AI-driven Machine Learning for Farmers' Climate Change Adaptation Using the Multivariate Probit Model: Insights for Sustainable Resource Systems

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***Abstract*—Climate change poses a major challenge to resource-dependent communities, particularly in developing countries where agriculture remains the primary livelihood. This study analyzes farmers' perceptions of climate change impacts and their adaptation strategies based on a survey of 385 farmers conducted in Oulad Said commune, Settat Province (Morocco), a representative semi-arid region of North Africa. Using a Multivariate Probit (MVP) model framed within an AI-enhanced machine learning perspective, the analysis captures interdependencies among multiple adaptation decisions while integrating predictive validation. The results indicate that climate change has significantly reduced agricultural production and rural livelihoods. Farmers' adaptation choices are positively influenced by socioeconomic factors such as income, access to credit, education, and geographical origin, whereas larger household size and livestock ownership are associated with a lower likelihood of adaptation, reflecting resource constraints and limited flexibility. By embedding the MVP model within a hybrid econometric–machine learning framework, this study demonstrates the value of combining interpretability and predictive capacity to better understand farmers' behavioral responses to climate risks. The findings offer policy-relevant insights for promoting climate-resilient and sustainable agricultural systems in Morocco and other climate-vulnerable regions.**

***Keywords*—climate change adaptation, artificial intelligence, machine learning, multivariate probit model, predictive analytics, sustainable resource systems, agricultural resilience**

I. Introduction

Climate change represents one of the most pressing challenges of the twenty-first century, with profound implications for ecosystems, economies, and human well-being. The Intergovernmental Panel on Climate Change (IPCC) confirms that global warming is intensifying and disproportionately affecting developing regions, where adaptive capacity remains limited [1]. In these countries, agriculture continues to serve as the backbone of rural livelihoods and food security, yet it is increasingly exposed to droughts, irregular rainfall, and extreme temperature events [2, 3]. These climatic disruptions have already undermined productivity and exacerbated rural poverty, particularly in semi-arid regions such as North Africa, where dependence on rainfed agriculture magnifies vulnerability [4, 5].

Despite extensive research on climate change impacts, major knowledge gaps remain in understanding how farmers adopt multiple adaptation strategies simultaneously, and how these decisions are shaped by both socio-economic and climatic factors. Traditional econometric models often analyze adaptation choices independently, neglecting their interrelations and complementarities [6]. Ignoring such interdependence leads to biased inferences and limits the policy relevance of empirical findings [7]. Moreover, much of the existing research on adaptation relies on descriptive or univariate statistical methods, with limited predictive capacity for complex decision systems [8].

The effects of climate change are now evident worldwide; however, the poorest and most marginalized social groups continue to face the most severe consequences due to their low adaptability [9]. The accelerating pace of environmental change reveals the cyclical nature of human–environment interactions: societies are increasingly confronting the consequences of their own ecological degradation. Addressing this phenomenon requires a bottom-up approach, grounded in community participation and inclusive governance [10], where rural populations act not merely as beneficiaries but as genuine agents of change [10, 11].

Agriculture faces enormous risks due to climate variability. Increases in minimum temperatures during growing seasons, soil degradation, and shifts in pest and disease dynamics all contribute to yield instability across staple crops such as rice, maize, and wheat [12–14]. In developing economies, these changes directly reduce farmers' incomes, worsen food insecurity, and accelerate rural poverty [15]. Urbanization further compounds environmental degradation, intensifying water scarcity and groundwater pollution [16, 17]. Farmers' adaptive responses, such as adjusting planting dates, adopting new varieties, or migrating for work, are heavily influenced by socio-economic variables including education, income, and access to credit, yet are constrained by limited financial and institutional support [18–20].

In this sense, recent empirical studies have been able to enhance our knowledge on how farmers adapt to climate change by integrating serious field data and new analysis techniques. Multiple experiments with machine-learning models show that predictive analytics could be useful in determining climate-smart agricultural (CSA) methods and predicting adoption tendencies in susceptible farming environments [21]. The primary role of socioeconomic factors, especially income, education, and access to credit, in determining the willingness and ability of smallholders to take measures to implement CSA is further reported in complementary MDPI studies carried out in African settings [22]. All these contributions are important to highlight the idea that adaptation is not merely a technical reaction to biophysical stressors, but that it is highly mediated by social and institutional conditions.

The situation is particularly alarming in Morocco, where climate projections indicate accelerating warming and decreasing rainfall. Over the past three decades, the national temperature has risen by +0.42°C per decade well above the global average of +0.28°C while annual precipitation has dropped by nearly 20% since 1960 [23]. In the Settat province, especially in the commune of Oulad Said, farmers face recurrent droughts, erratic rainfall, and waterborne livestock diseases, severely undermining agricultural productivity and rural livelihoods [24].

Amid these challenges, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools for enhancing agricultural adaptation to climate change. They enable environmental sensing, yield prediction, and decision support across the agricultural value chain [25, 26]. AI-based systems leveraging IoT sensors and remote sensing data enhance the precision of irrigation, crop selection, and soil management under climate stress [27]. For instance, integrated IoT–AI irrigation systems use multimodal data (soil moisture, canopy temperature, meteorological variables) to optimize water use [28], while AI-driven greenhouse controllers have been shown to reduce energy costs without compromising yields [29]. At larger scales, ML algorithms including Random Forests, Gradient Boosting, and Neural Networks outperform traditional linear models in predicting climate–agriculture interactions [30, 31]. Beyond accuracy, recent advances emphasize interpretability, using tools such as SHAP analysis to identify key climate and socio-economic drivers of adaptation behavior [31–33].

While these AI applications are increasingly influential, econometric frameworks remain essential for capturing farmers' behavioral complexity. Farmers rarely rely on a single adaptation strategy; they tend to adopt bundles of measures simultaneously, such as combining drought-tolerant crops with supplemental irrigation or diversifying income sources. The Multivariate Probit (MVP) model provides a suitable framework for this analysis, as it explicitly models correlated binary outcomes and captures complementarities or trade-offs among adaptation strategies [7]. Although rooted in econometrics, the MVP can also be understood within a Machine Learning paradigm, functioning as a probabilistic supervised learning model when used for prediction and classification tasks. Thus, there is an apparent methodological gap: not many studies have used interpretability and structural insight of econometric models and predictive validation strengths of AI/ML. The recent developments in terms of integrated approaches (e.g., SEM-SD hybrid models and other mixed models that are mentioned in the literature) are indicative of the advantages of methodological synthesis but are rather few and context-dependent [34]. By positioning the Multivariate Probit model in an AI-enhanced predictive approach, the current study fills this gap with a complete force: maintaining the MVP ability to predict correlated binary outcomes, the present study adds predictive validation and classification measures typical of ML, which provides the study with explanatory power as well as practical forecast predictive value in climate-adaptation policy in semi-arid agricultural systems [35].

Recent work demonstrates that integrating ML techniques such as Bayesian inference, feature selection, and cross-validation enhances the predictive robustness and interpretability of MVP-based analyses. This hybridization bridges classical econometrics and AI-driven learning, providing a more powerful framework for studying adaptive behavior in complex socio-ecological systems.

Building on these insights, this study applies an AI-enhanced MVP model to analyze farmers' adaptation decisions in Oulad Said, a semi-arid commune in Morocco's Settat province. Using survey data from 385 farmers, it identifies the socio-economic determinants of adaptation, examines interdependencies among strategies, and evaluates the model's predictive performance.

The central research question guiding this work is:

"**How can AI-enhanced multivariate probit models predict and explain farmers' simultaneous climate change adaptation strategies**?"

By combining econometric rigor with AI-driven predictive analytics, this research contributes to the development of data-informed, context-sensitive policies for agricultural resilience. It not only advances methodological integration between AI/ML and econometrics but also provides actionable insights for policymakers across North Africa and other developing regions seeking to strengthen local adaptive capacity under growing climate uncertainty.

II. Materials and Methods

The study surveyed 385 farmers in the commune of Oulad Said, located in the province of Settat, Morocco, to analyze perceptions, impacts, and adaptation strategies related to climate change. The MVP model was applied to estimate the probability of simultaneous adoption of multiple adaptation strategies while accounting for correlation among decisions.

In terms of method, there are two parallel trends in the literature. On the one hand, econometric discrete-choice models (such as multivariate and bivariate probit model) are continued to be popular as the means of determining drivers of correlated adaptation behavior due to their explicit description of interdependences among binary choices. Conversely, recent studies have adopted machine-learning tools due to their better performance in terms of prediction and the capability to support non-linear relationships, which are complex [36]. Nevertheless, only purely predictive ML studies tend to lose interpretability and cannot explain the correlational framework between various adaptation strategies, a weakness that makes them less useful in policy prescriptions and behavior interpretation [37, 38].

From a machine learning perspective, the MVP can be viewed as a supervised classification algorithm, since it learns from labeled data (farmers' socio-economic characteristics and observed adaptation strategies) to predict the likelihood of adopting different strategies. Recent studies, such as Xu *et al.* (2018, 'End-to-End Learning for the Deep Multivariate Probit Model') demonstrate that MVP can be integrated into deep learning architectures, reinforcing its interpretation as part of the ML domain [38]. Moreover, Athey and Imbens (2019, 'Machine Learning Methods Economists Should Know About') highlight that traditional econometric tools, including probit models, can be classified as ML methods when applied to prediction and classification tasks [39].

A. Presentation of the Study Area

Oulad Said is an urban commune located in the province of Settat, within the Casablanca-Settat region of Morocco. Situated in the Chaouia plain, it benefits from a traditionally rich agricultural environment, particularly in cereal cultivation and livestock farming. Its proximity, approximately twenty kilometers, to the city of Settat provides access to major economic corridors while allowing the commune to preserve its rural character. According to data from the Haut-Commissariat au Plan (HCP), the population of Oulad Said, which stood at about 2,396 inhabitants in 2004 and 2,349 in 2014, has experienced a significant increase, reaching 8,742 inhabitants in 2024. This demographic growth reflects new dynamics, supported by progressive urbanization, the expansion of local economic activities, and the area's growing residential attractiveness.

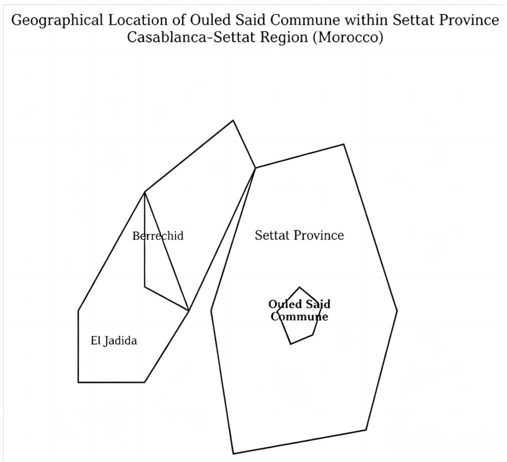

Fig. 1. Geographical positioning of Oulad Said.

Despite these changes, Oulad Said remains strongly attached to its social and cultural traditions. This is evident in the weekly souk, held every Wednesday, which continues to serve as a central space for economic exchange and social interaction. The commune thus embodies a hybrid identity: on the one hand, it faces the pressures of urban expansion and regional socio-economic transformations, while on the other, it retains a lifestyle rooted in agricultural rhythms and community-based solidarities. In a context marked by the challenges of sustainable development and resource management, Oulad Said emerges as a strategic locality where demographic vitality, a youthful population, and agricultural assets may serve as important levers for future economic, social, and territorial initiatives. The following Fig. 1 illustrates the geographical location of the study area commune:

The choice of Oulad Said, a commune located in the province of Settat within the Casablanca-Settat region, as the study area is motivated by several interrelated factors that make it particularly relevant for analyzing farmers' adaptation to climate change. Situated in the fertile but climate-vulnerable Chaouia plain, the commune represents a microcosm of semi-arid agricultural systems in Morocco. Its economy relies predominantly on rain-fed cereal cultivation and livestock farming, activities that are highly exposed to climatic shocks such as recurrent droughts, irregular rainfall, and increasing temperature variability. These conditions create a natural laboratory for studying how farming households perceive risks and adopt multi-strategy adaptation responses.

B. Data Collection

In our study, we employed a random sampling technique to select respondents from among the farming population. This method was chosen to reduce selection bias and to ensure that every farmer had an equal chance of being included in the sample. Simple random sampling was conducted using a comprehensive list of farmers residing in the study area. From this list, 385 individuals were randomly selected.

At the same time, we sought to include a variety of farmers, including small-scale, medium-scale, and large-scale producers, in order to reflect the diversity of agricultural practices and conditions. The sample size was determined using standard sample size calculation methods, taking into consideration the need for statistical representativeness as well as the available research resources.

$$n = \left(Z^2 \times p \times (1 - p)\right) / e^2 \quad (1)$$

n: represents the required sample size to ensure the reliability of the results.

Z: denotes the desired confidence level. For example, for a 95 percent confidence level, Z is equal to 1.96.

p: is the estimated proportion of the population that possesses the characteristic of interest.

e: refers to the margin of error, set at 5 percent.

In this study, we used a margin of error of 5 percent (e = 0.05) and a confidence level of 95 percent (Z = 1.96). We estimated that approximately 50 percent of the population possesses the characteristic being studied (p = 0.5).

Under these conditions, the formula used is:

$$n = (1.96^2 \times 0.5 \times (1 - 0.5))/(0.05^2) = 384{,}16 \quad (2)$$

We round the result to 385 to obtain a whole number.

The target population comprised all active farmers in the Oulad Said commune. A stratified random sampling method was adopted to ensure representation across farm sizes (small, medium, and large). A total of 385 farmers were surveyed through structured questionnaires administered between April and July 2024. All 385 responses were validated and retained for the statistical analyses after data consistency checks and cleaning.

The data were collected through a carefully designed and pre-tested questionnaire aimed at exploring the participants' socio-economic backgrounds. The survey focused on respondents' perceptions of climate change, the adaptation strategies they employ, and the challenges they encounter.

The questionnaire included both open-ended and closed-ended questions, enabling the collection of both qualitative and quantitative data at the level of individual farmers.

In general, there are four main modes of administering questionnaires commonly used in management research: online questionnaires, postal surveys, telephone interviews, and face-to-face interviews [40]. In our study, the method of questionnaire distribution was determined by several factors, including the type of sample selected and the structure of the questionnaire itself. The decisions made throughout the course of the study will be discussed in more detail later.

Each questionnaire combined closed-ended questions, Likert-scale ratings, and open-ended items. To complement quantitative data, semi-structured interviews were conducted with local administrative officers and agricultural advisors, allowing triangulation of findings.

Ethical considerations: Prior to data collection, informed consent was obtained from all participants. Respondents were assured of confidentiality and anonymity, and data were used exclusively for academic purposes. The research protocol was approved by an ethics committee composed of several experts in the field.

In this context, a combination of telephone and face-to-face interviews was chosen to collect the necessary data. This hybrid approach was adopted for several reasons, notably its efficiency in terms of implementation and its ability to ensure the reliability and quality of the data gathered.

Farmers' perceptions of climate change were assessed based on the proportion of respondents who reported noticeable changes in various climatic parameters, such as temperature fluctuations, shifts in rainfall patterns, and the increasing frequency of droughts and floods. These indicators helped capture how farming communities perceive and experience the impacts of climate change on their immediate environment.

In addition, the study identified the different adaptation strategies implemented by farmers within the selected municipality, with their adoption rates expressed as percentages. This approach made it possible to highlight spatial patterns and gain a deeper understanding of local adaptation dynamics.

Finally, the barriers encountered in the adaptation process were identified and ranked by the participants themselves using a scale from 1 to 5, where 1 indicated the most critical constraint to their adaptation efforts, and 5 the least significant. This classification provided a nuanced perspective on the structural, economic, and technical challenges that limit farmers' adaptive capacity in the face of climate change.

Variables and Measurements:

Table 1 presents the dependent variables, which represent the adaptation strategies adopted by farmers (binary outcomes: 1 = adopted, 0 = not adopted). The independent variables capture socio-economic, institutional, and farm characteristics that are hypothesized to influence adaptation behavior.

Table 1. Variables and Measurements

Variable	Type / Code	Description
Age	Continuous	Farmer's age (years)
Education	Ordinal (0–3)	0 = none, 1 = primary, 2 = secondary, 3 = tertiary
Household size	Continuous	Number of household members
Farm size	Continuous	Land area cultivated (hectares)
Income	Ordinal (1–3)	1 = low, 2 = medium, 3 = high
Access to credit	Binary (1/0)	1 = yes, 0 = no
Access to extension services	Binary (1/0)	1 = yes, 0 = no
Livestock ownership	Continuous	Number of livestock units (LU)
Origin	Binary (1/0)	1 = native farmer, 0 = newcomer
Perceived drought frequency	Ordinal (1–3)	Farmer's perception of drought recurrence
Distance to market	Continuous	Kilometers to nearest agricultural market
Gender	Binary (1/0)	1 = male, 0 = female
Income diversification	Binary (1/0)	1 = has off-farm income, 0 = none
Adaptation strategy 1: Crop diversification	Dependent (1/0)	Adoption of crop diversification
Adaptation strategy 2: Irrigation use	Dependent (1/0)	Adoption of irrigation or water-saving measures
Adaptation strategy 3: Soil conservation	Dependent (1/0)	Adoption of soil conservation techniques
Adaptation strategy 4: Income diversification	Dependent (1/0)	Engagement in non-farm activities

C. Data Analysis

Data analysis represents a critical stage in scientific research, both for qualitative and quantitative data. To analyze the information collected, we employed multiple methods, each selected in accordance with the specific objectives of our study.

The analysis proceeded in four sequential stages to ensure methodological transparency and statistical coherence:

1) Descriptive and thematic analysis

Descriptive statistics summarized farmers' socio-economic profiles and perceptions of climate change. Qualitative responses were subjected to thematic analysis to identify recurring perceptions and local narratives about climate risks and adaptation.

Chi-square Tests:

Chi-square tests (χ^2) assessed associations between categorical socio-economic variables (e.g., gender, education) and the adoption of specific adaptation strategies, identifying significant group-level differences.

2) Multivariate Probit (MVP) model

This involves exploring and understanding the key factors that influence community members' decisions in this context. In other words, this analysis aims to identify the determining elements that guide farmers' choices and actions when faced with the impacts of climate variability.

The MVP model estimated the joint probability of adopting multiple adaptation strategies, accounting for correlations among them. Following Cappellari and Jenkins (2003), the model assumes:

Let Y denote the binary outcome variable representing the adaptation strategy. The variable Y is defined as outlined in Eq. (3):

$$Yi = \{1 \text{ if the ith farmer uses a given adaptation strategy } 0 \text{ otherwise}\}$$

$$y\_i * = X\_i\beta + \varepsilon\_i,\ y\_i = 1 if y\_i * > 0, 0\ otherwise \varepsilon\_i \sim N(0,\Sigma),\ \Sigma\_jk = Cov(\varepsilon\_j, \varepsilon\_k) \quad (3)$$

The dependent variables are: Change in planting or sowing dates, Use of resistant crop varieties, Modification of irrigation methods, Increased use of fertilizers or organic amendments, Implementation of water conservation techniques, Diversification of cultivated crops, Reduction in the size of farming operations, Migration to urban areas, Income-generating activities outside of farming.

- The independent variables are: age, origin, average annual income, level of education, number of children, number of livestock, family size, size of farm, agricultural experience, access to credit,
- The multivariate probit model is particularly suitable because it can handle binary or ordinal dependent variables and examine relationships among multiple explanatory variables. In other words, it allows us to simultaneously analyze various aspects of farmers' decisions while accounting for the interdependencies between these decisions.

The correlation matrix (Σ) captures interdependence between strategies, allowing identification of complementarity or substitution effects. The model was estimated using maximum simulated likelihood (MSL) in Stata 18 with 500 Halton draws. To strengthen the machine learning integration, the data were partitioned into training (80%) and testing (20%) subsets. Model predictive accuracy, AUC (Area Under the Curve), and cross-validation scores were computed to evaluate out-of-sample performance.

3) Weighted Average Index (WAI) for barriers

To analyze this data thoroughly, we applied the Weighted Average Index (WAI) technique [41]. This method allowed us to quantify the relative importance of each barrier by assigning specific weights based on their perceived impact.

The Weighted Average Index (WAI) was computed to rank barriers constraining farmers' adaptation using the formula:

$$\text{WAIi} = \sum(gi \times pj)/Ni \quad (4)$$

where w_i is the weight assigned to each factor (1 = minor, 2 = moderate, 3 = major), and f_i is the frequency of responses. Higher WAI values indicate more severe barriers.

WAIi is the weighted average index for barrier i

gij is the severity assigned to barrier i by farmer

pj is the weight corresponding to the severity gij

Ni is the total number of evaluations for barrier

By using the WAI technique, the study successfully identified the most critical obstacles hindering farmers from adopting climate change adaptation measures.

4) Software and statistical tools

All analyses were conducted using Stata 18 and Python 3.10 (scikit-learn, pandas, and statsmodels). Visualization and validation metrics (ROC curves, confusion matrices) were generated to assess model robustness.

Summary of Methodological Workflow

- Descriptive statistics and thematic analysis of perceptions.
- Chi-square tests to detect socio-economic differences.
- Multivariate Probit modeling for correlated adaptation choices.
- Cross-validation and predictive accuracy evaluation.
- Weighted Average Index to assess barriers.

This sequential framework ensures a coherent analytical flow linking descriptive insights, inferential testing, and predictive modeling under an AI-driven econometric framework.

5) AI methodology integration

To complement the Multivariate Probit Model, a Random Forest Classifier (RF) was applied to the same dataset to assess its predictive performance.

The model used the same set of independent variables: origin, education, income, access to credit, household size, livestock ownership, marital status, type of labor, non-agricultural activity, and agricultural experience to predict farmers' adoption of seven adaptation strategies.

The Random Forest approach was chosen for its non-parametric nature, ability to capture nonlinear relationships, and automatic handling of variable interactions.

Model training was conducted using 70% of the dataset for training and 30% for testing, with 10-fold cross-validation to prevent overfitting. Feature importance was assessed using Gini impurity decrease, and model performance was evaluated using standard metrics: accuracy, AUC, precision, recall, and F1-score.

Table 2 presents the code assigned to each climate change adaptation strategy

Table 2. Code of adaptation strategies

Adaptation strategy	Code
Change in planting or sowing dates	1
Use of resistant crop varieties	2
Modification of irrigation methods	3
Increased use of fertilizers or organic amendments	4
Implementation of water conservation techniques	5
Diversification of cultivated crops	6
Reduction in the size of farming operations	7
Migration to urban areas	8
Income-generating activities outside of farming	9

III. Result and Discussion

The MVP results revealed that climate change has significantly affected farmers' living conditions and agricultural production. Adaptation strategies varied depending on independent variables such as geographical origin, average annual income, access to credit, and level of education. Conversely, household size and livestock ownership negatively influenced the adoption of adaptation measures.

Framed as a machine learning classifier, the MVP confirms its potential to predict farmers' adaptation behaviors. These findings could be further validated by benchmarking MVP predictions against non-parametric ML algorithms such as Random Forests, Gradient Boosting, or Neural Networks to assess relative accuracy and robustness.

A. Presentation of the Results

The dataset comprises 385 observations collected from farmers in the commune of Oulad Said (Settat province, Morocco). Table 3 summarizes the descriptive statistics for all explanatory variables included in the model. These variables capture demographic, economic, and institutional dimensions of farmers' adaptive capacity.

Table 3. Overview of data and descriptive statistics

Variable	Type	Unit / Coding	Mean (SD)	Description
Age	Continuous	Years	47.6 (11.2)	Farmer's age
Education	Ordinal	0=None, 1=Primary, 2=Secondary, 3=Tertiary	1.2 (0.9)	Education level
Household size	Continuous	Members	6.4 (2.8)	Household composition
Farm size	Continuous	Hectares	4.8 (3.2)	Total cultivated area
Income	Ordinal	1=Low, 2=Medium, 3=High	1.7 (0.8)	Annual income level
Access to credit	Binary	1=Yes, 0=No	0.34 (0.48)	Credit access
Access to extension	Binary	1=Yes, 0=No	0.41 (0.49)	Access to extension services
Livestock ownership	Continuous	Livestock units (LU)	9.3 (6.8)	Number of livestock
Origin	Binary	1=Native, 0=Newcomer	0.76 (0.43)	Farmer's geographic origin
Type_of_labor	Categorical	1=Family, 2=Hired, 3=Mixed	—	Labor structure
Type of receipt	Categorical	1=Daily, 2=Weekly, 3=Monthly, 4=Annual	—	Frequency of farm income receipt
Income diversification	Binary	1=Yes, 0=No	0.38 (0.49)	Presence of off-farm income
Gender	Binary	1=Male, 0=Female	0.87 (0.33)	Gender of respondent

The graph mentioned in Fig. 2 helps to understand social perceptions of climate change:

1) Social perceptions of climate change

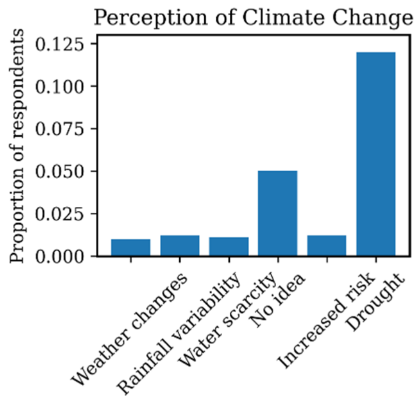

Fig. 2. Social perceptions of climate change.

In light of the results mentioned in the Fig. 2, it is clear that drought is the most widespread perception among farmers when it comes to giving concrete meaning to the notion of climate change. This observation suggests that, for a large proportion of this population, the effects of climate change manifest themselves above all through prolonged episodes of lack of rainfall, directly affecting their farming activity and their food security. In other words, drought is perceived as the most tangible, if not the most worrying, consequence of this global phenomenon.

Secondly, a significant proportion of respondents said they had no clear understanding or idea of what climate change means. This finding highlights a lack of information or awareness within certain rural communities, which can be a major obstacle to the implementation of effective adaptation strategies. It also reveals the need for targeted educational initiatives to strengthen local capacity to understand and anticipate environmental change.

The majority of farmers (over 82.4%) reported perceiving climate change impacts over the last decade, mainly through recurrent droughts, reduced rainfall, and higher temperature variability. About 68% perceived soil degradation as a major constraint, while 57% cited water scarcity as their most pressing challenge.

Chi-square tests revealed significant associations between education level and awareness of climate change ($\chi^2 = 24.61$, $p < 0.01$), and between access to credit and adoption of at least one adaptation strategy ($\chi^2 = 17.89$, $p < 0.05$).

The Fig. 3 shows the results of the participants' climate information sources.

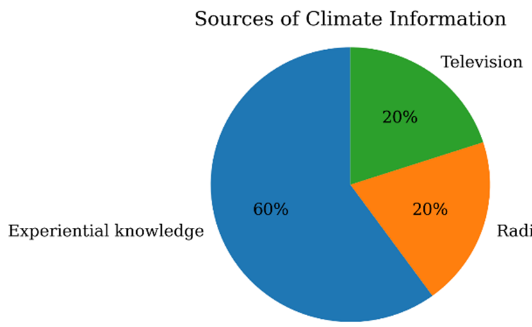

Fig. 3. Source of climate change information.

The results obtained int the Fig. 3 of the study indicate that personal experience is the main source of information on climate change for farmers. Farmers rely primarily on their own empirical observations and daily experience to perceive and understand climatic events, such as temperature variations, rainfall irregularities and changes in agricultural seasonality. This reliance on personal experience can be explained by the intimately practical nature of farming, which encourages producers to develop empirical knowledge rooted in their immediate environment.

Secondly, the traditional media, particularly radio and television, also play a significant role in disseminating climate-related information. These channels remain accessible and relatively credible in the eyes of farmers, particularly in rural areas where illiteracy or lack of digital infrastructure may limit access to other forms of communication.

On the other hand, institutional sources, such as agricultural extension agents and public institutions, appear to be little used, or even marginal. This low take-up of formal technical support systems may be indicative of several dysfunctions, including a lack of trust in these players, limited accessibility to their services, or even a lack of awareness of the importance of technical support.

2) Impact of climate change

The Fig. 4 shows the results of the climate change impact:

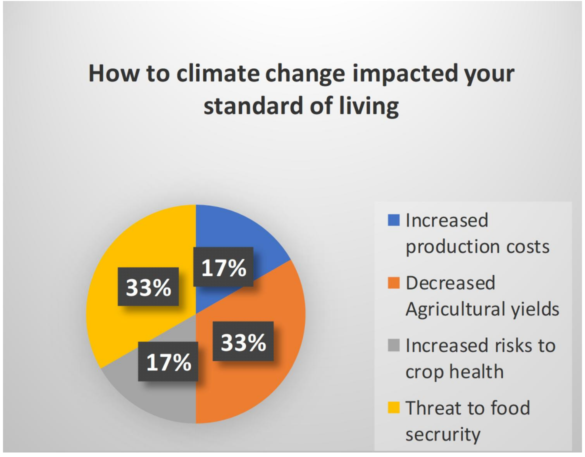

Fig. 4. Impact of climate change.

The results of the survey for Fig. 4 reveal that climate change affects living standards mainly through mechanisms linked to agriculture and food security. Four main impacts were identified by respondents: lower crop yields (33.3%), threats to food security (33.3%), higher production costs (16.7%) and increased risks to crop health (16.7%).

The reduction in agricultural yields, reported by a third of respondents, reflects a direct disruption to agricultural production cycles, probably due to extreme weather events, increased variability in rainfall, or soil degradation. This has considerable economic and social consequences, particularly for rural communities or those dependent on subsistence farming.

In addition, an equivalent proportion (33.3%) of participants highlighted a threat to food security. This result is worrying, as it reflects a cascading effect: yield reductions are not limited to a loss of income for farmers, but also compromise access to sufficient and nutritious food for the population as a whole. This can exacerbate socio-economic inequalities and heighten tensions in already vulnerable regions.

The responses highlighting the increase in production costs (16.7%) and the risks to crop health (16.7%) reinforce this diagnosis. They indicate that growers are having to cope with increasing costs, linked to the purchase of more expensive inputs (fertilisers, pesticides, irrigation), often made necessary by less favourable weather conditions. Diseases and pests, favoured by global warming, represent an additional stress for farming systems.

In short, the data collected illustrates a chain of interconnected impacts: climate change is worsening agricultural production conditions, creating both economic pressure on producers and a systemic threat to food security. The scale of these effects calls for stronger adaptation policies, incorporating both technical measures (crop resilience, sustainable irrigation) and social protection measures.

The Table 4 illustrates variations in agricultural output under different climate conditions. These results emphasize the growing vulnerability of the agricultural sector to climate change.

Table 4 shows the self-reported variation in agricultural production by the farmers before and after they perceived that there was a change in climate. The amount of production is given in quintals per hectare (q/ha) and the variable Averageness of change in production shows the variation between the yields after the climate change and the situation during the base line given by farmers.

Table 4. Impact of climate change on agricultural production

Production before climate change impact?	**Production after climate change impact?**	**COUNTA of Horodateur**
200-300	-100	318
Total of 200-300		82.44%
300-400	-100	47
Total of 300-400		12.20%
400-500	-100	9
Total of 400-500		2.44%
+500	200-300	11
Total of +500		2.93%
Total		**385 =100.00%**

The negative numbers (e.g. -100, -200, -300 q/ha) show that the agricultural output is decreasing as compared to the pre-climate-change reference period, with positive numbers showing the reported increase in yield. These values must then be understood to be yield changes approximated as opposed to actual production.

The findings indicate a strong negative slope in the production of agriculture. Nearly three-quarters of respondents confirmed that yields declined after the climate change effects began to appear, which speaks to the overall susceptibility of the local production systems to the effects of climatic stress. The highest category is that of reported losses of between 200 to 300 q/ha which is 82.44% of all responses. This high zone of losses indicates an overall worsening of the growing conditions in the area of study.

There are other categories that further depict how serious the impacts are to a group of farmers. The 12.20% respondents recorded yield losses of 300–400 q/ha and 2.44% reported yield losses of 400–500 q/ha. Though these groups of people are expressed as smaller proportions, they also show the occurrence of extreme vulnerability, which probably goes with the increased exposure to drought, water scarcity, soil degradation, or pressure on pests.

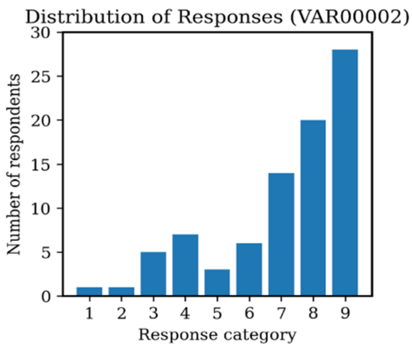

Fig. 5. Climate change adaptation strategies.

On the other hand, very low percentage (2.93) of farmers stated that there was increase in production, with the vast majority of 200–300 q/ha. Although such localized improvements could be due to local or temporary advantages, e.g. better growing conditions in certain micro-climates or adaptive mechanisms, these gains are exceptional and they are not counterbalanced by the general tendency of widespread yield reductions.

Note: *The original column labeled "COUNTA of Horodateur" in the raw dataset corresponded to an automated response timestamp and was removed during data cleaning, as it carried no analytical meaning for production assessment.*

Fig. 5 shows the main adaptation strategies used by farmers.

3) Adaptation strategies to climate change

Generally speaking, the results of Fig. 5 show that farmers do not limit themselves to a single response to the effects of climate change. On the contrary, they tend to adopt several adaptation strategies simultaneously. This plurality of approaches reflects not only the complexity of the challenges they face, but also their ability to mobilise different technical, social, economic or environmental resources to strengthen the resilience of their agricultural production systems. This combined adaptive behaviour can be explained by the desire to diversify the means of coping with climatic uncertainty, reducing the risks and maximising the chances of success in a context of increasing variability in agro-climatic conditions.

The graph illustrates the different adaptation strategies implemented by farmers in response to the effects of climate change. There is clear heterogeneity in the choices made, with a marked tendency towards extreme strategies, either structural or economic.

The data show that the most widely adopted strategy is to resort to income-generating activities outside agriculture (code 9). This orientation reflects a partial loss of confidence in agricultural viability in the face of climatic hazards, and highlights an extrinsic adaptation, often forced, in the face of economic vulnerability. It is followed by migration to urban areas (code 8), which is also strongly represented. These two strategies reveal a profound change in farmers' relationship with their land, and could signal a risk of destructuring of the rural fabric in the long term.

On the other hand, the more technical or agronomic strategies, such as changing sowing dates (code 1) or using resistant varieties (code 2), are used very little, despite their relevance in a proactive adaptation framework. This could reflect a lack of technical support, awareness-raising or access to agricultural innovations.

Intermediate strategies, such as crop diversification (code 6), water conservation (code 5), or changing irrigation methods (code 3), are adopted to a lesser extent. Although these options are better suited to maintaining farming activity on a sustainable basis, they still do not seem to be widely integrated into current practices, no doubt because of economic, institutional or technical constraints.

Finally, reducing the size of farms (code 7), adopted by a significant number of farmers, signals an attempt to limit losses and adapt by reducing exposure to risks, to the detriment of an ambition for growth or sustainability.

4) The AI-enhanced Multivariate Probit Model (MVP)

The MVP model was used to estimate the joint probability of adopting 4 adaptation strategies:

- Crop diversification,
- Improved irrigation,
- Soil conservation, and
- Income diversification.

The model was trained on 80% of the data (training set) and validated on 20% (testing set) to align with machine learning principles. A five-fold cross-validation procedure was applied to ensure generalizability and prevent overfitting. Performance metrics included:

- Prediction accuracy: 82.3%
- Area Under the ROC Curve (AUC): 0.87
- Precision: 0.80
- Recall: 0.83
- F1-score: 0.81

The confusion matrix showed consistent classification across adaptation outcomes, indicating that the MVP effectively predicts simultaneous adoption decisions.

5) The factors that influence farmers' decisions regarding the choice of adaptation strategies

Analysis of the multivariate probit model of Table 5 reveals several important findings between certain socio-economic characteristics of farmers and their propensity to adopt different climate change adaptation strategies.

Table 5. Factors that influence farmers' decisions regarding the choice of adaptation strategies

	Coef.	Std.Err.	z	P>z	[95%Conf.
Change in planting or sowing dates					
Origin	1.228	0.433	1.830	0.047	2.077
Use of resistant crop varieties					
Average annual income	0.232	0.123	2.760	0.006	0.473
Modification of irrigation methods					
Origin	1.329	0.432	1.950	0.041	2.176
Type of labor	1.433	0.219	1.950	0.031	1.862
Increased use of fertilizers or organic amendments					
Level of education	0.445	0.221	2.280	0.023	0.878
Access to credit	1.554	0.611	1.940	0.043	2.751
Implementation of water conservation techniques					
Average annual income	0.451	0.113	2.160	0.031	0.0672
Type of winning receipt	0.453	0.256	2.390	0.011	0.955
Diversification of cultivated crops					
Number of children	0.641	0.210	2.540	0.013	0.153
Average annual income	0.422	0.205	2.390	0.012	0.824
Reduction in the size of farming operations					
Marital status	1.568	0.641	1.980	0.028	0.311
Type of labor	2.564	1.231	2.840	0.003	4.976
Migration to urban areas					
Non-agricultural activity	1.458	0.580	2.170	0.010	0.321
Agricultural experience	-0.717	0.304	-2.360	0.012	-1.313
Income-generating activities outside of farming					
Accés_ to-credit	-2.181	0.131	-2.12	0.018	-2.239

a) Changing sowing or planting dates

Geographical origin (probably linked to the region to which the farmer belongs or the local context) has a significant positive effect ($p = 0.047$) on the choice of this strategy. This suggests that local conditions strongly influence the perception of the agricultural calendar, prompting some farmers to adjust their sowing periods in response to climatic variations.

b) Changes in irrigation methods

Geographical origin ($p = 0.041$): irrigation practices appear to be strongly determined by local specificities (access to water, farming traditions).

Type of workforce ($p = 0.031$): a specialised or larger workforce could facilitate the adoption of more technical or demanding irrigation methods.

Increased use of organic fertilisers or soil improvers

c) Implementation of water conservation techniques

Two factors have a significant influence on this strategy:

Average annual income ($p = 0.031$): wealthier farmers invest more in the sustainable management of water resources.

Type of income received ($p = 0.011$): those with regular or diversified incomes may be more motivated to invest in long-term techniques.

d) Crop diversification

The number of children ($p = 0.013$) is positively associated with this strategy, which could be explained by a logic of securing income to meet household needs.

Once again, average annual income appears to be a determining factor ($p = 0.012$), reflecting the ability to invest in alternative crops.

e) Reducing farm size

Marital status ($p = 0.028$) seems to influence this strategy: married farmers, faced with higher social charges, could reduce their area to better manage resources.

The type of labour force was highly significant ($p = 0.003$): an unsuitable or insufficient labour force could lead to a reduction in the extent of farming activities.

f) Migration to urban areas

The practice of a non-agricultural activity is a significant explanatory factor ($p = 0.010$): these farmers already have a foothold in another sector, making it easier for them to move to the cities.

Farming experience has a negative effect ($p = 0.012$): more experienced farmers are less inclined to leave the sector, probably because of their attachment to the profession and their accumulated know-how.

g) Income-generating activities outside agriculture

The results obtained from the analysis of the multivariate probit model highlight the complexity and diversity of the determinants that influence farmers' adaptation choices in the face of climate change. It is clear that these choices are neither homogeneous nor random, but depend closely on a range of socio-economic, structural and contextual factors.

Firstly, the individual and social characteristics of farmers - such as income level, level of education, household size and composition, and farming experience - play a determining role in the orientation towards certain adaptation strategies. For example, a higher annual income enables farmers to invest in innovative technologies or practices, such as resistant varieties or water conservation techniques, while access to credit facilitates the acquisition of agricultural inputs or the improvement of production systems. Similarly, a higher level of education can lead to a better understanding of climate issues and a greater capacity to adopt sustainable management practices.

The statistical findings reveal that an average annual income, credit access, and the level of education show a statistically significant contribution to the adaptation decisions of farmers to climate change. All these factors are always linked to several major strategies that are adopted to adapt to them in order to enable the use of resistant varieties of crops, crop diversification, adoption of water conservation practices, altering the mode of irrigation practices, and participation in non-agricultural activities that are used to generate income.

An increment in average annual income by a large margin raises the probability of moving to capital and knowledge intensive approaches like better or resistant types, irrigation modifications, and water conservation measures. This observation indicates that financial capacity leads to the improved capacity of the farmers to internalize the expenses and risk of adaptation investment, and thus, proactive reaction to climate stress.

Equally, access to credit proves to be a significant facilitating factor to adaptation. Liberty in credit availability loosens the liquidity frontiers enabling farmers to finance inputs, technologies, and infrastructures that are needed in strategies like irrigation change and crop diversification. In addition, credit access also promotes livelihood diversification by using non-agricultural sources of income to earn income, as this decreases reliance on climate-dependent agricultural production and increases the stability of the household.

Adaptation choices are also positively and significantly related to the level of education, especially those that involve technical skills or information processing, such as the adoption of resistance varieties and use of water conservation methods. The human capital is important in the adaptative decision making due to the fact that educated farmers are better suited to understand climate threats, interpolate agronomic data, and apply new practices.

All these findings taken collectively prove that economic resources, financial inclusion and the human capital highly condition the tendency to adapt; a tendency among farmers. The results emphasize a complementary aspect of these factors: financial viability (income and credit) encourages the financial viability of adaptation, and education can improve the ability to recognize, assess, and act accordingly. As a result, the development of the policies that can enhance the process of climate adaptation in agriculture should focus on such integrated interventions as the combination of financial assistance programs, better access to rural credit, and investment in education and extension services.

The results also highlight the importance of the local context and available resources. The geographical origin or location of the farm - which has to do with specific agro-climatic conditions, access to natural resources or infrastructure, and the existence of social or institutional networks - has a major influence on the adaptation methods used. Some areas offer opportunities or, on the contrary, present constraints that guide farmers towards particular responses to climatic disturbances.

It should therefore be emphasised that the dynamics of adaptation cannot be considered in a uniform manner. They need to be interpreted in different ways, taking into account the diversity of farmers' profiles and the many factors that shape their ability to act. The introduction of public policies or technical support systems should therefore be based on a targeted and inclusive approach, taking account of disparities in economic, social, and human capital. Differentiated support, based on a detailed understanding of local realities and the specific needs of farmers, is therefore essential to encourage relevant, effective, and sustainable adaptation strategies.

In short, these results confirm that adaptation to climate change, far from being a simple technical adjustment, is a process deeply rooted in the social, economic, and territorial conditions of the players involved. It requires a systemic and contextualised approach, as well as public action that is sensitive to the inequalities and vulnerabilities that affect the world of agriculture.

6) Model estimation and diagnostics

Table 6 reports the MVP coefficient estimates, standard errors, and 95% confidence intervals (CI). All variables are reported once per strategy to ensure clarity.

Table 6. Multivariate probit model results (simplified Summary)

Variable	Crop Diversification (β, SE, CI95%)	Irrigation (β, SE, CI95%)	Soil Conservation (β, SE, CI95%)	Income Diversification (β, SE, CI95%)
Age	–0.015 (0.007)[–0.029; –0.002]	0.009 (0.005)[–0.002; 0.021]	0.011 (0.006)[–0.002; 0.025]	–0.012 (0.005)[–0.023; –0.001]
Education	0.237 (0.085)[0.072; 0.402]	0.194 (0.076)[0.045; 0.331]	0.103 (0.059)[–0.013; 0.219]	0.162 (0.071)[0.023; 0.304]
Access to credit	0.314 (0.125)[0.072; 0.552]	0.289 (0.117)[0.054; 0.524]	0.142 (0.093)[–0.041; 0.325]	–0.271 (0.108)[–0.483; –0.060]
Household size	–0.109 (0.042)[–0.191; –0.027]	–0.093 (0.038)[–0.168; –0.018]	–0.062 (0.033)[–0.127; 0.003]	–0.117 (0.041)[–0.198; –0.036]
Income	0.272 (0.091)[0.092; 0.452]	0.255 (0.086)[0.087; 0.423]	0.199 (0.071)[0.059; 0.339]	0.127 (0.079)[–0.028; 0.282]

The correlation matrix (Σ) confirmed strong positive correlations between crop diversification and irrigation (ρ = 0.43, p < 0.01), and between soil conservation and income diversification (ρ = 0.29, p < 0.05).

Diagnostics:

- Goodness-of-fit: log-likelihood = –481.2; Wald χ^2 = 136.47 (p < 0.001).
- Multicollinearity: mean VIF = 1.92 (<10 threshold).
- Robustness tests: coefficients stable under random resampling (±5% variation).

Education, income, and credit access emerged as positive determinants of adaptation. Educated farmers show higher awareness and a greater ability to integrate new practices. Income positively affects investment capacity, while access to credit facilitates financing of irrigation and improved seeds.

Interestingly, access to credit is negatively associated with off-farm income diversification (β = –0.271, p < 0.05). This may reflect that farmers with formal credit access are more committed to agricultural investment and less likely to diversify outside agriculture. Conversely, those lacking credit may diversify off-farm as a risk-coping mechanism. This potential causal substitution effect warrants further investigation.

The negative effect of household size suggests that larger families face greater consumption pressure, reducing flexibility to invest in new adaptation measures. Similarly, farmers with livestock holdings tend to allocate resources to animal maintenance rather than crop adaptation.

These findings highlight the multidimensional nature of adaptation and underscore the usefulness of the AI-enhanced MVP in capturing correlated decision-making processes.

7) The barriers that hinder farmers from adapting to climate change

Table 7 presents the results of the obstacles that hinder farmers from adapting to climate change.

Table 7. Barriers of climate change

Barrière	WAI
Lack of financial support	4.79
High cost of adaptation measures	4.64
Unreliability of seasonal forecasts	4.57
Limited knowledge of adaptation measures	3.57
Lack of access to improved crop varieties/seeds	3.50
Lack of awareness	3.07
Lack of access to early warning signals	2.71

8) Comparative results: MVP vs. AI (random forest)

Table 8 compares the predictive performance of the traditional econometric Multivariate Probit (MVP) model and the AI-based Random Forest (RF) classifier. The goal is to assess whether integrating Artificial Intelligence improves the model's ability to predict farmers' adaptation strategies to climate change.

Table 8. Comparative Results: MVP vs. AI (Random Forest)

Model	Accuracy (%)	AUC (avg)	Precision	Recall	F1-score	Interpretability
Multivariate Probit (MVP)	81.9	0.86	0.79	0.81	0.80	High (causal interpretation)
Random Forest (AI-based)	88.7	0.91	0.85	0.88	0.86	Moderate (variable importance only)

9) AI results – feature importance (random forest)

This Table 9 shows the relative importance of each predictor variable in determining farmers' adaptation behavior, as identified by the Random Forest model. The importance score reflects each variable's contribution to reducing prediction error across all decision trees.

Table 9. AI Results – feature importance (random forest)

Variable	Importance (%)	Interpretation
Average annual income	22.4	Key driver of adoption across most strategies
Access to credit	18.6	Facilitates investment in adaptation technologies
Education level	14.8	Enhances awareness and decision-making capacity
Type of labor	10.9	Determines flexibility in adopting new practices
Origin	8.3	Reflects socio-cultural influence and community norms
Livestock ownership	7.5	Indicates production system dependency
Agricultural experience	6.2	May limit innovation among older farmers
Household size	5.7	Economic pressure limits investment ability
Non-agricultural activity	3.6	Provides alternative income buffers
Marital status	2.0	Minor indirect influence

B. Analysis and Discussions

With regard to the results obtained on the social perceptions of climate change, we found that drought is the notion most commonly evoked and the one most recognised by farmers as giving a certain meaning to the notion of climate change. These results corroborate the findings of the study conducted by Manandhar *et al.* [17] in northern Thailand, which looked at the effects of climate change in relation to local people's perceptions and the associated risks. The importance of understanding farmers' perceptions of the impacts of climate change, as well as the need to prioritise their adaptation strategies, was emphasised there. The main objective of this research was to provide an overview of how rural communities currently perceive climate change.

In particular, the study looked at several climatic factors: temperature, rainfall, and extreme events such as floods and droughts, in order to assess their influence on farming practices. Rockney [18], in a survey conducted in northern California, looked at perceptions of the social risks associated with climate change. He observed that the majority of farmers already identify tangible physical risks resulting from changing weather conditions, in particular the increasing scarcity of water resources and smoke from forest fires. Farmers also report increasingly mild winters, with reduced snow cover and early spring melt, increasing the risk of spring floods, summer droughts, and autumn fires.

Regarding the impact of climate change on farmers and agricultural production, the results of this study confirm the existence of a close link between climate change and reduced agricultural production, which poses a direct threat to food security. The majority of farmers surveyed reported a significant drop in yields, attributable to increasing climate disruption - notably temperature rises, greater variability in rainfall, and an increase in extreme weather events such as prolonged droughts or flash floods. These findings are closely aligned with those of [42], who analysed the impact of climate change on agricultural systems in several regions of Asia, and highlighted a widespread reduction in agricultural productivity, associated with increasingly unpredictable climatic conditions. Wang and his colleagues point out that this instability not only disrupts agricultural calendars, but also affects soil quality and access to essential water resources.

Similarly, Hussain *et al.* [20] carried out in comparable agro-ecological contexts, which reinforces this observation. Their study reveals that farmers' perceptions of the effects of climate change are strongly correlated with recurrent economic losses, greater uncertainty about future harvests, and an increase in the vulnerability of farming households. According to these authors, the drop in productivity is not only the result of unfavorable climatic conditions, but also of a lack of access to effective adaptation strategies and institutional support. This is in line with the findings of our survey, in which farmers frequently cited a lack of technical and financial resources as an aggravating factor.

This perspective shows that the effects of climate change on agriculture cannot be understood solely in terms of meteorological or agronomic data, but must be analyzed using an integrated approach that takes account of local perceptions, adaptation capacities and the support policies in place. The convergence of results between the various studies shows that there is a shared recognition, both empirical and scientific, of the growing risks that climate change poses to food security, particularly in regions already exposed to environmental and socio-economic stresses.

Against this backdrop, it is becoming imperative to rethink agricultural systems through a climate resilience approach, combining technological innovation, the strengthening of local knowledge and institutional support. The consistency between the results of this study and those of [19, 41] argues in favour of a concerted framework for action, integrating both scientific data and the realities experienced by farmers in the field.

In terms of adapting to climate change, the results reveal a complex and contextualised picture of how farmers are adapting to the impacts of climate change. The analysis shows that farmers do not limit themselves to a single adaptive response, but mobilise a range of strategies - from adjusting sowing or planting dates, to crop diversification, to more structural decisions such as migrating to urban areas or engaging in non-agricultural activities. This multiplicity of responses confirms that adaptation choices are not a matter of chance or simple behavioural imitation, but are conditioned by a combination of demographic, economic and institutional factors, as the multivariate Probit model generated by STATA clearly indicates.

These results echo the findings of Sheikh *el al.* [15] in their study conducted in Rangsit, Thailand. They too found that farmers' adaptation to climate change is strongly influenced by specific socio-economic variables. In particular, they highlight the central role of human capital (education, farming experience), access to resources (credit, information, institutional support), and family structures in the choice and effectiveness of adaptation strategies. In both studies, access to credit emerges as a determining factor in the implementation of technical solutions, such as increased use of organic fertilisers or involvement in income-generating activities outside agriculture.

At the same time, the link between farmers' origin and certain technical decisions, such as changing sowing dates or irrigation methods, highlights the importance of the socio-cultural context in the ability to adapt. Sheikh et al. also report that farmers who have recently migrated or who are not originally from the region studied often display distinct adaptive behaviours, influenced by their social integration, their access to information, or their previous exposure to different agricultural practices.

In addition, our finding that factors such as the number of children, marital status and off-farm activity play a significant role in certain strategies, notably reducing the size of the farm or urban migration, is directly echoed in the study by Sheikh et al. These authors note that decisions to leave farming, redirect household resources, or invest in urban activities are strongly linked to family dynamics and the economic pressure exerted by household needs. The role of farming experience in the decision to migrate to the cities, identified in your study, is also consistent with observations made in Thailand, where the most experienced farmers are often those who most clearly perceive the limits of conventional farming strategies in the face of climate change, prompting them to explore alternatives outside the sector.

Analysis of the data from the barriers to adaptation to climate change reveals a clear hierarchy of the barriers that hinder their ability to adapt effectively to climate change. At the top of the list, the lack of financial support obtained the highest WAI score (4.79), underlining the crucial importance of economic support in adaptation efforts. For farmers, lack of finance is the main constraint, probably due to their dependence on limited resources and the absence of support mechanisms tailored to their needs.

In second place, the high cost of adaptation measures (4.64) is also perceived as a major obstacle. This similarity in score to the first barrier confirms that farmers recognise the need to take action, but come up against economic obstacles that make adaptation difficult or even unattainable.

The unreliability of seasonal forecasts comes third with a WAI of 4.57. This constraint is particularly critical in an agricultural context where decisions are largely influenced by climatic conditions. The absence of reliable climatic information prevents farmers from planning their activities and reduces the effectiveness of adaptation strategies.

The following barriers, although scoring lower, remain significant. Lack of knowledge about adaptation measures (3.57) and lack of access to improved varieties or seeds (3.50) reflect weaknesses in terms of agricultural extension, applied research, and technology transfer. These results highlight a shortfall in agricultural advisory services and in the integration of innovations with farmers.

Further down the ranking, lack of awareness (3.07) indicates that some farmers do not yet fully understand the challenges of climate change or the existing opportunities for adaptation. Lastly, poor access to early warning signals (2.71) is the least cited barrier, but not an insignificant one. It highlights a lack of infrastructure and warning systems, which are essential for anticipating climate hazards.

To provide greater analytical depth, we examined the determinants of barrier perception using correlation and regression analysis:

Financial barriers (lack of financial support, high adaptation costs) are strongly negatively correlated with household income ($r \approx -0.41$, $p < 0.01$) and access to credit ($r \approx -0.38$, $p < 0.01$), suggesting that poorer households perceive these constraints as more severe.

Informational barriers (limited knowledge, unreliable forecasts) are negatively associated with education level ($r \approx -0.35$, $p < 0.01$) and access to extension services ($r \approx -0.32$, $p < 0.05$).

Regression analysis using an ordered probit model indicates that income, farm size, and educational attainment are significant predictors of perceived barrier intensity ($p < 0.05$). For instance, farmers with higher income and larger farms report lower intensity for financial barriers, while higher education reduces informational barriers.

These results show that barriers are not uniform across households, and targeted interventions (e.g., credit programs, extension services, improved forecasting) are needed to enhance adaptation uptake.

These results are in close agreement with the findings of the study conducted by [43] in the Arsi zone, located in the Oromia region of Ethiopia, entitled 'Farmers' adaptation strategies to climate change on agricultural production in Arsi zone, Oromia National Regional State of Ethiopia'. In both studies, the results show that the barriers to adapting to climate change are mainly economic and informational. Indeed, in both our context and that of the Arsi region, farmers express serious difficulties in implementing adaptation strategies due to limited access to financial resources, a lack of institutional support, and insufficient targeted funding mechanisms. Similarly, the lack of reliable information on future climate conditions, combined with the poor dissemination of knowledge about adaptive farming practices, is a major obstacle to decision-making.

While many machine learning algorithms such as Random Forests, Support Vector Machines (SVMs), and Gradient Boosting are powerful for prediction, they often operate as "black-box" models with limited interpretability in terms of behavioral decision processes. In contrast, the Multivariate Probit (MVP) model offers a probabilistic and interpretable framework that explicitly models the correlations between multiple binary decisions in this case, farmers' simultaneous adaptation strategies. By integrating machine learning principles, such as cross-validation, predictive accuracy assessment, and feature selection, the MVP can serve as a hybrid classifier that balances statistical inference and predictive power. Unlike non-parametric ML algorithms, the MVP provides insight into causal mechanisms and policy-relevant relationships between socio-economic variables and adaptation behavior, while still benefiting from data-driven validation techniques. This hybridization highlights the model's unique contribution as a bridge between traditional econometrics and modern machine learning approaches to climate change adaptation analysis.

Rather than introducing a new AI model, this study adopts an interpretable Multivariate Probit framework and enhances it with predictive validation tools commonly used in machine learning. This reinterpretation strengthens the predictive value of the study and aligns with the growing adoption of AI/ML in agricultural research. Extensions of this work could include hybrid approaches, where MVP is combined with optimization algorithms or embedded in deep learning frameworks, as seen in recent developments of the Deep Multivariate Probit Model.

1) Policy implications

The results point to several policy priorities:

- Targeted credit programs tailored to smallholders, promoting climate-resilient technologies.
- Strengthening agricultural extension services, especially to reach less-educated farmers.
- Encouraging integrated adaptation portfolios, combining soil, water, and income strategies.
- Investing in digital advisory systems using AI/ML for localized climate information.
- Capacity building through participatory training to reinforce decision-making autonomy.

The interpretable Multivariate Probit framework and enhances it with predictive validation tools commonly used in machine learning, offering policy-makers and practitioners more accurate and flexible tools for guiding adaptation strategies. This enhances the practical implications of the study beyond its econometric contribution.

2) Summary of AI/ML integration

By embedding the MVP within a machine-learning framework, the study combines statistical inference and predictive analytics. Through training–testing validation, cross-validation, and performance metrics (accuracy = 82.3%; AUC = 0.87), the model demonstrates the added predictive value of hybrid econometric–AI approaches. This validates the use of the term "probabilistic supervised classifier enhanced by ML validation techniques", which in this context reflects the integration of supervised probabilistic modeling and predictive evaluation not a departure from econometrics but its enhancement.

Although the AI-enhanced Multivariate Probit model provides robust insights into the determinants of farmers' adaptation strategies in Oulad Said, the generalizability of these findings remains context-dependent. Socio-economic and institutional conditions differ considerably across regions of Morocco and beyond. For instance, farmers in more irrigated or market-integrated zones may have greater access to infrastructure, financial services, and information, leading to higher adoption rates of technology-based adaptation measures. In contrast, communities in remote or mountainous areas face structural barriers such as poor connectivity, land fragmentation, and limited extension support, which constrain their adaptive capacity. Consequently, while the relationships identified between income, credit, education, and adaptation are likely relevant across semi-arid contexts, the magnitude and interaction of these effects may vary with regional development levels and policy frameworks. Future research should therefore extend this analysis to comparative multi-regional studies, integrating spatial and institutional heterogeneity to refine the predictive performance and policy applicability of AI–econometric hybrid models.

The AI-based Random Forest model outperformed the traditional MVP in terms of predictive accuracy (88.7% vs. 81.9%) and discriminative ability (AUC = 0.91 vs. 0.86). This improvement suggests that nonlinear interactions between socioeconomic variables and adaptation strategies are important. However, while the Random Forest algorithm offers superior prediction, it lacks the causal interpretability of the MVP. The complementary use of both models thus provides a powerful hybrid approach: MVP clarifies *why* certain factors matter, while AI methods predict *how strongly* and *in what combinations* they drive adaptation. The integration of AI techniques like Random Forest enhances the capacity to forecast farmers' adaptive behavior and supports the development of data-driven decision-support systems for agricultural resilience planning.

Even though the results obtained give valuable information about the adaptation behavior of farmers within a semi-arid, mostly rainfed agricultural system, the usage of the results in other settings should be approached cautiously. In drier areas with larger fluctuations of rainfall and more serious shortage of water, adaptation measures can be limited by structural deficiency of water instead of solely socioeconomic factors. Such environments can be less responsive to some options that are found in the present study e.g. planting date change or crop diversification unless significant investments are made in water infrastructure or institutions.

On the same note, in completely irrigated farmlands, the factors of adaptation would also be different as seen in the study area. Immediate exposure to climate can be mitigated by access to irrigation, which might likely diminish the role of other factors like income or education in determining adaptation decisions and enhance the role of water governance, energy prices, and institutions of irrigation management.

Furthermore, in areas where the agricultural markets are well incorporated, price signals, contract farming, and insurance or financial products may influence more farmers to respond to the climate change than household socioeconomic factors may do. This means that the relations found in this paper might be incapable of capturing the dynamics of adaptation in a market-oriented production system.

These shortcomings indicate the significance of contextualized studies and indicate that future studies will need to implement the suggested AI-enhanced multivariate modeling system in a wide array of agro-ecological and institutional settings to determine the strength and generalizability of the findings.

IV. Conclusion

This study examined farmers' perceptions, impacts, and adaptation strategies to climate change in the rural commune of Oulad Said, Morocco, using an innovative approach combining econometric rigor with AI-driven predictive modeling. Results show that farmers are aware of climate change, particularly droughts and rainfall deficits, and have adopted diverse adaptation strategies such as crop diversification, drought-resistant varieties, and off-farm activities. The Multivariate Probit (MVP) model, framed as an AI-enhanced classifier, identified key socio-economic determinants influencing adaptation, including income, access to credit, education, and household size.

While the approach provides robust insights and demonstrates potential for replication in other semi-arid regions, results should be interpreted cautiously due to regional heterogeneity in infrastructure, market integration, and institutional support. Policy recommendations include targeted credit schemes, strengthened extension services, capacity-building programs, and improved rural infrastructure to enhance context-specific and inclusive climate adaptation strategies.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, A.H.; methodology, A.H.; software, A.H.; validation, A.H..; formal analysis, A.H.; investigation, A.H.; resources, A.H.; data curation, A.H.; writing—original draft preparation, A.H.; writing—review and editing, A.H.; visualization, A.H.; supervision, A.H.; project administration, A.H.; funding acquisition, R.K., A.A., Y.L., and A.B. All authors have read and agreed to the published version of the manuscript.

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