Journal of Agricultural Extension
Vol. 30 (3) July, 2026
ISSN (e): 24086851; ISSN (Print): 1119944X
Website: https://www.journal.aesonnigeria.org; https://www.ajol.info/index.php/jae
Email: editorinchief@aesonnigeria.org; agricultural.extension.nigeria@gmail.com

Factors Influencing Crop Farmers' Willingness to Use Digital Decision Support Tools for Climate Change Adaptation in Ogun State, Nigeria

https://dx.doi.org/10.4314/jae.v30i3.5

Fadipe, Mubarak Olaide
Corresponding author
Department of Agricultural Extension and Rural Sociology, Olabisi Onabanjo University, Ayetoro Campus, Ogun State, Nigeria.
Email: mubarakolaide@gmail.com
Phone no: +234 805 281 3570
https://orcid.org/0000-0002-4611-6434

Ilori, Afolasade Rosemary
Department of Agricultural Extension and Rural Sociology, Olabisi Onabanjo University, Ayetoro Campus, Ogun State, Nigeria.
Email: ilori.afolasade@oouagoiwoye.edu.ng
Phone no: +234 805 9371025
https://orcid.org/0000-0002-1377-9856

Adewunmi, Abdulbasit Adeola
Department of Agricultural Extension and Rural Sociology, Olabisi Onabanjo University, Ayetoro Campus, Ogun State, Nigeria.
Email: adewunmiadeola.aa@gmail.com
Phone no: +234 816 996 1855

Olusanya, Jesubori Daniel
Department of Agricultural Extension and Rural Sociology, Olabisi Onabanjo University, Ayetoro Campus, Ogun State, Nigeria.
Email: olusanyajesubori@gmail.com
Phone no: +234 816 128 9610

Submitted: 19 April 2026
First Request for Revision: 14 May 2026
Revisions: 25, 28 May, 19, 21, 24 June 2026
Accepted: 2nd July, 2026
Published: 10 July, 2026
Cite as: Fadipe, M. O., Ilori, A. R., Adewunmi, A. A., and Olusanya, J. D. (2026). Factors influencing crop farmers' willingness to use digital decision support tools for climate change adaptation in Ogun State, Nigeria: The effects of barriers, risk perception and self-efficacy. *Journal of Agricultural Extension 30*(3)
Keywords: Climate change adaptation, digital decision support tools, willingness to use.
Conflict of interest: The authors hereby declare that there is no conflict of interest
Acknowledgements: The authors would like to express their appreciation to the farmers who took the time to participate in the survey and to the extension agents who assisted with data collection.
Funding: This research received no specific grant from public, commercial, or not-for-profit funding agencies.
Authors' contributions:
FMO: Conception/design, development of data collection instrument, analysis, interpretation of data, revised manuscript (60%)
AAA: Literature review, data collection, interpretation of data, and first draft (20%)
IAR: Curation, supervision, and review (10%)
OJD: Interpretation of data and presentation (10%)

Abstract

This study examined factors influencing farmers' willingness to use digital decision support tools for climate change adaptation in Ogun State, Nigeria. A multistage sampling procedure was used to select 233 arable crop farmers. Data were collected through a structured interview schedule *and analysed using frequencies, means, and multiple linear regression. The results show that the lack of adequate financial resources ($\bar{x}$ = 2.98) was the most frequently experienced adaptation barrier by the farmers. While a slight majority (51.1%) had a high level of risk perception, about half (50.2%) of the farmers had high self-efficacy. Most of the farmers (83.7%) were highly willing to use DSTs. Education (β = 0.141), participation in agricultural associations (β = 0.209), land ownership (β = 0.177), risk perception (β = 0.161), and self-efficacy (β = 0.201) contributed significantly to farmers' willingness to use DSTs for climate change adaptation. It is concluded that the farmers' desire to use DSTs was strongly influenced by participation in an* *association, self-efficacy, mode of land ownership, risk perception, and education. Farmers' participation in associations should be encouraged, while extension agents should improve adaptive efficacy through training and support to enhance farmers' willingness to use DSTs.*

Introduction

An increase in climate variability continues to threaten agricultural sustainability. Globally, agriculture remains one of the most climate-sensitive sectors, particularly in developing countries like Nigeria, where crop production is predominantly rain-fed and highly vulnerable to climate shocks and variability (Agboola et al., 2024). Consequently, the Intergovernmental Panel on Climate Change (IPCC, 2022) reported that smallholder crop farmers are vulnerable due to limited access to timely information on weather and agronomic practices, as well as the adaptive capacity needed to respond effectively to this climate variability. Therefore, to ensure sustained production, climate change adaptation has become necessary. As a result, farmers must now make more timely and informed decisions on agronomic practices, such as crop selection, planting and harvesting dates, pest control, and soil conservation.

In view of this, digital decision support tools (DSTs) have emerged as an effective option that could enhance farmers' adaptive capacity. These include mobile applications for farm management and climate advisory, offering location-specific and real-time data that helps with decision-making in the face of climate variability. According to Petraki et al. (2025), digital tools are used to detect weather patterns, manage production resources, optimise irrigation, monitor crop health, and enhance decision-making processes. Similarly, Larbaigt et al. (2024) emphasised that digital tools are increasingly applied across the entire agricultural value chain, enhancing the sustainable management of soil, water, and other natural resources.

Furthermore, digital technologies are being integrated into agricultural production systems to improve farmers' resilience and productivity. According to Abdurrauf et al. (2025), digital extension services and decision-support platforms can help farmers manage uncertainties arising from weather variability, pest outbreaks, and market fluctuations. Decision support tools such as mobile-based advisory systems and climate-smart applications enable farmers to optimise resource use and improve planning efficiency.

Despite the considerable potential of agricultural decision-support tools to improve climate resilience and farm management, their utilisation among farmers remains low (Adereti et al. 2024). This ineffective utilisation could result from several barriers, such as limited internet access, poor electricity supply, high cost of digital devices, and low digital literacy, among others (Abdurrauf et al., 2025). Similarly, Adereti et al. (2024) reported that the low utilisation of DSTs among farmers was a result of limited awareness, cost concerns, and trust issues. Given the various factors limiting the utilisation of DSTs among farmers as reported above, a gap exists: previous studies have focused on the characteristics of DSTs without prioritizing farmers' desires or interests and the behavioral and psychological factors that could influence farmers' decisions to utilise DSTs. Therefore, understanding farmers' willingness to use DSTs is essential, as willingness often precedes actual adoption. Without addressing the behavioural determinants of technology use, efforts to scale digital agricultural innovations may continue to yield limited results.

In Ogun State, where crop farming contributes significantly to the livelihood sustainability of rural households, the increasing effect of climate variability necessitates the adoption of innovative adaptation strategies. Various DSTs have been introduced to selected farmers in the state through training by the extension agents. DSTs such as AKILIMO, a smart agricultural tool developed and introduced by the African Cassava Agronomy Initiative (ACAI) to provide agronomic advisory services, including site-specific recommendations for fertilizer application, intercropping, and tailored planting and harvesting schedules. Similarly, the IITA Herbicide Calculator, a mobile application introduced by the International Institute of Tropical Agriculture (IITA), helps farmers accurately estimate the quantity of herbicides to be added to sprayers to avoid underdose or overdose by farmers. In addition, GeaGrow has been introduced to arable crop farmers by the SmartSoil Project in collaboration with researchers from FUNAAB and other Southwest institutions to help predict soil health for farmers and agronomists. However, understanding the extent to which the behavioral factors influence farmers' willingness to use digital decision-support tools for climate adaptation becomes imperative. Thus, the study assessed the factors influencing crop farmers' willingness to use digital decision support tools for climate change adaptation in Ogun State, Nigeria. This study specifically;

i. identified farmers' adaptation barriers to climate change;
ii. ascertained the level of farmers' risk perception to climate change;
iii. assessed the level of self-efficacy of the farmers on climate change adaptation; and
iv. examined farmers' extent of willingness to use digital decision support tools for climate change adaptation.

Methodology

The study was conducted in Ogun State, Nigeria. Ogun State is located in the South-West geopolitical zone of Nigeria, and spans between latitudes 6°15′00″N and 7°58′00″N and longitudes 2°45′00″E and 4°45′00″E. The population for the study comprised 560 farmers trained by extension agents from the Ogun State Agricultural Development Programme on the use of DSTs. Using Taro Yamane's formula with a 5% margin of error, the representative sample size is 233 farmers. A multistage sampling procedure was used to select the farmers. In the first stage, eight LGAs where the farmers were trained were purposively selected. The LGAs are Yewa North (105), Ijebu North (35), Odeda (140), Odogbolu (35), Ifo (35), Obafemi-Owode (35), Ikenne (105), and Yewa South (70). In the second stage, a simple random sampling technique was used to select a total of 233 farmers across the eight LGAs proportionately (44 in Yewa North, 15 in Ijebu North, 56 in Odeda, 15 in Odogbolu, 15 in Ifo, 15 in Obafemi-Owode, 44 in Ikenne, and 29 in Yewa South LGAs).

Data were collected using a structured interview schedule. The instrument contained questions to identify adaptation barriers; a list of possible barriers to adaptation (e. g. lack of adequate finance, lack of risk sharing mechanisms) was provided for the farmers. This was measured with a three-point rating format of strong barrier (3), mild barrier (2), and not a barrier (1). Furthermore, the level of risk perception was measured with a list of perceptual statements (e. g. in recent years, I think there has been a noticeable shift in climate patterns, such as temperature and rainfall; I am worried that climate change will reduce my crop yield in the next few years) using a Likert-type scale of strongly agree (5), agree (4), Not sure (3), disagree (2), and strongly disagree (1). The index scores of the respondents were obtained, with the maximum score being 55, while the minimum score was 11. Therefore, the farmers were categorised into two groups, with a midpoint of 33 (i.e., (55+11)/2). The decision rule was that index scores above 33 indicate high risk perception, while scores below or equal to 33 indicate low risk perception.

In addition, the level of self-efficacy to climate change adaptation was measured with a list of perceptual statements (such as, I am sure in my ability to use water management technique during dry spell; I am sure in my ability to modify planting dates to cope with changing climate patterns) using Likert-type scale of strongly agree (5), agree (4), Not sure (3), disagree (2), and strongly disagree (1). The respondents' index scores were obtained, with a maximum of 45 and a minimum of 9. Therefore, the farmers were categorised into two groups, with a cut-off point of 27 (i.e., (45+9)/2). The decision rule was that index scores above 27 indicate high self-efficacy, while scores below or equal to 27 indicate low self-efficacy.

Furthermore, the extent of farmers' willingness to use DSTs for climate change adaptation was measured using a 15-item statement (e.g., "I would be willing to use digital decision support tools if they guarantee an effective plant and harvest schedule; If DSTs are available to me, I am willing to use them"). This was measured on a rating scale of strongly willing (5), willing (4), undecided (3), unwilling (2), and strongly unwilling (1). To establish the farmers' extent of willingness, the index scores of the respondents were obtained, with the maximum score being 75, while the minimum score was 15. Thereafter, the farmers were categorised into two groups, with a cut-off point of 45 (i.e., (75+15)/2). Therefore, the decision rule was that farmers who scored less than or equal to 45 were categorised as low willingness to use DSTs, while those who scored above 45 were categorised as highly willing.

The data were analysed using percentages, mean, and standard deviation. The multiple linear regression analysis was done to determine the factors influencing farmers' willingness to use DSTs for climate change adaptation. Furthermore, the scale items used to measure risk perception, self-efficacy, and willingness to use DSTs were adjudged to have acceptable reliability coefficients. Risk perception had an omega coefficient of 0.808, while self-efficacy had an omega coefficient of 0.836, and willingness to use DST had an omega coefficient of 0.818. These indicate a good internal consistency of the scale items because they were all greater than 0.70. The regression model is explicitly stated below;

$$Y = b+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4+\beta_5X_5+\beta_6X_6+e$$

Where:

Y = Willingness to use DSTs (willingness index score)

b = Constant/intercept

β_1 - β_6 = (Beta coefficients) the coefficient of the independent variables

e = error term

X_1 = Education (no formal education = 0, formal education = 1)
X_2 = Frequency of participation in the association (always = 1, otherwise = 0)
X_3 = Land tenure (purchased = 1, otherwise = 0)
X_4 = Adaptation barrier (pooled index scores of adaptation barriers)
X_5 = Risk perception (pooled index scores of risk perception)
X_6 = Self-efficacy (pooled index scores of self-efficacy)

Results and Discussion

Farmers' Adaptation Barriers to Climate Change

Table 1 shows that barriers to climate change adaptation were a lack of adequate financial resources ($\bar{x}$= 2.98), lack of risk-sharing mechanisms ($\bar{x}$= 2.94), and inadequate agricultural extension support ($\bar{x}$= 2.80). These results suggest a funding deficit for climate change adaptation, which would limit farmers' capacity to invest in adaptable technologies. This claim supports the findings of Meraj and Hashimoto (2025) and Adisa et al. (2024), who stated that small-scale farmers still struggle to obtain adaptation financing and that sufficient access to green financing will support sustainable agricultural production by lowering the obstacles to successful adaptation uptake.

In a similar vein, the lack of risk-sharing arrangements suggests that farmers are solely responsible for climatic shocks. This increases vulnerability to crop failure, income loss, and food insecurity while discouraging innovation. In addition, the lack of extension supports indicates that farmers' exposure to the acquisition of skills, awareness, and technical competence to adapt to climate unpredictability is diminished. This report aligns with Gemeda et al. (2023), who posited that farmers' ability to adapt would be suppressed by a lack of extension services and limited access to climatic information, which would make them unwilling to use different adaptation measures and expose them to food insecurity.

Table 1: Barriers to climate change adaptation

Adaptation barriers	Mean ($\bar{x}$)	Std. deviation
Lack of adequate financial resources	2.98	0.13
Expensive drought-tolerant seeds	2.50	0.76
The cost of the irrigation package	2.78	0.46
Lack of available risk-sharing mechanisms	2.94	0.27
Lack of access to a timely forecast	2.40	0.79
Inadequate skills in using climate-smart tools	2.22	0.92
Inadequate agricultural extension support	2.80	0.43
Discouragement in the adoption of innovative adaptation practices due to community influence	1.85	0.68
Difficulty in understanding adaptation strategies	2.48	0.73

Cut-off point: 2.00
Source: Field survey, 2025

Level of Farmers' Risk Perception of Climate Change

The results in Table 2 show that a slight majority (51.1%) had high risk perception, while nearly half (48.9%) of the farmers had low risk perception. The results suggest a disparity in risk perception among farmers, which could lead to inconsistent adaptation behaviour, where some farmers successfully adjust while others continue to be vulnerable to climate change. In the same area, this variation may lead to differences in productivity. In addition, the relatively large proportion of farmers with low-risk perception indicates a perception gap, which can hinder widespread adoption of adaptation measures. Therefore, farmers who underestimate climate risks are less likely to take proactive steps, thereby slowing community-level resilience efforts. The results suggest that risk communication and climate education are urgently needed, especially for farmers who perceive little risk. In addition to providing technical guidance, extension services should emphasise localised climate information and raise awareness of climate risk. This agrees with Pooja et al. (2025), who reported that farmers' risk perceptions of climate change are crucial in determining adaptation techniques and have a direct influence on their decision-making during uncertainty. Similarly, Ifeanyi-obi et al. (2023) posited that the right perception of climate change would make farmers more receptive to available adaptation options.

However, the presence of a substantial proportion of farmers with low-risk perception may limit the demand for such technologies, as farmers who perceive climate change as less threatening may not see the need for digital advisory tools.

Table 2: Farmers level of risk perception

Perception index score	Percentage (n = 233)	Remark
11 – 33	48.9	Low
33.1 – 55	51.1	High

Field survey, 2025

Farmers' Level of Self-efficacy on Climate Change Adaptation

Table 3 shows that the farmers were relatively equal on the self-efficacy to climate change adaptation, as 50.2% expressed high self-efficacy, while 49.8% of the farmers reported low self-efficacy. The nearly equal distribution of self-efficacy among farmers indicates mixed psychological readiness to use digital Decision Support Tools (DSTs). This suggests that a significant proportion of farmers may continue to face high climate risk despite the availability of adaptation options if self-efficacy is not improved. This underscores the importance of capacity building to increase confidence in adaptation strategies. This is in line with the report that farmers with low self-efficacy may be willing to use these tools but lack the confidence or skills required, contributing to the commonly observed willingness–adoption gap (Akinbode et al., 2024).

Table 3: Farmers' level of self-efficacy

Self-efficacy index score	Percentage (n = 233)
9 – 27	49.8
27.1 – 45	50.2

Field survey, 2025

Farmers' Level of Willingness to Utilise DSTs

Figure 1 shows that most (83.7%) of the farmers were willing to utilise DSTs for agricultural production. This suggests a high readiness for the adoption of digital agriculture. This result indicates farmers are receptive to innovation, which facilitates the introduction and scaling of climate-smart decision tools and, if properly implemented, significantly enhances climate adaptation. This agrees with Abioye et al. (2025), who reported that the use of digital advisory tools significantly improves production, indicating that, with training and access, farmers' willingness may result in favourable benefits and the actual adoption.

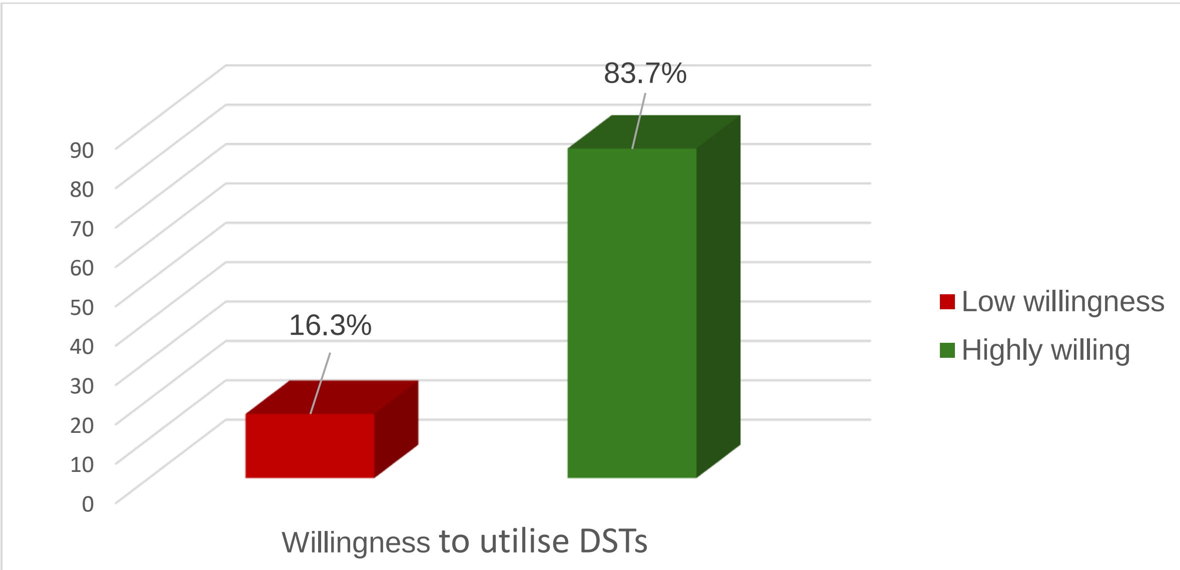

Figure 1: Farmers' willingness to utilise DSTs

Factors Influencing Farmers' Willingness to Use DSTs

The coefficient of determination ($R^2 = 0.286$) indicates that the independent variables entered into the regression model account for 28.6% of the variation in farmers' willingness to use DSTs. Furthermore, Table 4 shows that participation in farmer associations had the strongest positive prediction on farmers' willingness to use DSTs ($\beta = 0.209$, $p < 0.001$). This is followed strongly by self-efficacy ($\beta = 0.201$, $p = 0.003$). This implies that farmers' confidence in their ability to use digital technologies significantly increases their willingness to adopt DSTs. This finding aligns with a previous study, which posited that perceived capability is a key driver of digital technology adoption in agriculture (Abioye et al., 2024). In addition, education is a significant contributor ($\beta = 0.141$, $p = 0.013$). These results suggest that literacy and training directly increase uptake, as farmers with higher levels of education are better equipped to understand innovations. Additionally, being a part of farmer associations or groups promotes trust, peer learning, and information exchange, which speeds up the spread of ideas. This assertion agrees with previous findings, which emphasised that education helps reduce technical barriers to technology use, while membership in a farmers' association improves access to information and exposure to agricultural innovations (Esiobu et al., 2025; Oparaojiaku et al., 2025).

Similarly, risk perception ($\beta = 0.161$, $p = 0.016$) and land tenure ($\beta = 0.177$, $p = 0.005$) positively influence willingness to use DSTs. This indicates that farmers' urgency to use innovation is favourable when they have a high-risk perception and secured land for production. Therefore, this result is in agreement with Lambarraa-Lehnhardt et al.

(2024), who reported that land tenure, and climate change perception influenced farmers' choice to adopt adaptation measures. However, adaptation barriers ($\beta = -0.088$, $p = 0.159$) showed a negative relationship but insignificant influence on willingness, indicating that although there are barriers to utilisation of agricultural innovation, their influence on farmers' willingness to use may not be sufficient as compared with the behavioural factors. This agrees with Diakoulakis et al. (2025), who concluded that farmers' willingness to use innovation is often influenced more by psychological and attitudinal factors than by the existence of constraints alone.

Table 4: Factors influencing farmers' willingness to use DSTs

Variables	Std. Error	B	t-value
Education	1.760	0.141	2.511*
Frequency of participation in the association	1.055	0.209	3.444*
Land tenure	1.035	0.177	2.849*
Adaptation barriers	0.209	-0.088	-1.414
Risk perception	0.116	0.161	2.419*
Self-efficacy	0.115	0.201	3.026*
$R^2 = 0.286$			

*P≤0.05

Conclusion and Recommendations

The study reveals that the primary barriers faced by the farmers were a lack of risk-sharing structures, access to financing, and extension services. Farmers' readiness to adopt DSTs for climate adaptation was very high. Behavioural factors (risk perception, self-efficacy) and socioeconomic factors (participation in farmers' associations, land tenure, and education) had a significant effect on willingness. However, barriers to adaptation had a negative but insignificant influence on farmers' desire to use DSTs. It is recommended that extension agents use training and extension support to help farmers become more efficient in adapting to climate change with technology. The government and development experts strive to improve rural digital infrastructure, including internet access and electricity. Additionally, farmers' associations can be used to disseminate innovation and facilitate peer learning. Extension services should incorporate climate risk communication, and policies that provide risk-sharing, such as easily accessible financing and affordable insurance, should be developed in collaboration with nearby farms and administered effectively.

References

Abdurrauf, I. A., Hussain, L.A., Adeyinka, M.S., Ibironke, E.A., Ajala, O.S., & Ayorinde, B.J.O. (2025). Assessment of adoption of digital extension services for sustainable agriculture by farmers in Lagos State, Nigeria. *European Academic Development Journal*, 1(2), 124 – 132

Abioye, D. O., Fadare, D. A., Omitoyin, S. A., Ogunniyi, A. I., Olinya, P., Shaibu, A., & Nwilene, F. (2025). Adoption impact and heterogeneity of mobile agricultural advisory technologies among smallholder farmers in Nigeria. *Discover Agriculture*, 3, 251. https://doi.org/10.1007/s44279-025-00427-w

Abioye, D.O., Popoola, O., Akande, A., Fadare, D.A., Omitoyin, S.A., Yinusa, B., & Kolade, O.O. (2024). Farmers' willingness to adopt digital application tools in Ogun State, Nigeria. *Journal of Strategy and Management*. https://doi.org/10.1108/JSMA-06-2023-0135

Adereti, D. T., Gardezi, M., Wang, T., & McMaine, J. (2024). Understanding farmers' engagement and barriers to machine learning-based intelligent agricultural decision support systems. *Agronomy Journal*, 116, 1237–1249. https://doi.org/10.1002/agj2.21358

Adisa, O., Ilugbusi, B.S., Obi, O.C., Awonuga, K.F., & Asuzu, O.F. (2024). Green bonds in climate finance: A review of USA and African initiatives. *International Journal of Science and Research Archive,* 11(1): 2376–2383. https://doi.org/10.30574/ijsra.2024.11.1.0147

Agboola, A. F., Famakinwa, M., Williams, S. O., & Akerele, O. A. (2024). Indigenous climate change adaptation strategies among crop farmers in Osun State, Nigeria. *Journal of Agricultural Extension*, 28(3), 134–143. https://dx.doi.org/10.4314/jae.v28i3.14

Akinbode, S. O., Folorunso, O., Olutoberu, T. S., Olowokere, F. A., Adebayo, M., Azeez, S. O., Hammed, S. G., & Busari, M. A. (2024). Farmers' perception and practice of soil fertility management and conservation in the era of digital soil information systems in Southwest Nigeria. *Agriculture*, 14(7), 1182. https://doi.org/10.3390/agriculture14071182

Diakoulakis, G. N., Tzouramani, I., Gemtou, M., & Anastasiou, E. (2025). Exploring socio-psychological factors to the adoption of decision support systems and meteorological stations in agriculture: The case of peach orchards in Greece. *Smart Agricultural Technology*, 12, article 101441. https://doi.org/10.1016/j.atech.2025.101441

Esiobu, N. S., Nwaiwu, C. J., Nwaodu, K. T., Nzeadibe, U. U., Ubaferem-Nwaoha, O. P., Agunanne, U. T., Osuagwu, C. O., Akanda, N. S., & Ugochukwu, G. C. (2025). What determines arable crop farmers' climate change adaptation decisions? Evidence from Nigeria. *Research Journal of Agricultural Economics and Development* 4(1), 24-42. https://doi.org/10.52589/RJAED-T6PHMCDL

Gemeda, D.O., Korecha, D., & Garedew, W. (2023), Determinants of climate change adaptation strategies and existing barriers in Southwestern parts of Ethiopia. *Climate Services*, 30: 1-12. https://doi.org/10.1016/j.cliser.2023.100376.

Ifeanyi-obi, C. C., Wigwe, C. C., Adesope, O. M., & Obafemi, A. (2023). Traditional perceptions of climate change phenomenon influencing adaptation decisions among women crop farmers in Southern Nigeria. *Journal of Agricultural Extension*, 27(2), 15–27. https://dx.doi.org/10.4314/jae.v27i2.2

IPCC. (2022). *Climate change 2022: Impacts, adaptation and vulnerability*. Cambridge University Press.

Lambarraa-Lehnhardt, F., Ceesay, S., Ndiaye, M. B. O., Thiaw, D., & Saweneh, M. (2024). Climate risk perception and adaptation strategies of smallholder farmers in The Gambia. Discover Sustainability 5:506. https://doi.org/*10*.1007/s43621-024-00616-5

Larbaigt, J., Barcellini, F., & Zouinar, M. (2024). Transitioning towards agroecology through digital technology: An empirical study of design activities in an agroliving lab. In Proceedings of the European Conference on Cognitive Ergonomics 2024, Paris, France, 8–11 October 2024.

Meraj, G., & Hashimoto, S. (2025). Bridging the adaptation finance gap: The role of nature-based solutions for climate resilience. *Sustain Science*, *20*, 1093–1107 (2025). https://doi.org/10.1007/s11625-025-01655-1

Oparaojiaku, J. O., Izuogu, C. U., Njoku, L. C., Igwe, O. O., Nwabuisi, C. J., Ankrah, D. A., Ominikari, A. G., Umeh, N. E., Ismail, I. I. H., & Abdulmumini, A. L. (2025). Adoption of climate smart agricultural practices among cassava farmers in Abia State, Nigeria. *Journal of Agricultural Extension*, 29(3), 185–195. https://doi.org/10.4314/jae.v29i3.18

Petraki, D., Gazoulis, I., Kokkini, M., Danaskos, M., Kanatas, P., Rekkas, A., & Travlos, I (2025). Digital tools and decision support systems in agroecology: Benefits, challenges, and

practical implementations. *Agronomy*, *15*(1), 236. https://doi.org/10.3390/agronomy15010236.
Pooja, K.J., Anupama, S., Holy, M. D. M., Megha, A.M., & Anjana, P.M. (2025). Climate change perception and adaptation strategies among farmers: A socio-economic synthesis across agro-ecological zones. *Journal of Agricultural Extension and Rural Development*, 8(9), 807-824. https://doi.org/10.33545/26180723.2025.v8.i9k.2494