result of the calculation, the sample volume was found to be 384. The sample volume obtained was proportioned depending on the number of farmers carrying out agricultural activities in Aydin. Briefly, the ratio is based on the number of farmers by region. Different statistical test techniques were used in the analysis of the questionnaire items, which were created in accordance with the objectives. The important items are listed below.

#### 3.2. Fuzzy Pairwise Comparison Method

The fuzzy pairwise comparison method is a decision-making technique. It transforms the problem under consideration into a hierarchical structure and relies on pairwise comparisons. These comparisons are performed using actual measurement values for each pair of criteria and options or using a scale that reflects the relative strength of judgments and preferences. The resulting values are represented in matrices known as pairwise comparison matrices. These matrices are then analyzed to determine which of the two criteria is more important, preferable, or dominant. In this method, subjective judgments that

cannot be directly expressed numerically can be easily analyzed. Therefore, this method was selected.

Farmers were first informed of the cost and typical usage of AUAV technology before being asked whether they would be open to purchasing this product. Then, in order to determine whether different government subsidies affect the purchase and, therefore, the adoption of this technological product, they were required to make a binary decision from a number of criteria. Farmers were given the chance to compare all five options side by side and then choose the one that, in their opinion, was more crucial. These borrowing instruments were constructed using current agricultural machinery and equipment subsidies. The policy instruments that were compared were as follows: (1) grant support for 50% of the cost of an AUAV; (2) interest-free loans for 75% of the cost of an AUAV; (3) loans with low-interest rates for the entire cost of an AUAV; (4) extra premium support for products grown by a farmer who has bought an AUAV. For the analysis of these criteria, the fuzzy pairwise comparison method was used. In order to compare the specified policies, six comparisons were presented to the farmers. For each of these comparisons, the farmers were asked to assign a value between 0 and 1. The structure of this comparison was created using a Likert-type scale, allowing the farmers to choose an intermediate value.

The steps used to carry out the method can be summarized as follows [67]: Pairwise comparisons were presented to determine farmer preferences. The total distance in the comparison was equal to 1. If  $G_{KH} = 0.5$ , then  $K \approx H$ ; if  $G_{KH} > 0.5$ , then  $K > H$ ; and if  $G_{KH} < 0.5$ , then  $K < H$ . A fuzzy paired representation was used to create comparisons between K and H. It represents the degree of preference for K over H. The change in the value was between 0 and 1 for each element. The number of paired comparisons of the objectives (C) was determined as  $C = [(Z \times (Z - 1))/2]$ . Z refers to the preferred number of objectives in the formula. In this research, 6 comparisons (C) of 4 different policies (Z) were presented to each farmer. For each pairwise comparison,  $G_{cr}$  preference was obtained. The measurement of the preference degree of r according to c can be expressed as  $G_{cr} = 1 - G_{rc}$ . In the second step, a fuzzy matrix was created. Then, the fuzzy preference matrix was generated.

$$G_{cr} = \begin{cases} 0 & \text{if } c = r \forall c, r = 1, \dots, n \\ g_{cr} & \text{if } c \neq r \forall c, r = 1, \dots, n \end{cases} \tag{2}$$

In this research, a  $4 \times 4$  fuzzy preference matrix was created for each individual, as seen below (G):

$$G = \begin{vmatrix} g_{11} & g_{12} & g_{13} & g_{14} \\ g_{21} & g_{22} & g_{23} & g_{24} \\ g_{31} & g_{32} & g_{33} & g_{34} \\ g_{41} & g_{42} & g_{43} & g_{44} \end{vmatrix} \tag{3}$$

Separately, the preferred density of each objective ( $\mu_j$ ) was obtained using the following equation:

$$\mu_j = 1 - \left( \sum_{c=1}^n G_{cr}^2 / (n - 1) \right)^{1/2} \tag{4}$$

The value of  $\mu_j$  ranges between 0 and 1.

### 3.3. Conditional Valuation Method and Lower Bound Mean

The conditional evaluation method was used to reveal the attitude regarding the desire to finance various proposed projects. This method can be used in markets that have not yet experienced significant growth [68]. Therefore, this method was adopted in this study to determine the price that farmers were willing to pay for the lease of an AUAV. Farmers were told about the advantages of using an AUAV and then asked whether they were willing to adopt this technology through a lease. From the farmers who were willing to lease, the final price they were willing to pay was requested. The obtained fees were

minimized by the lower bound meaning (LBM) method and converted into the farmers' willingness to pay to lease an AUAV [69]. The following formula was used:

$$LBM = \pi_0 P_0 + \sum_{i=1}^K \pi (P_i - P_{i-1}) \quad (5)$$

$\pi_0$  = the cumulative percentage of respondents willing to pay the initial or smallest finite amount;

$P_0$  = smallest finite amount;

$K_0$  = number for the subsequent amount.

### 3.4. VIKOR Technique

The VIKOR technique was proposed by Opricovic and Tzeng (2004) [70]. It is applicable to multi-criteria decision-making problems. The VIKOR technique allows conflicting criteria to be ranked with a common assumption and the most appropriate criterion to be selected. This method was used in our study to determine the best arrangement for farmers to purchase an AUAV service via a lease. The criteria used as the basis for the evaluation were as follows: C1: price; C2: delivery on time; C3: satisfaction with the work performed; C4: technological competence of the organization; C5: satisfaction with the personnel; C6: quality of the products used; C7: guarantee of the work performed. In Türkiye, in the near future, there will be 4 different types of institutions that can offer AUAV rental services: private sector enterprises; agricultural cooperatives; agricultural unions; and agricultural province/district centers (official state institutions). Farmers were asked to assign points for the criteria for the 4 different institutions separately. While determining the weight values of the criteria, farmers were asked to compare the criteria by giving a score between 1 and 100. Criteria weights were determined with the help of the values obtained as a result of this comparison. In brief, the application of this method was as follows:

Creating the decision matrix: A decision matrix was created with the alternatives, criteria, and the values of each alternative according to the criteria. Then, the best ( $f_j^*$ ) and worst ( $f_j^-$ ) score values were determined for each criterion;

Normalization process and creation of normalized decision matrix: where R is the normalized decision matrix;  $x_{ij}$  is the decision matrix element, and  $r_{ij}$  values for each alternative were calculated as follows:

$$r_{ij} = \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \quad (6)$$

Weighting the normalized decision matrix: the weighting for each alternative was calculated using the formula  $v_{ij} = r_{ij} \times w_j$ , where  $w_j$  represents the criteria weights;

Calculation of average group benefit ( $S_i$ ) and biggest regret ( $R_i$ ) Values:  $S_i$  is the average group score for alternative i and represents the average group benefit, and  $R_i$  is the worst group score for alternative i and represents the biggest regret. The  $Q_i$  value was calculated as follows:

$$Q_i = (q \times (S_i - S^*) / (S^- - S^*)) + ((1 - q) \times (R_i - R^*) / (R^- - R^*)) \quad (7)$$

where the value of q denotes the weight of the strategy that provides the maximum group benefit, and (1 - q) denotes the weight of the minimum regret of the dissenters. This value can be taken as (q = 0.5). The smallest values of  $S_i$ ,  $R_i$ , and  $Q_i$  denote the best alternative. The test was evaluated according to the DQ parameter. The alternative (m) was found using the formula  $DQ = 1 / (m - 1)$ . The difference between the 1st and the 2nd best alternative must be greater than DQ.

### 3.5. Probit Model

The probit model was used to measure the factors affecting the farmers’ willingness to adopt the AUAV technology. The dependent variable of willingness to adopt was binary (willing or unwilling). Therefore, this method was selected. If  $Y_i = 1$ , then the farmer was willing to adopt the AUAV technology through leasing, and if  $Y_i = 0$ , then the farmer was unwilling to adopt it. The responses of the 259 farmers who answered “no” were coded as “0” and the responses of the 125 farmers who answered “yes” were coded as “1”. This method can be defined briefly as follows:

$$Y_i^* = \alpha + \beta X_i + \mu_i \tag{8}$$

$$\Pr (Y_i = 1|X_i) = \Pr (Y_i > 1|X_i) = \Pr (\mu_i \geq -X_i\beta|X_i) = \varphi(X_i\beta) \tag{9}$$

where  $Y_i$  is the farmer’s acceptance, and  $X_i$  is a vector of all independent variables. The factors affecting technological adoption in agriculture were analyzed under the guidance of the relevant literature.

## 4. Findings

### 4.1. Description of this Study’s Population

Table 1 shows certain selected demographic and socioeconomic characteristics of the farmers surveyed. The average age of the respondents was approximately 52 years, and their work experience was 29 years. Approximately 67% of them had primary-level education. The average household size was four, and 63.3% of the farmers had more than one person in their family that was involved in farming. Of the farmers surveyed, 28.9% of the respondents stated that they intensively engaged in vineyard agriculture and 71.1% in field agriculture. Approximately 81% of the respondents stated that their most profitable land type was on the plain, while 19% of them had sloping land. The average land size of the surveyed farmers was approximately 9.83 hectares, and their income was TRY 250,000.

**Table 1.** Sociodemographic characteristics of farmers ( $n = 384$ ).

Variable	Category	Frequency	Percent	Mean	Variable	Category	Frequency	Percent	Mean
Education	Primary education	256	66.7	-	Age (year)	<42	98	25.5	51.52
	High school	94	24.5			42–53	114	29.7	
	Associate degree	18	4.7			54–61	84	21.9	
	Licence	16	4.2			61<	88	22.9	
* Annual agricultural income	<95,000	127	33.1	250,106	Land size (hectare)	<3.1	128	33.3	9.83
	95,000–200,000	127	33.1			3.1–8.0	129	33.6	
	>200,000	130	33.9			8.0<	127	33.1	
Land structure	plain	310	80.7	-	Experienced (year)	<21	99	25.8	29.47
	slope	74	19.3			21–30	115	29.9	
Help with family chores	No	141	36.7	-		31–40	101	26.3	
	Yes	243	63.3			40<	69	18.0	
Number of households	4 and below	251	65.4	3.94	Land type	Horticulture	111	28.9	-
	5 and above	133	34.6			Field agriculture	273	71.1	

\* (Research period: TRY 1 = USD 0.053).

#### 4.2. Opinions on the Use of Technology

At this stage of the research, using factor analysis, item dimensions related to farmers' attitudes toward technology adaptation were created. The data in this study were obtained with a five-point Likert-type scale (a Likert scale in which 1 denoted strongly disagree and 5 strongly agree). In the preparation of the items, 16 items were created for the questionnaire by reviewing the relevant literature, and this was reduced to 7 items with the help of factor analysis. In Table 2, information about these items, which constitutes the attitude of farmers toward technology adoption, is given. Exploratory factor analysis was used to transform inter-related data structures into independent and other new data structures. Farmers' attitudes toward technology adoption were grouped into a single dimension. Bartlett's test results showed that the items were consistent, and the Kaiser–Maher–Olkin (KMO) test results showed that the sample was adequate (KMO = 0.843; Bartlett's Test of Sphericity  $\chi^2 = 107.754$ ;  $p = 0.000 < 0.05$ ). The ratio of eigenvalues explaining the total variance was 51.90%, and the Cronbach Alpha value showing the reliability of the data was 0.837. The factor loadings of the items in the dimension varied between 0.84 and 0.51. Accordingly, the attitudes of the farmers participating in the survey toward technology adoption can be summed up by the following statements: "I feel uneasy when using a new technological tool"; "I find myself old to learn technological developments"; "Learning the use of a new technological tool is troublesome"; "The use of technology always challenges me"; "Learning technological developments is an extra burden for me"; "Using technological elements while farming scares me"; "I think technology is useful while farming".

**Table 2.** Farmer adoption of technology (factor analysis summary).

Behavioural Statements	Mean	Std. Deviation	Factor Loading	Cronbach's Alpha If Item Deleted
* I feel uneasy when using a new technological tool	3.54	0.99	0.84	0.794
* I find myself too old to learn about technological developments	3.51	1.28	0.80	0.797
* Learning the use of a new technological tool is troublesome	3.21	1.08	0.76	0.808
* The use of technology always challenges me	3.38	1.02	0.73	0.813
* Learning technological developments is an extra burden for me	3.67	0.92	0.68	0.820
* Using technological elements while farming scares me	3.00	1.33	0.66	0.829
* I think technology is useful while farming	3.92	0.94	0.51	0.841

Likert scale, where 1 = strongly disagree and 5 = strongly agree. \* Scoring is reverse calculated (KMO = 0.843; Bartlett's Test of Sphericity  $\chi^2 = 107.754$ ;  $p = 0.000 < 0.01$ ; Cronbach's Alpha 0.837).

#### 4.3. Farmers' Attitudes toward Traditional Spraying Methods

Table 3 presents farmers' attitudes toward traditional spraying methods. Half of the farmers thought that the traditional spraying methods that they used were not efficient (47.6%). However, more than half of the farmers thought that spraying with a pulverizer was very costly and damaging to their health (53.4%). On the other hand, a significant number of farmers expressed uncertainty about whether spraying with conventional spraying methods leaves residues, is harmful to the environment, and is the best way to spray. Overall, the farmers' viewpoints were complex, comprising part satisfaction and part concern about current pesticide spraying methods.

**Table 3.** Attitudes of farmers toward traditional spraying methods.

Behavioural Statements		1	2	3	4	5	Mean	Std. Deviation
I think traditional spraying is efficient	Frequency (f)	50	133	117	67	17	2.6563	1.05046
	Percent (p)	13	34.6	30.5	17.4	4.4		
I think the cost of conventional spraying is high	Frequency (f)	18	61	103	147	55	3.4167	1.06368
	Percent (p)	4.7	15.9	26.8	38.3	14.3		
Conventional spraying can leave too much pesticide residue	Frequency (f)	15	46	141	158	24	3.3385	0.90832
	Percent (p)	3.9	12.0	36.7	41.1	6.3		
I think traditional spraying is harmful to my own health	Frequency (f)	16	52	111	159	46	3.4349	1.00439
	Percent (p)	4.2	13.5	28.9	41.4	12.0		
I think traditional spraying is harmful to the environment	Frequency (f)	10	63	135	143	33	3.3281	0.93755
	Percent (p)	2.6	16.4	35.2	37.2	8.6		
I think traditional spraying is the most accurate spraying method	Frequency (f)	27	83	176	75	23	2.9583	0.96591
	Percent (p)	7.0	21.6	45.8	19.5	6.0		

Choices: strongly agree = 5; agree = 4; neutral = 3; disagree = 2; strongly disagree = 1.

#### 4.4. Farmers' Intention to Purchase Agricultural Drones

##### 4.4.1. Farmers' Attitude toward AUAV Technology

At this stage, the farmers were given a general introduction to AUAV technology and the advantages it could provide for the farm. Then, the general expectations and attitudes of the farmers concerning AUAV technology were determined (Table 4). The vast majority of farmers agreed that AUAVs could reduce the spraying time on the farm compared to a pulverizer and reduce diesel oil expenditure. Moreover, more than half of the farmers thought that AUAVs would not harm their health. However, the majority stated that the initial purchase cost was high (67.2%). On the other hand, they were hesitant about the ease of spraying and whether it would be possible to spray everywhere on their land. In addition, few farmers thought that they would be able to fly the drone even if they attended a course.

**Table 4.** Attitude of farmers toward agricultural drones.

Behavioural Statements		1	2	3	4	5	Mean	S.D.
I think the agricultural drone will provide convenience in spraying compared to the traditional method	f	2	94	170	88	30	3.13	0.89
	p	0.5	24.5	44.3	22.9	7.8		
I think that the agricultural drone will spray in a shorter time than the traditional method	f	6	35	75	175	93	3.81	0.95
	p	1.6	9.1	19.5	45.6	24.2		
I can save a lot of diesel using an agricultural drone	f	1	14	113	156	100	3.88	0.84
	p	0.3	3.6	29.4	40.6	26.0		
I can increase the yield of my field using agricultural drone	f	3	92	115	134	40	3.30	0.97
	p	0.8	24.0	29.9	34.9	10.4		
I think the purchasing cost of an agricultural drone is high	f	4	35	87	123	135	3.91	1.01
	p	1.0	9.1	22.7	32.0	35.2		
Thanks to agricultural drones, I think I can spray at every point of my land	f	21	130	125	94	14	2.86	0.99
	p	5.5	33.9	32.6	24.5	3.6		

Table 4. Cont.

Behavioural Statements		1	2	3	4	5	Mean	S.D.
If I attend a course, I will be able to fly an agricultural drone	f	149	81	78	48	28	2.28	1.29
	p	38.8	21.1	20.3	12.5	7.3		
I can save labor using an agricultural drone	f	15	104	124	113	28	3.09	1.00
	p	3.9	27.1	32.3	29.4	7.3		
I think that spraying with an agricultural drone will harm my health	f	135	139	53	37	20	2.13	1.15
	p	35.2	36.2	13.8	9.6	5.2		

Choices: strongly agree = 5; agree = 4; neutral = 3; disagree = 2; strongly disagree = 1.

#### 4.4.2. The Effect of Borrowing Channels on the Purchasing Attitude for AUAV Technology

Farmers were presented with prices for different models (USD 15,000–25,000). Farmers were asked about their preferences concerning purchasing this product. Only 12 farmers (3.12%) indicated that they would consider purchasing it. In Türkiye, various borrowing channels exist for farmers to purchase agricultural machinery. Farmers' financing opportunities are supported by the government. The government uses the Agricultural Bank, a state agricultural bank, to realize subsidies. The subsidies available vary according to the price of the equipment to be purchased. These can range from grants to long-term, low-interest, or interest-free loans. Drones have yet to be included within the scope of the support provided by the state. In the survey, farmers were asked whether the inclusion of AUAVs in such support would affect their purchase decision. After considering this, the number of farmers who stated that they would like to purchase an AUAV increased to 41. This represents 10.67% of the farmers surveyed. Thanks to the provided support, 10.67% of the surveyed farmers tended to buy AUAVs. The findings show that a possible support policy would have a positive impact on the purchase of AUAV technology (Wilcoxon test,  $Z_{-3.983}$   $p < 0.01$ ).

#### 4.4.3. Preference for Borrowing Channels

Farmers want borrowing channels to be accessible and advantageous. Therefore, the identification of the most suitable borrowing channel positively favors the purchase of AUAV technology. Therefore, the priority preferences concerning the borrowing channels of the farmers who wanted to purchase AUAVs through subsidies were determined. For this, the fuzzy pairwise comparison method was used. The farmers ( $n = 41$ –10.67%) were asked to make paired comparisons between options for agricultural support policies. They were each presented with four alternative policy instruments for comparison and asked to indicate which one they preferred in order of importance. These borrowing instruments were constructed using current agricultural machinery and equipment subsidies. The policy instruments that were compared were as follows: (1) grant support for 50% of the cost of an AUAV; (2) interest-free loans for 75% of the cost of an AUAV; (3) loans with low-interest rates for the entire cost of an AUAV; (4) extra premium support for products grown by a farmer who has bought an AUAV. Descriptive statistics of the fuzzy pairwise comparison (FPC) model showing farmer borrowing channel preferences are given in Table 5. Farmers' policy preferences were ranked from most preferred to least preferred. Within the scope of tool and equipment support, the most desired support for AUAVs was the provision of interest-free loans for 75% of the price. This was followed by a low-rate loan for the entire price of an AUAV and grant support for 50% of the price. Grant support for agricultural machinery in Türkiye is only provided for one piece of equipment and is determined by lottery. Due to the lottery system, the rate of benefiting from the support of farmers is low. The least preferred type of support was additional premium support for their products. The Friedman test was used to assess whether there was a difference between preferences. Accordingly, there was a difference. Kendall's  $W$  test was used to measure the degree of compliance (Table 5).

**Table 5.** Farmer borrowing channel preference (FPC method).

Criteria	Mean	Std. Deviation	Preference	Farmer Feature	Mean	Z	H <sub>0</sub>
If the government gives a 75% interest-free loan	0.878	0.069	1	Land Size (da)	181.85	−3.499 ***	Rejection
If the government gives 50% of the loan with normal interest	0.846	0.048	2	Annual Agricultural Income (TRY)	439,535	−3.604 ***	Rejection
If the government lends all of the money at low interest	0.765	0.081	3	Experienced (years)	29.34	−0.072	Acceptance
If the state provides additional premium support	0.746	0.115	4	Age (years)	49.60	−1.029	Acceptance

Significance level at \*\*\* < 0.01.

#### 4.4.4. Demographic Variables That Are Influential in the Purchase of an AUAV

In addition, various demographic characteristics of farmers who were willing to purchase an AUAV and farmers who were not willing to purchase an AUAV were compared (Table 5). The Mann–Whitney U test was performed to determine the differences between groups. It was determined that the land size and agricultural income of the farmers who were in favor of purchasing an AUAV were statistically different from the farmers who did not want to purchase one. A higher agricultural income and land size had a positive effect on the attitude toward purchasing an AUAV. Therefore, it can be said that farmers who owned large enterprises were more willing to purchase an AUAV. On the other hand, no statistical difference was found between the groups for age and work experience (Table 5).

#### 4.5. Farmers' Attitude to Agricultural Drone Rental

##### 4.5.1. Willingness to Pay

As an alternative, the contingent valuation method (CVM) was used to determine the preference of farmers to lease an AUAV for their own use and to determine the price they would be willing to pay for it. The advantages of using an AUAV on the farm were again stated. Then, farmers were asked how much they would be willing to pay per hectare to rent an AUAV if there was a healthy market for doing so in Türkiye. Farmers indicated the amount they would be willing to pay for the rental service. In total, 67.4% of the farmers (259 farmers) were reluctant to rent an AUAV. On the other hand, 32.6% (125 farmers) of the surveyed farmers were willing to rent an AUAV.

The lowest price farmers were willing to pay for rental services was TRY 10, and the highest was TRY 80 per hectare. The amount of money farmers were willing to pay for the AUAV rental services was converted into an overall payment trend using a lower bound mean (LBM) estimate. Those who did not want to rent services were not included in the calculation. The findings obtained from the LBM method indicated that farmers were willing to pay TRY 287.54 per hectare for the AUAV rental service (Table 6).

**Table 6.** Willingness to pay for AUAV rental services using the contingent valuation method (CVM).

Willingness to Pay (WTP)	Frequency	Percentage	Cumulative Percentage
800	5	4.0	4.0
750	1	0.8	4.8
600	1	0.8	5.6
500	6	4.8	10.4
450	6	4.8	15.2

**Table 6.** *Cont.*

Willingness to Pay (WTP)	Frequency	Percentage	Cumulative Percentage
400	9	7.2	22.4
350	8	6.4	28.8
300	41	32.8	61.6
250	22	17.6	79.2
200	20	16.0	95.2
150	1	0.8	96
100	5	4.0	100
Total respondents	125	100	

LBM = TRY 287.54 (amount agreed to be paid per hectare); TRY 1 = USD 0.053.

#### 4.5.2. Procurement of Services for AUAV Leasing

In addition to the above, we also assessed from whom farmers would like to receive the service if there was a regular market for renting AUAVs. In terms of agriculture in Türkiye, there are four different structures that can purchase AUAVs and provide technical staff employment. These are private sector enterprises, agricultural cooperatives, chambers of agriculture, and agricultural province/district centers. The VIKOR technique was utilized to determine which of these institutions stood out in the provision of rental services from the farmers' perspective. The scores obtained in the evaluation of alternatives reflect the expectations of the farmers based on their experiences since there is no market for the service yet.

The farmers that wanted to purchase AUAV services for their farms were asked to evaluate four institutions (private sector enterprises, agricultural cooperatives, chambers of agriculture, and agricultural province/district centers) as alternatives (Table 6). The criteria used in the evaluation of alternatives were as follows: C1: price advantage; C2: delivery of work on time; C3: satisfaction with the work performed; C4: technological competence; C5: satisfaction with personnel; C6: professional competence; C7: quality of materials used; C8: guarantee for unsatisfied work. All criteria were calculated according to the maximum values. These criteria were created according to the literature and were weighted by the farmers. The weighting of the criteria was as follows: C1 20%; C2 13%; C3 10%; C4 10%; C5 10%; C6 10%; C7 12%; C8 15% (Table 7).

**Table 7.** AUAV rental service selection, result of VIKOR analysis.

Criteria	Direction of Criterion	Max.							
	Criterion	C1	C2	C3	C4	C5	C6	C7	C8
	Weight of Criterion	20%	13%	10%	10%	10%	10%	12%	15%
Alternatives	Private sector institutions	47.031	80.912	80.651	63.997	95.326	50.138	65.352	83.307
	Agricultural cooperative	72.724	75.469	74.232	73.854	75.156	74.815	82.370	74.023
	Agriculture chambers	61.281	64.818	66.198	60.917	64.466	65.078	49.662	63.268
	Government personnel	83.451	50.417	51.510	83.581	53.672	83.555	78.138	51.380
f*	The best point	83.451	80.912	80.651	83.581	95.326	83.555	82.370	83.307
f <sup>-</sup>	Worst point	47.031	50.417	51.510	60.917	53.672	50.138	49.662	51.380

Table 7. Cont.

Weighted Normalized Decision Matrix									
Alternatives	Private sector institutions	0.200	0.000	0.000	0.086	0.000	0.100	0.062	0.000
	Agricultural cooperative	0.059	0.023	0.022	0.043	0.048	0.026	0.000	0.044
	Agriculture chambers	0.105	0.069	0.050	0.100	0.074	0.055	0.120	0.094
	Government personnel	0.000	0.130	0.100	0.000	0.100	0.000	0.016	0.150
		Si	Ri	Qi	Row	DQ	Order of preference		
	Private sector institutions	0.449	0.200	0.728	A3	0.333	3		
	Agricultural cooperative	0.265	0.059	0.000	A1		1		
	Agriculture chambers	0.683	0.120	0.737	A4		4		
	Government personnel	0.496	0.130	0.539	A2		2		

When the scores of the private sector were evaluated, it was observed that the highest scores were for delivery of work on time, guarantee of work, satisfaction with the work performed, and satisfaction with personnel, but the lowest scores were for the price and professional competence expectation criteria. For the government assessment, the rental price of the service and the professional and technological competence scores were high, but the delivery of work on time, the guarantee of work, and satisfaction with work scores were low. For cooperatives, the overall scores had ideal averages, while for chambers of agriculture, there were no criteria with the highest scores at all. The results of the VIKOR analysis are presented in Table 7. The agricultural cooperative alternative, which ranked first in terms of the smallest value in the Q ranking, also ranked first in terms of the smallest value in both the S and R rankings. Moreover, in the Q ranking, the difference between the score of the agricultural cooperative alternative (A1) in the first place and the provision of service from the state (A2) in the second place was greater than DQ ( $0.539 - 0.333 \geq 0$ ). Because this meets the two stability conditions, it can be stated that the findings are reliable. Accordingly, farmers would prefer to receive the service from cooperatives provided that there is a stable market for AUAV leasing (Table 7).

#### 4.5.3. Factors Affecting the Desire to Rent a Drone

Factors affecting farmers' willingness to rent drones were analyzed with the probit model (Table 8). According to the loglikelihood value, the null hypothesis was rejected, and it was decided that the model was usable. The classification ratio shows that the number of correctly predicted observations in the model is 78.6%. The rate of explaining the dependent variable of the independent variables in the model is 15.42% ( $R^2 = 15.42$ ). The model results exhibited a statistical fit. In general, when the tests are evaluated, it can be stated that the model is interpretable (Table 8).

Table 8. Factors affecting the desire to rent a drone according to the probit model results.

	Coefficient	Std. Error	Z Statistic	p-Value	Marginal Effect
Constant term	−1.23714	0.632878	−1.955	0.0506 *	
Farmer adoption of technology	0.06854	0.014719	4.657	$3.21 \times 10^{-6}$ ***	0.0236339
Agricultural income	0.31996	0.119542	2.677	0.0074 ***	0.110318
Land type	−0.33653	0.169345	−1.987	0.0469 **	−0.116031

Table 8. Cont.

	Coefficient	Std. Error	Z Statistic	p-Value	Marginal Effect
Age	−0.02267	0.010939	−2.073	0.0382 **	−0.00781861
Land size	0.00086	0.000721	1.203	0.2289	0.000299095
Experienced	0.00659	0.009385	0.703	0.4821	0.00227491
Education level	−0.09857	0.097592	−1.010	0.3125	−0.0339866

Notes: Numbers in parentheses are Z-statistics. Significance level at \* < 0.10; \*\* < 0.05; \*\*\* < 0.01. Loglikelihood = 204.911; R<sup>2</sup> = 15.42; classification ratio = 0.768; Akaike criterion = 425.822.

The variables consisted of personal characteristics, production characteristics, and farmer's attitude. These characteristics were selected based on the literature on technology adoption among farmers.

The dependent variable of this model was the response received from the following statement: "I would rent an AUAV". The response of the 259 farmers who said no was coded as "0", and the response of the 125 farmers who said yes was coded as "1". The attitude toward technology was included in the model as the average of the statements described in the section "Opinions on the use of technology". These attitudes proved to be consistent with the exploratory factor analysis. Age and land size were included in the model as open-ended, while income and land type were included categorically. Variable definitions were made in Tables 1 and 2. In light of these data, explanations were formed. Farm income and a farmer's positive attitude toward the technology positively affected the willingness to rent an AUAV, while age had a negative effect. Horticulture farmers were more likely to rent an AUAV than field crops farmers. Land size, education, and experience were statistically insignificant. According to the slope values (marginal effect), when the age of the farmer increased by 10 years, the desire to rent an AUAV decreased by 7.81%. In each income category, the willingness to rent an AUAV increased by 11.03% compared to the previous category. For horticulture farmers, the desire to rent an AUAV increased by 11.60% compared to those engaged in field farming.

## 5. Discussion and Conclusions

By contributing to environmental sustainability, unmanned aerial vehicle technology offers unique opportunities for farmers to both increase crop yields and reduce farm costs. Therefore, understanding the conditions that influence the adoption of drone technology is critical for developing new policies and initiatives.

Therefore, in this study, the factors affecting the intentions of farmers to adopt drones for agricultural work were investigated. In this research, the adoption of drone technology by farmers has been extensively studied with the help of many advanced and different testing techniques. The results obtained in this research were determined according to the information obtained from the face-to-face surveys with 368 farmers using the proportional sample volume formula. Farmers' willingness to purchase the product and some influential variables were tested with hypothesis tests. The priority of borrowing channels that farmers can use when choosing to purchase agricultural unmanned aerial vehicles has been determined using the fuzzy paired comparison method. In the research, in addition to the farmers' tendency to buy agricultural drones, the attitudes toward renting them were also examined. Factors affecting farmers' willingness to rent agricultural drones were analyzed using the probit model. The willingness of farmers to pay for agricultural drone rental was determined using the conditional valuation method. The rental cost for farmers was calculated using the lower-bound mean method. Answers to the question of which institution the farmers would like to receive rental services from were determined using the VIKOR technique.

The empirical analyses developed provide new evidence and significant contributions to the literature on the farmers' behavior toward adopting drone technologies.

The results showed a very low propensity to purchase AUAVs (3.12%). A significant proportion of farmers shared the view that the initial investment cost of AUAVs is high (67.2%). These results support those in the literature that examine the negative impact of acquisition costs on farmers' adoption of agricultural technologies [15,53,54]. When farmers were given the option of government support, their willingness to buy AUAVs increased almost three times (10.70%). Various borrowing channels had a positive impact on the purchase of AUAVs. In fact, a range of agricultural equipment and machines are within the scope of government subsidies in Türkiye, but AUAVs have yet to be included. The results show that if AUAV technology were included in the scope of support, attitudes toward purchasing agricultural drones would improve. Our results are in line with those of previous studies [24,59,61].

However, which borrowing channels are preferable for Turkish farmers? Farmers want support to be accessible and advantageous. Identifying the most suitable borrowing channel is essential to supporting the purchase of AUAVs. The empirical results show that, from the government-supported borrowing channels assessed, farmers preferred interest-free loans. Inflation rates in Türkiye are quite high. Thus, the purchase of an AUAV with an interest-free loan would reduce the price in the face of rising inflation, making it more advantageous for farmers. Therefore, it seems quite rational for farmers to incline toward this type of support. Grant support, on the other hand, has historically been a very unpopular source of credit for farmers. In fact, the grant is a no-payback alternative; however, it was their third choice. This may be due to the fact that this type of support in Türkiye is given once a year via a lottery method, and very few people benefit from it. In summary, farmers' choice of borrowing channels may differ depending on the country's structure. Policymakers can increase adoption by providing access to the most suitable borrowing channels. The existing literature will benefit from new research that concentrates on these concerns.

The research also considered the idea of leasing AUAVs as an alternative approach in addition to the option of buying them. In developing countries such as Türkiye, in particular, leasing can be an important method for adoption. In this regard, many arguments that provide possible market flows were examined in detail from the farmers' perspective. According to the empirical results, the desire to rent was higher among farmers than the desire to buy (32.6%). Farmers agreed to pay an average of TRY 287.54 per hectare for the AUAV rental service. This amount can serve as a reference for actors who want to participate in this market.

In Türkiye, there are various actors who can purchase AUAVs and offer rental services to farmers. Various private entrepreneurs, agricultural cooperatives, chambers of agriculture, and government personnel have the financial means and knowledge to actively offer this service. If such a market emerges, these four organizations will create the supply, while farmers will create the demand. Therefore, the opinions of the farmers are important.

According to the empirical analysis, farmers feel that agricultural cooperatives can deliver this service best. Cooperatives play an important role in the development of rural areas by providing consolidation for small- and medium-sized farmers. Cooperatives can use farmers' funds to purchase and lease AUAVs. This could greatly accelerate the adoption of AUAV technology by farmers.

The farmers' second choice for service procurement was government personnel. However, the number of government personnel may be insufficient to carry out this service. The farmers believed that private entrepreneurs would be more disadvantageous in terms of price compared to other service providers. In this context, what the farmers saw as a reasonable price for the service was determined as 287.54 TRY/hectare. Entrepreneurs can shape their promotion policies according to their desire to pay. In addition, agricultural income and the farmer's attitude toward technology were positively associated with the willingness to acquire an AUAV [24,63]. The age variable had no effect on the purchase of an AUAV but had an effect on the leasing trend. There was a negative relationship between willingness to rent and age. In addition, land size had a positive effect on pur-

chase. Our results support those from various other studies [59]. There was a positive but statistically insignificant effect on renting. Education and experience were statistically insignificant. These results were in contradiction with certain studies [60,64] and overlapped with others [24,62]. This is because the sociodemographic characteristics in rural areas across countries differ. The results obtained in this study support the research of Groher et al. (2020) [71]. In general, farmers who are young, interested in technology, and have high agricultural incomes make up the profile of those who will spearhead Türkiye's adoption of AUAVs.

Encouraging the use of AUAVs as a complement to precision agriculture tools will accelerate agricultural modernization and have a beneficial impact on human and environmental health. This research provides new information that can be used by policy-makers and industry representatives to promote the adoption of AUAV technology.

First, government agricultural reforms could be used to facilitate farmers' access to large economies and to encourage the adoption of AUAV technology. For example, currently, farmers can obtain a certificate for flying agricultural aircraft obtained from private institutions in Türkiye by participating in short-term courses. In order for unmanned aerial vehicle systems to be used in plant protection, product applications within the scope of agricultural difficulties, necessary permits regarding flight conditions, and permits within the scope of legislation regarding unmanned aerial vehicle systems must be obtained from the General Directorate of Civil Aviation [72]. Legal arrangements can be made to facilitate the use of drones by farmers. Agricultural extension services can be capitalized in this regard.

Secondly, the creation of an efficient market for AUAV rental, especially for Turkish farmers, will contribute to sustainable development and pave the way for the formation of new commercial sectors.

Third, agricultural cooperatives should be supported to ensure that all groups of farmers have access to the service. Farmers may have trouble obtaining certification and training. Therefore, we suggest that agricultural cooperatives develop rental processes by introducing expert personnel. Thus, a new employment area can be developed. Experienced people in the field of agriculture can support farmers who need assistance in flying drones, for a fee, through cooperatives by obtaining the necessary certificates. New scientific studies should combine the goals of legislation, certification, and job creation with regard to agricultural drones.

Finally, access to the right borrowing channels will accelerate adoption, and it should, therefore, be encouraged.

Although this study has an empirical perspective, some limitations should be mentioned. This research analyzes a market that is not yet fully completed and is open to development. Therefore, responses from the farmers reflect current attitudes, and the behavioral tendencies of farmers may differ. In addition, this study has a geographical limitation: it only includes farmers operating in Türkiye. Based on the limitations of this study, it is recommended to be replicated in more countries while it is still in its early stages. In this way, the adoption process of AUAVs by farmers can be better understood, and the adoption can be accelerated.

**Author Contributions:** All authors approved the submitted article. The authors' contribution to the article is as follows: conceptualization, G.C. and O.P.; methodology, G.C.; software, G.C.; validation, G.C. and O.P.; formal analysis, G.C.; investigation, G.C.; resources, G.C.; data curation, G.C. and O.P.; writing—original draft preparation, G.C.; writing—review and editing, G.C.; visualization, G.C.; supervision, G.C.; project administration, G.C. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** The data were collected via face-to-face surveys with the consent of the farmers involved. Participation was based on the farmers' explicit consent.

**Conflicts of Interest:** The authors have no financial or proprietary interest in any material discussed in this article. The presented article is original. The submitted article has not been published in any other journal. The article was not submitted for publication in any other journal.

## References

1. Gomiero, T.; Pimentel, D.; Paoletti, M.G. Is there a need for a more sustainable agriculture? *Crit. Rev. Plant Sci.* **2011**, *30*, 6–23. [CrossRef]
2. Tahat, M.M.; Alananbeh, K.M.; Othman, Y.A.; Leskovar, D.I. Soil health and sustainable agriculture. *Sustainability* **2020**, *12*, 4859. [CrossRef]
3. UNEP. *The Environmental Food Crisis: The Environment's Role in Averting Future Food Crises*; United Nations Environment Programme: Nairobi, Kenya, 2009.
4. Gomiero, T.; Paoletti, M.G.; Pimentel, D. Energy and environmental issues in organic and conventional agriculture. *Crit. Rev. Plant Sci.* **2008**, *27*, 239–254. [CrossRef]
5. Hrustek, L. Sustainability driven by agriculture through digital transformation. *Sustainability* **2020**, *12*, 8596. [CrossRef]
6. Gebbers, R.; Adamchuk, V.I. Precision agriculture and food security. *Science* **2010**, *327*, 828–831. [CrossRef]
7. Li, W.; Clark, B.; Taylor, J.A.; Kendall, H.; Jones, G.; Li, Z.; Jin, S.; Zhao, C.; Yang, G.; Shuai, C. A hybrid modelling approach to understanding adoption of precision agriculture technologies in Chinese cropping systems. *Comput. Electron. Agric.* **2020**, *172*, 105305. [CrossRef]
8. Bahn, R.A.; Yehya, A.A.K.; Zurayk, R. Digitalization for sustainable agri-food systems: Potential, status, and risks for the MENA region. *Sustainability* **2021**, *13*, 3223. [CrossRef]
9. ISPA. Precision Ag Definition. 2018. Available online: <https://www.ispag.org/about/definition> (accessed on 22 May 2020).
10. Fulton, J.P.; Port, K. Precision agriculture data management. In *Precision Agriculture Basics*; Shannon, D.K., Clay, D.E., Kitchen, N.R., Eds.; Wiley Online Library: Hoboken, NJ, USA, 2018; pp. 169–187. [CrossRef]
11. Sishodia, R.P.; Ray, R.L.; Singh, S.K. Applications of remote sensing in precision agriculture: A review. *Remote Sens.* **2020**, *12*, 3136. [CrossRef]
12. Lamb, D.W.; Brown, R.B. Pa—Precision agriculture: Remote-sensing and mapping of weeds in crops. *J. Agric. Eng. Res.* **2001**, *78*, 117–125. [CrossRef]
13. Usery, E.L.; Pocknee, S.; Boydell, B. Precision farming data management using geographic information systems. *Photogramm. Eng. Remote Sens.* **1995**, *61*, 1383–1392.
14. Tey, Y.S.; Brindal, M. Factors influencing the adoption of precision agricultural technologies: A review for policy implications. *Precis. Agric.* **2012**, *13*, 713–730. [CrossRef]
15. Schimmelpfennig, D. Crop Production Costs, Profits, and Ecosystem Stewardship with Precision Agriculture. *J. Agric. Appl. Econ.* **2018**, *50*, 81–103. [CrossRef]
16. Ma, L.; Feng, S.; Reidsma, P.; Qu, F.; Heerink, N. Identifying entry points to improve fertilizer use efficiency in Taihu Basin, China. *Land Use Policy* **2014**, *37*, 52–59. [CrossRef]
17. Kolady, D.E.; Van der Sluis, E.; Uddin, M.M.; Deutz, A.P. Determinants of adoption and adoption intensity of precision agriculture technologies: Evidence from South Dakota. *Precis. Agric.* **2021**, *22*, 689–710. [CrossRef]
18. Puri, V.; Nayyar, A.; Raja, L. Agriculture drones: A modern breakthrough in precision agriculture. *J. Stat. Manag. Syst.* **2017**, *20*, 507–518. [CrossRef]
19. Shafi, U.; Mumtaz, R.; García-Nieto, J.; Hassan, S.A.; Zaidi, S.A.R.; Iqbal, N. Precision agriculture techniques and practices: From considerations to applications. *Sensors* **2019**, *19*, 3796. [CrossRef]
20. Sharma, N.; Singhvi, R. Effects of chemical fertilizers and pesticides on human health and environment: A review. *Int. J. Agric. Environ. Biotechnol.* **2017**, *10*, 675–680. [CrossRef]
21. Bhalli, J.A.; Ali, T.; Asi, M.R.; Khalid, Z.M.; Ceppi, M.; Khan, Q.M. DNA damage in Pakistani agricultural workers exposed to mixture of pesticides. *Environ. Mol. Mutagen.* **2009**, *50*, 37–45. [CrossRef]
22. Antle, J.M.; Capalbo, S.M. Pesticides, productivity, and farmer health: Implications for regulatory policy and agricultural research. *Am. J. Agric. Econ.* **1994**, *76*, 598–602. [CrossRef]
23. Dhananjayan, V.; Jayakumar, S.; Ravichandran, B. Conventional methods of pesticide application in agricultural field and fate of the pesticides in the environment and human health. In *Controlled Release of Pesticides for Sustainable Agriculture*; Springer Nature: Cham, Switzerland, 2020; pp. 1–39.
24. Zheng, S.; Wang, Z.; Waheim, C.J. Technology adoption among farmers in Jilin Province, China: The case of aerial pesticide application. *China Agric. Econ. Rev.* **2019**, *11*, 206–216. [CrossRef]
25. Schmale, D.G., III; Dingus, B.R.; Reinholtz, C. Development and Application of an Autonomous Unmanned Aerial Vehicle for Precise Aerobiological Sampling Above Agricultural Fields. *J. Field Robot.* **2008**, *25*, 133–147. [CrossRef]
26. Zhang, C.; Kovacs, J.M. The application of small unmanned aerial systems for precision agriculture: A review. *Precis. Agric.* **2012**, *13*, 693–712. [CrossRef]
27. Urbahs, A.; Jonaite, I. Features of the use of unmanned aerial vehicles for agriculture applications. *Aviation* **2013**, *17*, 170–175. [CrossRef]

28. Kim, H.G.; Park, J.-S.; Lee, D.-H. Potential of Unmanned Aerial Sampling for Monitoring Insect Populations in Rice Fields. *Fla. Entomol.* **2018**, *101*, 330–334. [[CrossRef](#)]
29. Talaviya, T.; Shah, D.; Patel, N.; Yagnik, H.; Shah, M. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artif. Intell. Agric.* **2020**, *4*, 58–73. [[CrossRef](#)]
30. Maes, W.H.; Steppe, K. Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. *Trends Plant Sci.* **2019**, *24*, 152–164. [[CrossRef](#)]
31. Cavallo, E.; Ferrari, E.; Bollani, L.; Coccia, M. Attitudes and behaviour of adopters of technological innovations in agricultural tractors: A case study in Italian agricultural system. *Agric. Syst.* **2014**, *130*, 44–54. [[CrossRef](#)]
32. Sheahan, M.; Black, R.; Jayne, T.S. Are Kenyan farmers under-utilizing fertilizer? Implications for input intensification strategies and research. *Food Policy* **2013**, *41*, 39–52. [[CrossRef](#)]
33. Dhraief, M.Z.; Bedhief, S.; Dhehibi, B.; Oueslati-Zlaoui, M.; Jebali, O.; Ben-Youssef, S. Factors affecting innovative technologies adoption by livestock holders in arid area of Tunisia. *New Medit Mediterr. J. Econ.* **2019**, *4*, 3–18. [[CrossRef](#)]
34. Takahashi, K.; Muraoka, R.; Otsuka, K. Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agric. Econ.* **2020**, *51*, 31–45. [[CrossRef](#)]
35. Nowak, B. Precision agriculture: Where do we stand? A review of the adoption of precision agriculture technologies on field crops farms in developed countries. *Agric. Res.* **2021**, *10*, 515–522. [[CrossRef](#)]
36. McBride, W.D.; Daberkow, S.G. Information and the adoption of precision farming technologies. *J. Agribus.* **2003**, *21*, 21–38. [[CrossRef](#)]
37. Roberts, R.K.; English, B.C.; Larson, J.A.; Cochran, R.L.; Goodman, W.R.; Larkin, S.L.; Marra, M.C.; Martin, S.W.; Shurley, W.D.; Reeves, J.M. Adoption of site-specific information and variable-rate technologies in cotton precision farming. *J. Agric. Appl. Econ.* **2004**, *36*, 143–158. [[CrossRef](#)]
38. Briggeman, B.C.; Whitacre, B.E. Farming and the internet: Reasons for non-use. *Agric. Resour. Econ. Rev.* **2010**, *39*, 571–584. [[CrossRef](#)]
39. Smith, A.; Goe, W.R.; Kenney, M.; Morrison Paul, C.J. Computer and Internet use by Great Plains farmers. *J. Agric. Resour. Econ.* **2004**, *70*, 481–500. Available online: <https://www.jstor.org/stable/40987245> (accessed on 11 May 2022). [[CrossRef](#)]
40. Balogh, P.; Bai, A.; Czibere, I.; Kovách, I.; Fodor, L.; Bujdos, Á.; Sulyok, D.; Gabnai, Z.; Birkner, Z. Economic and social barriers of precision farming in Hungary. *Agronomy* **2021**, *11*, 1112. [[CrossRef](#)]
41. Vecchio, Y.; Agnusdei, G.P.; Miglietta, P.P.; Capitanio, F. Adoption of precision farming tools: The case of Italian farmers. *Int. J. Environ. Res. Public Health* **2020**, *17*, 869. [[CrossRef](#)]
42. Batte, M.T.; Arnholt, M.W. Precision farming adoption and use in Ohio: Case studies of six leading-edge adopters. *Comput. Electron. Agric.* **2003**, *38*, 125–139. [[CrossRef](#)]
43. Adrian, A.M.; Norwood, S.H.; Mask, P.L. Producers' perceptions and attitudes toward precision agriculture technologies. *Comput. Electron. Agric.* **2005**, *48*, 256–271. [[CrossRef](#)]
44. Caffaro, F.; Cremasco, M.M.; Roccato, M.; Cavallo, E. Drivers of farmers' intention to adopt technological innovations in Italy: The role of information sources, perceived usefulness, and perceived ease of use. *J. Rural Stud.* **2020**, *76*, 264–271. [[CrossRef](#)]
45. Tamirat, T.W.; Pedersen, S.M.; Lind, K.M. Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany. *Acta Agric. Scand. Sect. B Soil Plant Sci.* **2018**, *68*, 349–357. [[CrossRef](#)]
46. Tiffin, R.; Balcombe, K. The determinants of technology adoption by UK farmers using Bayesian model averaging: The cases of organic production and computer usage. *Aust. J. Agric. Resour. Econ.* **2011**, *55*, 579–598. [[CrossRef](#)]
47. Michels, M.; Fecke, W.; Feil, J.H.; Musshoff, O.; Pigisch, J.; Krone, S. Smartphone adoption and use in agriculture: Empirical evidence from Germany. *Precis. Agric.* **2020**, *21*, 403–425. [[CrossRef](#)]
48. Carrer, M.J.; de Souza Filho, H.M.; Batalha, M.O. Factors influencing the adoption of Farm Management Information Systems (FMIS) by Brazilian citrus farmers. *Comput. Electron. Agric.* **2017**, *138*, 11–19. [[CrossRef](#)]
49. Paustian, M.; Theuvsen, L. Adoption of precision agriculture technologies by German crop farmers. *Precis. Agric.* **2017**, *18*, 701–716. [[CrossRef](#)]
50. Robertson, M.J.; Llewellyn, R.S.; Mandel, R.; Lawes, R.; Bramley, R.G.V.; Swift, L. Adoption of variable rate fertiliser application in the Australian grains industry: Status, issues and prospects. *Precis. Agric.* **2012**, *13*, 181–199. [[CrossRef](#)]
51. Reichardt, M.; Jürgens, C. Adoption and future perspective of precision farming in Germany: Results of several surveys among different agricultural target groups. *Precis. Agric.* **2009**, *10*, 73–94. [[CrossRef](#)]
52. Shockley, J.M.; Dillon, C.R.; Stombaugh, T.S. A whole farm analysis of the influence of auto-steer navigation on net returns, risk, and production practices. *J. Agric. Appl. Econ.* **2011**, *43*, 57–75. [[CrossRef](#)]
53. Schimmelpfennig, D.; Ebel, R. Sequential Adoption and Cost Savings from Precision Agriculture. *J. Agric. Resour. Econ.* **2016**, *41*, 97–115. Available online: <https://www.jstor.org/stable/44131378> (accessed on 14 March 2022).
54. Lambert, D.M.; Paudel, K.P.; Larson, J.A. Bundled adoption of precision agriculture technologies by cotton producers. *J. Agric. Resour. Econ.* **2015**, *40*, 325–345. Available online: <https://www.jstor.org/stable/44131864> (accessed on 20 April 2022).
55. Anonymous. 2023. Available online: [https://mriha.com/raven-tar16/?gclid=CjwKCAjwlJimBhAsEiwA1hrp5gTZrK8j6AC8g7PPvvtr4EDFVJxuiiRbdK79-o6-IE6ndCLNAz1rBoChqMQAvD\\_BwE](https://mriha.com/raven-tar16/?gclid=CjwKCAjwlJimBhAsEiwA1hrp5gTZrK8j6AC8g7PPvvtr4EDFVJxuiiRbdK79-o6-IE6ndCLNAz1rBoChqMQAvD_BwE) (accessed on 25 July 2023).
56. Munz, J.; Schuele, H. Influencing the Success of Precision Farming Technology Adoption—A Model-Based Investigation of Economic Success Factors in Small-Scale Agriculture. *Agriculture* **2022**, *12*, 1773. [[CrossRef](#)]

57. Giua, C.; Materia, V.C.; Camanzi, L. Smart farming technologies adoption: Which factors play a role in the digital transition? *Technol. Soc.* **2022**, *68*, 101869. [[CrossRef](#)]
58. Michels, M.; von Hobe, C.F.; von Ahlefeld, P.J.W.; Musshoff, O. The adoption of drones in German agriculture: A structural equation model. *Precis. Agric.* **2021**, *22*, 1728–1748. [[CrossRef](#)]
59. Wachenheim, C.; Fan, L.; Zheng, S. Adoption of unmanned aerial vehicles for pesticide application: Role of social network, resource endowment, and perceptions. *Technol. Soc.* **2021**, *64*, 101470. [[CrossRef](#)]
60. Chen, Q.; Wachenheim, C.; Zheng, S. Land scale, cooperative membership and benefits information: Unmanned aerial vehicle adoption in China. *Sustain. Futures* **2020**, *2*, 100025. [[CrossRef](#)]
61. Skevas, T.; Kalaitzandonakes, N. Farmer awareness, perceptions and adoption of unmanned aerial vehicles: Evidence from Missouri. *Int. Food Agribus. Manag. Rev.* **2020**, *23*, 469–485. [[CrossRef](#)]
62. Michels, M.; von Hobe, C.F.; Musshoff, O. A trans-theoretical model for the adoption of drones by large-scale German farmers. *J. Rural Stud.* **2020**, *75*, 80–88. [[CrossRef](#)]
63. Bai, A.; Kovách, I.; Czibere, I.; Megyesi, B.; Balogh, P. Examining the Adoption of Drones and Categorisation of Precision Elements among Hungarian Precision Farmers Using a Trans-Theoretical Model. *Drones* **2022**, *6*, 200. [[CrossRef](#)]
64. Zuo, A.; Wheeler, S.A.; Sun, H. Flying over the farm: Understanding drone adoption by Australian irrigators. *Precis. Agric.* **2021**, *22*, 1973–1991. [[CrossRef](#)]
65. Anonymous. 2023. Available online: <http://www.vodafoneakillikoy.com/> (accessed on 11 May 2023).
66. Newbold, P. *Statistics for Business and Economics*; Prentice-Hall International: Hoboken, NJ, USA, 1995.
67. Tanaka, K. *An Introduction to Fuzzy Logic for Practical Applications*; Springer: New York, NY, USA, 1997.
68. Carson, R.T. Contingent valuation: A user's guide. *Environ. Sci. Technol.* **2000**, *34*, 1413–1418. [[CrossRef](#)]
69. Blaine, W.T.; Lichtkoppler, F.R.; Standbro, R. An assessment of residents' willingness to pay for green space and farmland preservation conservation easements using the contingent valuation method (CVM). *J. Ext.* **2003**, *41*, 5.
70. Opricovic, S.; ve Tzeng, G.-H. Compromise Solution by MCDM Methods: A Comparative Analysis of VIKOR and TOPSIS. *Eur. J. Oper. Res.* **2004**, *156*, 445–455. [[CrossRef](#)]
71. Groher, T.; Heitkämper, K.; Walter, A.; Liebisch, F.; Umstätter, C. Status quo of adoption of precision agriculture enabling technologies in Swiss plant production. *Precis. Agric.* **2020**, *21*, 1327–1350. [[CrossRef](#)]
72. Anonymous. 2023. Available online: <https://iha.shgm.gov.tr/public/index?ReturnUrl=%2f> (accessed on 20 July 2023).

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.