PLANT SCIENCE TODAY
Vol 12(sp4): 1-7
https://doi.org/10.14719/pst.9539

eISSN 2348-1900

RESEARCH ARTICLE

Farmers' intention to adopt drone technology: A structural equation modelling approach

S Kowsalya[1], N Venkatesa Palanichamy[2*], A Rohini[1], M Kalpana[3], D Murugananthi[4] & R Parimalarangan[5]

[1]Department of Agricultural and Rural Management, Tamil Nadu Agricultural University, Coimbatore 641 003, India
[2]Agriculture College and Research Institute, Tamil Nadu Agricultural University, Coimbatore 641 003, India
[3]Office of the Dean (Agriculture), Tamil Nadu Agricultural University, Coimbatore 641 003, India
[4]Directorate of Agribusiness Development, Tamil Nadu Agricultural University, Coimbatore 641 003, India
[5]Directorate of Research, Tamil Nadu Agricultural University, Coimbatore 641 003, India

*Correspondence email - nvpchamy@tnau.ac.in

Received: 20 May 2025; Accepted: 16 October 2025; Available online: Version 1.0: 01 December 2025

Cite this article: Kowsalya S, Venkatesa PN, Rohini A, Kalpana M, Murugananthi D, Parimalarangan R. Farmers' intention to adopt drone technology: A structural equation modelling approach. Plant Science Today. 2025; 12(sp4): 1-7. https://doi.org/10.14719/pst.9539

Abstract

Drones have recently become a part of the precision agriculture (PA) technology toolkit. Drones are transforming agricultural methods by improving crop management's accuracy and efficiency. However, despite their potential benefits, adoption rates remain low and research on drone adoption in agriculture is limited. Thus, the paper aims to assess factors influencing farmers' perceptions of adopting drone technology in agriculture and identify the challenges farmers face when incorporating it into farming practices in the Western Zone of Tamil Nadu. A total of 228 farmers were personally interviewed in 2024 as part of the survey. The Structural Equation Modelling indicated that perceived importance of drones ($\beta = 0.908$, $p < 0.01$), job relevance ($\beta = 0.603$, $p < 0.01$) and farmers' attitude ($\beta = 0.187$, $p < 0.01$) were significant predictors of adoption intention. The model showed strong internal consistency and validity, with Cronbach's Alpha (CA) values between 0.79 and 0.92 and AVE values above 0.70. The findings suggest that increasing farmers' awareness of drone applications specific to their farms and boosting their confidence in using drones can enhance adoption rates. High cost, poor connectivity, limited awareness about the benefits, lack of timely availability of drones during peak seasons, fear of unemployment and limited availability of training programs emerged as key barriers to drone adoption among farmers. Addressing these challenges is crucial for promoting effective and widespread use of drone technology in agriculture. These insights are valuable for agribusinesses involved in drone development, sales and services and for research on PA technologies.

Keywords: constraints; precision agriculture; precision farming; technology adoption; unmanned aerial vehicle

Introduction

Agricultural production meets the difficulty of supplying the world's expanding population with food and raw materials. At the same time, as agriculture is anticipated to significantly contribute to environmental and climatic protection, sustainability and resource efficiency issues are seen as becoming ever more important parts of agricultural production (1, 2). The term PA refers to management techniques, strategies and related technologies that assist in making decisions about how best to use resources, increase productivity, profitability and simultaneously reduce externalities from agricultural production by analyzing individual, time-based and geographic data (3-5). Unmanned aerial vehicles (UAVs), also called drones, are an exciting new tool for farmers' PA technology. Drones provide greater flexibility because they may begin almost at any desired moment and increase spatial and spectral resolution (6-9). It is pointed out that because drones are perhaps the newest technology for PA (8, 9), their use in agriculture has not yet taken off. Precision Agriculture will eventually use 80 % of all drones (10). Sensors and digital cameras installed on drones are the main components that give them a high degree of multifunctionality (11). Precision farming is beneficial for accurately locating geographical positions using remote sensing. Drone technology has quickly become a revolutionary technology in contemporary agriculture, providing farm management systems with previously unimaginable levels of efficiency, accuracy and sustainability (12, 13). Various applications, including crop health monitoring, early disease and pest identification, irrigation management, precision pesticide and fertilizer spraying, soil analysis and real-time yield estimation, are made possible by agricultural drones equipped with advanced detectors and data analytics (14). It provides a solid basis for many contemporary agricultural operations, including insecticide and fertilizer application, seeding, irrigation, harvesting and crop monitoring. UAV spray technology is one that a pilot on a ground station may operate independently using pre-programmed flight patterns (15-17). Drones help farmers make timely, well-informed decisions that maximize crop output, reduce environmental impact and optimize resource use by delivering high-resolution imagery and relevant field data (18). Soil compaction and drudgery can be eliminated using UAVs instead of ground machinery and human labor (19, 20). Drones' capabilities have been further enhanced by recent developments, such as the incorporation of artificial intelligence (AI) and machine learning, making them essential for intelligent, data-driven agriculture and facilitating the global transition to more sustainable farming methods (21). The transition from conventional to mechanized farming opens up intensive farming opportunities (22). Precision farming supports sustainable agriculture by maximizing resource utilization at the lowest possible cost and time (23).

Drone applications have grown exponentially during the past ten years. Based on the statistical report, the drone industry is expected to generate USD 4.4 billion in sales globally in 2024 and expand at a compound annual growth rate (CAGR) of 2.26 % each year. The United States dominates the drone industry, which is expected to generate USD 1.4 billion in sales by 2024. The Indian drone market is expected to grow at a compound annual growth rate (CAGR, 2024-2028) of 5.96 %, bringing in USD 27.0 million in 2024. However, several problems affect the agricultural industry, including low productivity, declining soil quality, water scarcity and rising input and commodity prices. The need for agricultural drones with advanced cameras and sensors to handle these issues is increasing as more people become aware of cutting-edge technology in agriculture (8). Integrating them into sustainable agriculture techniques may be remarkable because drones effectively oversee farmers' operations and reduce environmental impact. In sustainable agriculture, drones provide several advantages, including soil quality monitoring, precise irrigation by determining the crop's water and heat stress level (24), accurate, safe and cost-effective pesticide spraying to crops, weed management by creating a precise weed cover map, livestock monitoring and crop health monitoring through the capture of visuals with a multispectral camera (25).

Additionally, through effective process automation, pattern identification and insight creation, combining drone technology with AI and machine learning may enhance data analysis. This development can help farmers make data-driven decisions to manage resources, reduce pest infestations and increase harvest yields. In conclusion, drones have become essential instruments in sustainable agriculture, helping to achieve the United Nations' Sustainable Development Goals (SDG) 2 as "Zero Hunger" and 13 as "Climate Action" in 2015 by providing economical, secure, effective and sustainable agricultural methods. The use of drones for implementing sustainable farming techniques has yet to reach the intended level, despite their enormous potential (26). The Indian Government has promoted the use of drones in agriculture in a number of recent responses. The government is eager to use the word "Kisan" drone to understand farmers better and develop the country's agricultural economy (27).

In light of this, the goal is to determine which latent factors affect farmers' intentions to use drones and the adoption process holistically. Therefore, the paper aims to investigate the adoption process of drones. Considering how PA technology and drones can contribute to a more sustainable agricultural production, it is possible to assess how farmers' perceptions affect their adoption behavior and comprehend the causal relationship between latent variables. This enables the identification of options that will facilitate adoption and speed up the adoption process.

Methodology

A well-structured questionnaire was used to survey 250 farmers in the Western Zone of Tamil Nadu to gather primary data using a non-probability purposive sampling technique. The demographic analysis was also performed by documenting the details of the respondents. Of these, 228 completed responses were found valid and subsequently considered for analysis to estimate farmers' intention to adopt drone technology. The Western Zone was chosen as the study area due to its intensive cultivation practices, progressive farming systems and higher potential for adopting modern precision technologies such as drones.

Structural equation model specification

According to the model's theoretical framework, factors such as perceived job relevance, perceived importance, perceived ease of operation and farmers' attitudes significantly impacted adoption (28, 29). Fig. 1 shows an illustration of the model. It was used to assess the statistical approaches that allow measuring the association between discrete or continuous variables. They were quantified using the structural equation model (SEM), which directly connects path diagrams and equations and fit statistics through a mix of factor analysis and regression (30). The statistical connection between exogenous and endogenous latent variables was described by SEM. The equation of the SEM is given as:

$$\theta = \beta\theta + \alpha\xi + \zeta \qquad \text{(Eqn. 1)}$$

Where, θ = endogenous latent variable,

β = Coefficient of θ, representing the effect of its own prior values,

ξ = Exogenous variable,

α = Coefficient of ξ, representing the strength of its effect,

ζ = Random error term, accounting for unexplained variation.

The measurement model below provides an association between the endogenous or exogenous variable and its observed variable:

$$A = \Lambda a\xi + \delta \qquad \text{(Eqn. 2)}$$

Where, A = Endogenous latent variable,

Λa = Coefficient linking the exogenous variable to A

ξ = Exogenous variable (independent variable influencing A)

δ = Random error term, capturing unexplained variation

$$B = \Lambda b\eta + \varepsilon \qquad \text{(Eqn. 3)}$$

Where, B = endogenous latent variable,

Λb = Coefficient linking the exogenous variable to A

η = Exogenous variable (independent variable influencing A)

ε = Random error term, capturing unexplained variation

In this case, δ represents the measurement error of A, ε represents the measurement error of B and A is the observation index of ξ. The association between measurement variables and latent variables is measured using the factor load matrices, Λa and Λb. The following is the empirical formula used to estimate intention to adopt:

$$AD = \beta 0 + \beta 1JR + \beta 2PI + \beta 3PE + \beta 4AT + \delta \qquad \text{(Eqn. 4)}$$

Where, AD = Adoption of drone in agriculture or the dependent variable under study,

β_0 = Intercept,

JR = Job relevance of drones in agriculture

PI = Perceived importance of drones in agriculture

PE = Perceived ease of operation of drones in agriculture

AT = Attitude of farmers in the use of drones in agriculture

$\beta_1, \beta_2, \beta_3, \beta_4$ = Coefficient representing the strength of each independent variable's effect on AD

δ = error term, representing unexplained variation

The endogenous and exogenous latent variables and their description are given in Table 1. Five latent variables were included in the model: adoption of drones in agriculture, perceived job relevance of drones in agriculture, perceived importance of drones in agriculture, perceived ease of operation of drones in agriculture, and attitude of farmers in the use of drones in agriculture. The adoption of drones in agriculture was considered the endogenous variable, and other latent variables were taken as exogenous latent variables. The statements were modified and put into context to align with the discussion of drones in agriculture (23). A series of questions with varying Likert values was used as a measurement variable to measure the latent variables shown in Table 1. Drone adoption has only two measurement variables, whereas farmer attitudes and perceived work relevance have four and perceived drone importance and perceived ease of operation have five variables. To prevent confusion, the measurement variables for every latent variable were coded individually. A five-point Likert scale, with 1 denoting strongly disagree and 5 denoting strongly agree, was used to rate each measurement variable. Cronbach's alpha, composite reliability, and average variance extracted (AVE) were employed to assess the model's validity and dependability. Except for the perceived simplicity of use, every element proposed to identify the factors influencing farmers' adoption of drone technology had a favorable impact on this adoption. The computer-aided program SMART PLS4 was used to represent the structural equations.

Garret ranking

The Garrett's ranking system was used to identify the challenges associated with drone use in agriculture. Garrett's ranking approach was applied to convert the sample respondents' order of value into scores. A sample of respondents ranked each aspect using this technique and the formula was then used to translate the rankings into a score value. Using the formula below, the Garett ranking was calculated.

$$\text{Per cent position} = 100*(R_{ij} - 0.5)N_j \quad \text{(Eqn. 5)}$$

Where R_{ij} = Ranking given to the i^{th} attribute by the j^{th} individual

N_j = Number of attributes ranked by the j^{th} individual

In this study, Garrett's ranking was used to identify the constraints faced by farmers when using drone technology in their farming practices.

Results and Discussion

Demographic characteristics

The demographic characteristics of the farmers in the study area are illustrated in Table 2. Among 228 farmers, the majority were male (93 %), followed by female (7 %), which shows that male farmers are generally more likely to be recognized as the primary decision-makers and thus are overrepresented in surveys on technology adoption (31). The majority of the farmers were in the age group of 35-44 years (33 %), followed by 45-54 years (24 %), followed by 55 and above years (19 %), followed by 25-34 years (14 %), followed by 15-24 years (10 %) which shows

Table 1. Description of the latent variables included in the structural equation model

Latent variables	Measurement variables	Measurement variable code
Perceived importance of drones in farming	Drones provide valuable data that aids in making informed decisions on the farm.	PI1
	Drones ensure precise application of resources, minimizing waste and environmental impact.	PI2
	Drones optimize farm productivity through efficient resource use and precision farming techniques.	PI3
	Drones improve operational efficiency by reducing time and enhancing task execution.	PI4
	Drones offer an innovative way to enhance farming efficiency and sustainability.	PI5
Perceived ease of operation of drones in farming	I perceive the process of learning to operate drones as seamless and manageable.	PE1
	I perceive the drones as efficient and accessible tools for operational use.	PE2
	I perceive the operation of drones as easy to understand.	PE3
	Learning to operate a drone is not a challenge for me.	PE4
	The maintenance requirements for the drone are easy to understand and perform.	PE5
Attitude of farmers using drones	I view myself as gaining expertise in using drones and digital technologies in farming.	AT1
	I perceive drone usage as simple and beneficial in encouraging its adoption in farming.	AT2
	I feel confident in using drones effectively for various agricultural tasks.	AT3
	I feel confident in using drones without requiring extensive technical knowledge.	AT4
Job relevance of drones in agriculture	The use has a significant impact on several farm operational processes.	JR1
	The Usage of drones is important for my farm job.	JR2
	Drones are highly relevant to my agricultural job by enhancing efficiency and precision in farming tasks.	JR3
	Drones are vital for improving the safety and ease of agricultural jobs.	JR4
Adoptions of drones in agriculture	I anticipate using drones in agricultural production purposes.	AD1
	Drones could be an aspect I utilise in the near future.	AD2

Table 2. Demographic characteristics

Demographic factors	Percentage (%)
Gender	
Male	93
Female	7
Age	
15-24	10
25-34	14
35-44	33
45-54	24
55 and above	19
Education Status	
Illiterate	3
Primary School	27
Higher Secondary	29
Graduation	21
Post Graduation	20
Annual Income	
3 or less (lakhs)	24
3 to 5 lakhs	34
5 to 10 lakhs	30
Above 10 lakhs	12
Farming Experience	
5 or less years	10
6 to 10 years	26
11 to 15 years	29
16 to 20 years	20
Above 20 years	15
Awareness on drone technology	
Aware	95
Unaware	5
Adoption of drone technology	
Adopters	70
Non adopters	30

that middle-aged farmers are more inclined to adopt new agricultural technologies since they have more expertise and are more eager to try out innovative technology (32). Regarding the level of education, the majority of the farmers were secondary level (29 %), followed by primary level (27 %), followed by graduation (21 %), followed by post-graduation (20 %) and illiterate were only (3 %) which showed that farmers with higher levels of education typically adopt digital agricultural technologies more quickly because they are better able to understand the operational advantages and recognize technical instructions (32). With respect to the annual income of the farmers, the majority of the farmers had an income of 3-5 lakhs (34 %), followed by 5 to 10 lakhs (30 %), 3 or less lakhs (24 %) and more than 10 lakhs (12 %). Regarding farming experience, the majority of the farmers have farming experience of about 11-15 years (29 %), followed by 6-10 years (26 %), followed by 16-20 years (20 %), followed by 20 years and above (15 %) and 5 years or less (10 %). Regarding awareness, most of the farmers (95 %) were aware of drone technology and only 5 % were unaware. Regarding the adoption of drone technology, most farmers (70 %) were adopters and about 30 % were non-adopters. The demographic analysis indicates that most farmers in the study area are middle-aged males with secondary-level education and an annual income of 3-10 lakhs. A considerable proportion of farmers possess extensive farming experience, with a predominant awareness of drone technology (95 %). Furthermore, the adoption rate of drone technology stands at 70 %, highlighting its increasing integration into modern agricultural practices.

Structural equation model

Cronbach's alpha and composite reliability (CR) were used to assess the model's internal consistency and AVE was used to check its convergent validity. According to reports, the threshold values for CR, AVE and CA were 0.7, 0.8 and 0.5, respectively (30, 33). In light of the above information, the results presented in Table 1 show that every latent variable was internally consistent and suitable for estimation.

Table 3 presents the reliability and validity assessment of the latent variables used in the study, evaluated through CA, CR and AVE. The CA values for all latent variables range from 0.79 to 0.92, indicating strong internal consistency. The CR values exceed the recommended threshold of 0.70, confirming the reliability of the constructs. The AVE values are above 0.50, demonstrating adequate convergent validity. The constructs "Perceived Ease of Operation of Drones in Farming" (CR = 0.93, AVE = 0.75) and "Adoption of Drones in Agriculture" (CR = 0.96, AVE = 0.81) exhibit the highest reliability and variance extracted, reinforcing their measurement robustness. These results validate the structural model, ensuring its suitability for further analysis.

Table 3. Reliability and validity analysis for the structural equation model

Latent Variables	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Perceived importance of drone in farming	0.87	0.90	0.72
Perceived ease of operation of drones in farming	0.92	0.93	0.75
Attitude of farmers using drones	0.84	0.82	0.70
Job relevance of drones in agriculture	0.79	0.90	0.78
Adoptions of drones in agriculture	0.91	0.96	0.81

Table 4 shows the results of the structural model analysis, which indicate that the perceived importance of drones in farming significantly influences their adoption (β = 0.908, $p < 0.01$), suggesting that farmers are more inclined to use technologies that they believe would immediately increase sustainability, productivity and resource efficiency. Promoting adoption requires highlighting the useful benefits of drones, such as improved decision-making and accurate input application (34, 35). However, the perceived ease of operation of drones (β = - 0.786) did not directly impact adoption, implying that ease alone does not drive adoption decisions (5). The attitude of farmers using drones strongly affects their perceived ease of operation (β = 0.920, $p < 0.01$), indicating that a positive mindset enhances the recognition of drones' benefits and usage. Additionally, the job relevance of drones in agriculture significantly impacts both perceived importance (β = 0.426, $p < 0.01$) and adoption (β = 0.603, $p < 0.01$), demonstrating that farmers are more likely to adopt drones when they perceive them as essential to their agricultural tasks and suggesting that farmers are more willing to embrace technology that improve productivity, safety and task performance that are obviously relevant to their farm operations. Therefore, proving a connection to the real world might help promote adoption (35). Although attitude also positively influences adoption (β = 0.187, $p < 0.01$), its effect is relatively weaker than that of other factors. These findings highlight that perceived importance, job relevance and attitude are key determinants of drone adoption in agriculture, rather than ease of operation alone. To enhance adoption, it is essential to focus on improving farmers' perceptions of drone benefits, aligning drone applications with their needs and

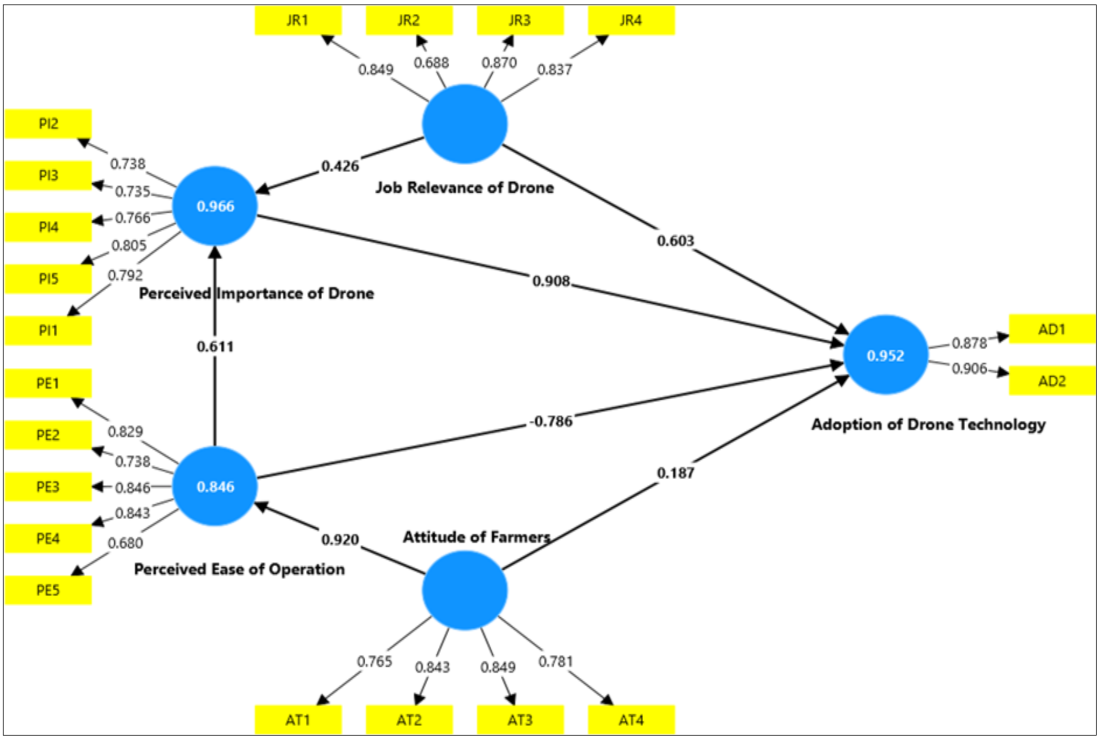

Fig. 1. Structural equation model.

Table 4. Structural equation estimates for the construct

Hypothesized path		Path Coefficient	*p*-value	Results
PE ⟶ PI	H1	0.611	<0.01	Accepted
PE ⟶ AD	H2	-0.786	-	Rejected
PI ⟶ AD	H3	0.908	<0.01	Accepted
AT ⟶ PE	H4	0.920	<0.01	Accepted
AT ⟶ AD	H5	0.187	<0.01	Accepted
JR ⟶ PI	H6	0.426	<0.01	Accepted
JR ⟶ AD	H7	0.603	<0.01	Accepted

fostering a positive attitude toward their usage.

Constraints on the usage of drone technology in agriculture

Table 5 illustrates the constraints in the usage of drone technology in agriculture. Adopting drone technology in agriculture involves several difficulties for farmers. One of the biggest obstacles is still the high initial cost (36), particularly for smallholder farmers. Poor rural connections further restrict drone operations since they require proper internet connections. Many farmers do not know the advantages of drones and delays result from their unavailability during peak seasons (37). Even though 95 % of farmers indicated they were aware of drone technology, it's possible that their self-reported knowledge may not accurately represent their deep knowledge of the benefits and uses of drones in agriculture. In reality, many farmers were aware of drones as a technology but still ignorant of how they can improve production, save labor costs, or maximize input use. This implies that although studies indicate a high level of awareness, there is still a lack of in-depth information about the advantages of drones, underscoring the necessity of focused training and extension initiatives to enhance successful adoption. Drone operation requires technical expertise, but there is a lack of training. Fear of job displacement among agricultural workers is a constraint on using drone technology. Usage is further discouraged by unfavorable weather and privacy concerns (21). Wider adoption of drone technology in agriculture can be facilitated by addressing these problems through accessible training, improved infrastructure and awareness campaigns.

Table 5. Constraints faced in the usage of drone technology

S.No	Statements	Garret Score	Rank
1	The high initial cost of drones is a significant barrier for farmers	70.42	I
2	Poor connectivity and infrastructure in rural areas affect drone operation	67.74	II
3	Limited awareness about the benefits of drone technology	66.45	III
4	Lack of timely availability of drones during peak seasons causes delays	61.38	IV
5	Operating drones requires technical expertise, which is difficult to acquire	55.16	V
6	Fear of unemployment among agricultural workers acts as a barrier to drone adoption	54.97	VI
7	Limited availability of training programs is a significant constraint to practical drone usage	54.08	VII
8	Unfavorable weather conditions limit drone operations and disrupt data collection	51.85	VIII
9	Privacy and security concerns constrain drone usage due to the collection of sensitive data	50.94	IX

Conclusion

This study offered empirical evidence that analysed the adoption of drones in agriculture and can also gather a lot of data on the process's hidden characteristics. In conclusion, the findings imply that besides conveying the financial advantages, farmers must be given a meaningful explanation and demonstration of drones and their benefits to alter their opinions and beliefs about them and eventually become more inclined to use them. Individual farmers' financial burden can be reduced by promoting rental models and app-based booking systems, especially during peak farming seasons. Costs can also be further reduced by encouraging group investment from farmers. Farmers' technical proficiency in drone operation, data interpretation and precision farming applications can be enhanced by skill development programs provided by agricultural universities, extension services and research organizations. Furthermore, tactics need to be customized to meet the unique requirements of small and marginal farmers, guaranteeing that drones are available, reasonably priced and appropriate for their crop types and farm sizes. Drone integration with real-time monitoring systems, precision agricultural technologies and farm management software can maximize input consumption, boost crop health and increase output. Adoption of drone technology in agriculture can be further accelerated and made sustainable with the help of policy assistance, early adopter subsidies and awareness campaigns emphasizing the technology's labor-saving and environmental advantages. This will increase the likelihood of success for marketing campaigns and guided applications tailored to farmers' requirements and pertinent drone application regions on the particular farm.

Acknowledgements

We express gratitude to the research facilities and library for making pertinent databases accessible. I would especially like to thank my mentors and peers for their unwavering encouragement and support. Their combined efforts have significantly improved the caliber of this work.

Authors' contributions

KS collected and analysed the data. VPN, KM and RA conceived the study and participated in its design and coordination. MD and PR participated in the study design. KS and RA participated in the design of the study and performed the analysis. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

While preparing this work, the authors used the Grammarly AI tool to improve grammar and increase the article's readability. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of publication.

References

1. EU SCAR. Agricultural knowledge and innovation systems in transition - A reflection paper. Brussels, Belgium; 2012. https://doi.org/10.2777/34991
2. Valin H, Sands RD, Van der Mensbrugghe D, Nelson GC, Ahammad H, Blanc E, et al. The future of food demand: understanding differences in global economic models. Agricultural Economics. 2014;45(1):51-67. https://doi.org/10.1111/agec.12089
3. Gebbers R, Adamchuk VI. Precision agriculture and food security. Science. 2010;327(5967):828-31. https://doi.org/10.1126/science.1183899
4. International Society of Precision Agriculture. The International Society of Precision Agriculture (ISPA). 2020. https://www.ispag.org/
5. Prabowo GS, Adi AP, Budiyanta AS, Wirawan A, Aziz A, Pranoto FS, et al. Drone-assisted climate-smart agriculture (DACSA): A spatially based outcome prediction model as an initial approach to track yield changes in shallot planting areas. Kuwait Journal of Science. 2025;100388.
6. Candiago S, Remondino F, De Giglio M, Dubbini M, Gattelli M. Evaluating multispectral images and vegetation indices for precision farming applications from UAV images. Remote Sensing. 2015;7(4):4026-47. https://doi.org/10.3390/rs70404026
7. European Commission. Drones in agriculture. Brussels, Belgium; 2018.
8. Moskvitch K. Take off: are drones the future of farming? Engineering & Technology. 2015;10(7-8):62-6. https://doi.org/10.1049/et.2015.0721
9. Bramley RG, Ouzman J. Farmer attitudes to the use of sensors and automation in fertilizer decision-making: Nitrogen fertilization in the Australian grains sector. Precision Agriculture. 2019;20(1):157-75. https://doi.org/10.1007/s11119-018-9589-y
10. Zalavadiya UB, Vasoya RN. Significance of drones in precision agriculture. Agric Environ E-Newsletter. 2020;1(2):36-40.
11. Parameswari P, Walia S. Precision farming: The future of Indian agriculture. In: Conference Proceedings of National Symposium on IFS for 3Es; 2019.
12. Singh R, Singh S. A review of Indian-based drones in the agriculture sector: Issues, challenges and solutions. Sensors. 2025;25(15):4876.
13. Datta S, Rathod MK, Mendhe HS, Pimpale AR, Ambarkar DN, Mante GS, et al. Drone technology in agriculture: A study on economic motivation of farmers. Int J Agric Food Sci. 2025;7(7):330-2.
14. Rathinavel S, Kavitha R, Surendrakumar A, Mohankumar AP, Suthakar B. Drones for horticulture.
15. Huang H, Deng J, Lan Y, Yang A, Deng X, Zhang L. A fully convolutional network for weed mapping of unmanned aerial vehicle (UAV) imagery. PLoS One. 2018;13(4):e0196302.
16. Yao W, Wang X, Lan Y, Jin J. Effect of UAV prewetting application during the flowering period of cotton on pesticide droplet deposition. Front Agric Sci Eng. 2018;5(4):455-61.
17. Xiongkui H, Bonds J, Herbst A, Langenakens J. Recent development of unmanned aerial vehicles for plant protection in East Asia. Int J Agric Biol Eng. 2017;10(3):18-30.
18. Panotra N, Kadam DM, Raj A, GD DK, Mohanty LK, Wani R, et al. Optimizing crop monitoring efficiency and precision with drone technology. Arch Curr Res Int. 2025;25(7):1-7.
19. Rathinavel S, Kavitha R, Gitanjali J, Saiprasanth R. Role of 5G technology in enhancing agricultural mechanization. In: IOP Conf Ser Earth Environ Sci. 2023;1258(1):012010. (Repetitive author: Rathinavel S, Kavitha R)
20. Otani T, Itoh A, Mizukami H, Murakami M, Yoshida S, Terae K, et al. Agricultural robot under solar panels for sowing, pruning and harvesting in a synecoculture environment. Agriculture. 2022;13(1):18.
21. Pradhan SK, Nayek D, Muduli S, Patel MA, Padhy C, Mandal A. Revolutionizing Indian agriculture with drones: A comprehensive review of applications, challenges and future prospects. J Geogr Environ Earth Sci Int. 2025;29(3):74-81.
22. Pingali P. Agricultural mechanization: adoption patterns and economic impact. In: Handbook of Agricultural Economics. 2007;3:2779-805.
23. Venkatesh V, Davis FD. A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management

Science. 2000;46(2):186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

24. Ahirwar S, Swarnkar R, Bhukya S, Namwade G. Application of drone in agriculture. Int J Curr Microbiol Appl Sci. 2019;8(1):2500-5.
25. Haenlein M, Kaplan M. A beginner's guide to partial least squares analysis. Understanding Statistics. 2004;3(4):283-97.
26. Anonymous. Budget at a glance 2022-23. India Budget; 2023.
27. Davis F. Perceived usefulness, perceived ease of use and user acceptance of information technology. MIS Q. 1989;13(3):319-40. https://doi.org/10.2307/249008
28. Sarstedt M, Ringle CM, Smith D, Reams R, Hair Jr JF. Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. J Fam Bus Strategy. 2014;5(1):105-15. https://doi.org/10.1016/j.jfbs.2014.01.002
29. Sarstedt M, Ringle M, Hair J. Partial least squares structural equation modelling. In: Handbook of Market Research. Springer; 2017;13:1-40. (Repetitive author group)
30. Hair J, Hult T, Ringle M, Sarstedt M. A primer on partial least squares structural equation modelling (PLS-SEM). Sage Publications; 2017.
31. Doss CR. Designing agricultural technology for African women farmers: Lessons from 25 years of experience. World Dev. 2001;29(12):2075-92.
32. Dawodu DA. Drone technology in precision agriculture: Are there no environmental concerns? J Environ Earth Sci. 2020;2224-3216.
33. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci. 2015;43(1):115-35. https://doi.org/10.1007/s11747-014-0403-8
34. Balafoutis AT, Beck B, Fountas S, Tsiropoulos Z, Vangeyte J, van der Wal T, et al. Smart farming technologies: Description, taxonomy and economic impact. In: Precision Agriculture: Technology and Economic Perspectives. Springer; 2017. p. 21-77.
35. Zhang W, Li H, Xia Z, Hu J, Xin M. Grain farmers' technology acceptance behaviour of plant protection UAVs. Front Sustain Food Syst. 2025;9:1583949.
36. Singh P, Singh P. Drones in Indian agriculture: Trends, challenges and policy implications. New Delhi: Indian Chamber of Food and Agriculture; 2023:1-28. https://doi.org/10.13140/RG.2.2.29651.35366/2
37. Pathak H, Kumar G, Mohapatra S, Gaikwad B, Rane J. Use of drones in agriculture: Potentials, problems and policy needs. ICAR-Natl Inst Abio Stress Manage. 2020;300:4-15.

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonepublishing.com/journals/index.php/PST/open_access_policy

Publisher's Note: Horizon e-Publishing Group remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc
See https://horizonepublishing.com/journals/index.php/PST/indexing_abstracting

Publisher information: Plant Science Today is published by HORIZON e-Publishing Group with support from Empirion Publishers Private Limited, Thiruvananthapuram, India.