ORIGINAL ARTICLE

Determinants of Farmers' Crop Management Strategies to Climate Change in Northwest Ethiopia: The Role of Agro-ecological Zones

Menberu Teshome Zeleke [1]

Abstract

Climate change is a major, constant threat to farmers globally, especially in less developed countries like Ethiopia. This study examined how farmers choose adaptation methods, recognizing that their ability to adapt is heavily determined by their local social, economic, and environmental conditions, including their agro-ecological zone. The study surveyed 525 farm household heads selected using a systematic random sampling method in Northwest Ethiopia. Instead of using one general model, the study ran a set of seven distinct Binary Logistic Regression Models (for a specific strategy (Yes/No)) to find the factors driving each choice. This prevents the error of grouping separate decisions together. The finding reveals that using these strategies is a complex process influenced by both factors those help and holdback farmers. Major limiting factors include repeated drought, poor land quality, water scarcity, lack of timely weather information, top-down formal extension service, illiteracy, and limited financial services. However, agro-ecology and farmer-to-farmer extension are the strongest influencers across most strategies. This confirms that effective adaptation must be location-specific. Moreover, it relies on the farmers' trust in the knowledge more shared by their peers than formal extension service. A key finding is that the reasons for adoption are unique to specific location and to each crop management strategy. Furthermore, planned adaptation is vital to protect the highly vulnerable lowland and midland areas, pointing to a major disconnect in formal, top-down government extension services. The study concludes that public efforts must be customized to match the specific problems and strategies of each location, mainly by supporting farmer networks for delivering information and services.

Keywords: Adaptation Strategies, Agro-ecological Zones, Binary Logistic Regression, Climate Change, Crop Management, Determinants, Ethiopia

1. Background of the Study

Climate change is a profound statistical shift in global climate patterns, a phenomenon that has escalated into an existential threat to biodiversity and human systems (IPCC, 2023). This crisis reached a historic peak in 2024, when global temperatures reached approximately 1.55°C above the pre-industrial average, marking the first time the

1 *Department of Geography and Environmental Studies, Debre Tabor University, Ethiopia P.O.Box 272, Email: menberuteshome@gmail.com*
ORCID: https://orcid.org/0000-0002-2110-1789

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critical 1.5°C threshold was exceeded (IPCC, 2023; WMO, 2024). In Ethiopia, the impact is particularly acute because the agricultural sector, which supports over 70% of the population, is almost entirely dependent on rain-fed systems (Worede et al., 2020; Simane et al., 2023). This reliance makes the country's food security and economic development highly sensitive to fluctuations in rainfall and temperature, necessitating the adoption of adaptation strategies to protect rural livelihoods from climate-induced shocks (FAO, 2021; Tilahun and Simane, 2017).

The theoretical foundation for understanding how farmers navigate these challenges is provided by Random Utility Theory, which posits that the decision to adopt a specific adaptation strategy is a rational choice based on perceived benefits. According to this framework, a farmer will implement a new practice only if the expected utility of that choice outweighs the benefits of remaining with traditional methods or alternative options (Maddison, 2007). Because this utility is not directly visible, it is modeled as a function of the farmer's unique socio-economic, institutional, and environmental circumstances (Simane et al., 2013). These circumstances form the core determinants that dictate whether a household can successfully transition from perceiving a climate risk to taking concrete action on the ground, specifically regarding crop management strategies like adjusting planting dates or adopting improved seed varieties (Worede et al., 2020).

Socio-economic factors serve as the first major set of determinants, reflecting the household's internal capacity and resource base. Education level is a critical driver, as it enhances a farmer's ability to interpret and respond to new technologies (Dawit and Boka, 2025), while farming experience provides local knowledge that can either promote adaptation or lead to risk aversion (Yesuf et al., 2008). Furthermore, the physical and financial resources of the household, such as the size of the labor pool (Girma et al., 2022), total farm acreage, and access to farm or off-farm income, determine the ability to relax financial constraints necessary for investing in new inputs (Shita et al., 2022; Tadesse et al., 2025). These internal factors are often mediated by the sex of the household head, which historically influences the degree of access to resources and information (Alemayehu, 2022).

Beyond the household level, institutional determinants represent the external policy and support environments that facilitate adaptation. Access to credit is essential for overcoming liquidity barriers to purchasing inputs (Yirga et al., 2022), while extension services and farmer-to-farmer networks provide the necessary channels for disseminating information and building skills (Shita et al., 2022). The security of land tenure also plays a fundamental role, as farmers are far more likely to invest in long-term, land-improving strategies like conservation farming if they have guaranteed rights to their land (Tesfaye et al., 2011; Yami and van Asten, 2017). Additionally, the availability of timely weather and market information empowers farmers to make economically rational decisions based on real-time data rather than current climate variability (Bryan et al., 2009; Simane et al., 2013).

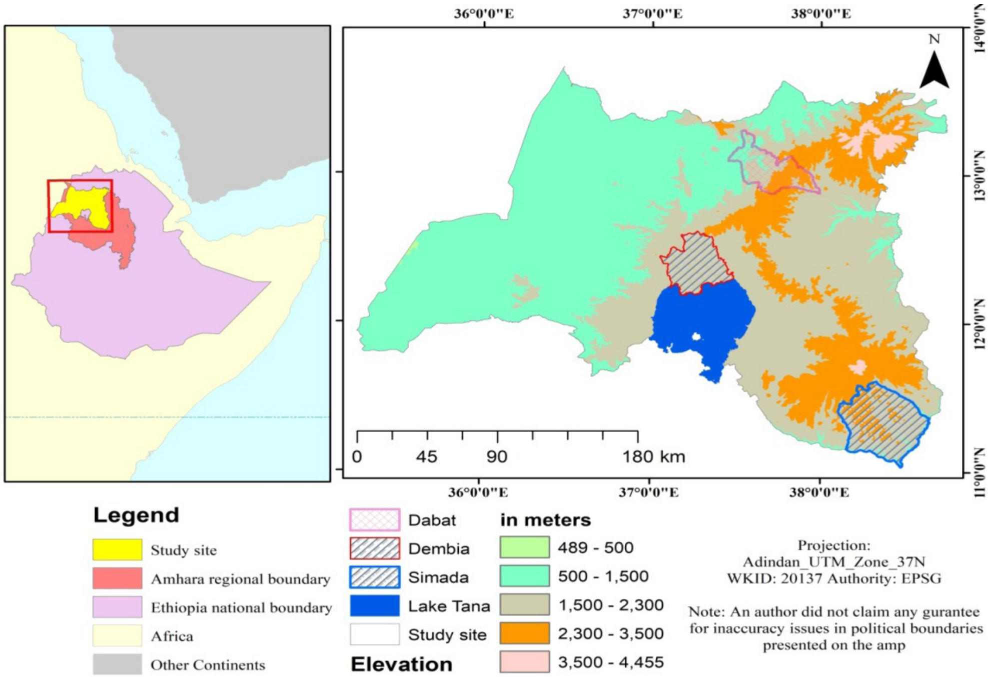
Environmental and biophysical determinants constitute the final layer of influence, as the local landscape dictates the feasibility of specific strategies. A farmer's subjective perception of changing temperature and rainfall patterns is typically the primary initial driver for taking adaptive action (Demissie and Asfaw, 2024; Dawit and Boka, 2025). Localized conditions, such as the inherent fertility of the soil and the overarching agro-ecological zone, further define the viability and necessity of specific crop management choices (Tadesse et al., 2025). Finally, high weather variability and unpredictable rainfall increase production risks, driving farmers toward risk-mitigating strategies like crop diversification (Tadesse and Teklay, 2024).

Despite the wealth of existing literature, a significant contextual and methodological gap remains in how research translates these broad factors into localized action. Much of the previous work has utilized top-down modeling focused on large-scale impact predictions, which contrasts with the need for a bottom-up approach that seeks to understand the strategy-specific determinants of farmer-led choices (Maddison, 2007; Tilahun and Simane, 2017). Existing research has not adequately isolated the factors influencing specific crop management strategies, particularly regarding the heterogeneous influence of distinct agro ecological zones. This study addresses that gap by employing a bottom-up method in Northwest Ethiopia to evaluate how local contexts shape adaptation, ultimately providing the evidence-based insights needed for targeted policy and extension interventions.

2. Research Methodology

2.1. Study Area Justification and Agro-ecological Zones

This study utilizes a purposive sampling strategy to select three districts within the Amhara region, representing the full environmental and economic spectrum of Northwest Ethiopia. By spanning the elevation gradient from the Abay-Beshilo River gorges to the Semien Mountains, the selection captures the diverse agro-ecological zones (AEZs) that fundamentally dictate cropping choices and adaptation strategies (FAO, 2003; Simane et al., 2013) (Refer Figure 1).



Source: Researchers own computation from Ethio GIS Database

Figure 1: Location of the study districts with reference to varied elevation zones

The Highland Zone (Dega) is represented by the Dabat district, a high-altitude area characterized by cold temperatures and high rainfall. Farming here follows the Highland Cereals and Livestock (HCL) system, focusing on cold-tolerant crops like barley, wheat, and pulses. Due to the steep terrain and climate profile, adaptation strategies in this zone prioritize frost mitigation, moisture management, and intensive soil conservation (Gashaw et al., 2021).

The Midland Zone (Woyna-Dega) is represented by the Dembia district, situated on the productive Lake Tana plain. As a transitional zone with moderate temperatures, it supports the Northwest Mixed Cereal (NMC) system, where farmers cultivate diverse crops including teff, sorghum, and maize. In this highly productive, yet, weather-sensitive area, crop management focuses on navigating rainfall variability and maximizing yields through intensive inputs like fertilizers and improved seed varieties (Worede et al., 2020).

The Lowland Zone (Kolla) is represented by the Simada district, specifically the communities nestled within the deep gorges of the Blue Nile and Beshilo Rivers. This zone is characterized by intense heat and high moisture stress, falling under the Abay/ Sorghum/Pulses (ABSP) farming profile. Agricultural practices here rely on drought-tolerant crops like pearl millet and sorghum, with adaptation efforts strictly dedicated to moisture conservation, heat stress reduction, and coping with recurrent droughts and flash floods (Ayalew et al., 2023).

By integrating physical AEZ classifications with socio-economic livelihood profiles (HCL, NMC, ABSP), this site selection provides a robust framework for the study. This dual-system approach ensures that the research captures how widely varied environmental and economic contexts influence the specific decisions of smallholder farmers to adopt various crop management strategies across the region.

2.2. Research Approach and Design

This study employs a bottom-up adaptation assessment approach, prioritizing local-level details and farmers' perspectives to ensure a context-specific analysis across the selected agro-ecological zones. Given the complex interplay of natural and socioeconomic factors inherent in climate change research, a mixed-methods research design was adopted within a pragmatic framework (Adger et al., 2020; IPCC, 2023; Creswell, 2014). This approach leverages the complementary strengths of both quantitative and qualitative methods to provide a more comprehensive understanding of adaptation behavior (Raune, 2012; Creswell and Clark, 2017).

The quantitative component utilizes a cross-sectional survey design systematically to collect numerical data from a large household sample at a single point in time. This design is specifically intended to statistically identify the key determinants influencing the adoption of crop management strategies, ensuring that the findings are reliable and can be generalized to the broader farming population (Creswell, 2014). Conversely, the qualitative component provides a deeper exploration of the social and institutional context through in-depth interviews, focus group discussions, and direct field observations. These methods capture the lived experiences and underlying motivations of farmers, explaining the "why" and "how" behind their decision-making processes (Creswell and Clark, 2017).

To integrate these approaches, the study follows a sequential explanatory (QUAN-QUAL) procedure. Quantitative data are collected and analyzed first, followed by qualitative data collection to interpret and contextualize the statistical results. While the household serves as the primary unit of analysis for strategy adoption, environmental factors such as elevation, temperature, and rainfall are analyzed at the agroecological zone level to provide a robust framework for understanding the influence of the biophysical environment on farmer choices.

2.3. Sampling Techniques

Following the selection of the three districts (Dabat, Dembia, Simada), kebele administrations (KAs) within each were stratified into the respective AEZs (Highland, Midland, Lowland). A total of eleven KAs were randomly selected: three from the Highland zone, and four each from the midland and lowland zones. This proportional allocation (three KAs from 29 total in the highland vs. four KAs from over 40 in the midland/lowland) was necessary to accurately represent the greater geographical area and population distribution found across the different zones.

The minimum required sample household size was determined using the established mathematical formula developed by Yemane (1967), employing a 5% margin of error (e=0.05):

$$n = \frac{N}{1 + N(e)^2} \tag{1}$$

Where: n = designates the sample size the research uses;

N = designates total number of households in all kebeles;

e = designates maximum variability or margin of error 5% (0.05);

1= designates the probability of the event occurring.

The calculation yielded a minimum size of 389 households. To compensate for potential non-response and incomplete responses (Feige and Marr, 2012), the sample size was proportionally increased, resulting in a final working sample of 576 households. These households were distributed among the selected districts and KAs using the Probability Proportional to Size (PPS) method. This ensured that the sample size from each KA was proportional to its total household population, thereby guaranteeing a representative sample given the unequal household sizes across the different elevation zones.

$$ni = \frac{n \times Ni}{\sum Ni} \tag{2}$$

where: n_i is proportional sample size of the i^{th} kebele/agroecology; Ni is population size of the i^{th}kebele/agroecology.

The final sample distribution was: lowland (263), midland (181), and highland (132). This disparity is justified by: (1) selecting more KAs from the midland and lowland zones was necessary due to their larger geographic and total population coverage. (2) consistent with demographic trends in the Abbay Basin and arid/semi-arid regions (Pison et al., 2012), the lowland area, despite being a challenging landscape, exhibits higher population density due to intensive settlement clustering around permanent water sources (tributaries of Abay and Beshilo Rivers). This pattern is further supported by historical census data.

Table 1: Distribution of sample population by elevation zone

	Sample Kebeles	No. of households	Sample size
Lowland	4	5033	263
Midland	4	3976	181
Highland	3	2722	132
	Grand Total	11732	576

*NH = North Highland **Source**: *Woreda* Administration Offices

The sampling frame (household lists) was obtained from respective kebele administration offices. Sample households were selected from each KA using a systematic random sampling technique. This involved: (1) calculating the sampling interval (K); (2) selecting a random start number between one and K; and (3) subsequently selecting every Kth household head until the required sample size was reached. This method assumed a uniform distribution of rural farmers within each stratum (Feige and Marr, 2012), guaranteeing a well-distributed and representative final sample.

2.4. Sources and Methods of Data Collection

This study used an integrated mixed-methods approach (primary and secondary data) to ensure a robust understanding of crop management strategies for adapting to climate change.

2.4.1. Primary Data Sources

A detailed household survey was administered to the sampled household heads or rarely their spouses. The instrument was designed to capture comprehensive information on demographics, socio-economic characteristics, institutional access, perceived climate risk, and specific crop management strategies. The survey instrument was rigorously translated into Amharic language and refined following a pilot test in a non-sampled kebele to ensure clarity and validity. Data collection involved trained enumerators, with close follow-up and the replacement of persistently absent or unwilling households with the next household on the systematic random sampling list (Dillman et al., 2014).

Qualitative data were gathered using in-depth interviews and focus group discussions for exploring the underlying reasons, processes, and contextual nuances (“how” and “why”) of farmers’ adaptive choices, thereby complementingthe quantitative findings (Creswell and Creswell, 2018).

2.4.2. Secondary Data Sources

Secondary data provided the crucial contextual and climatic foundation for the analysis: A review of scholarly literature and international policy documents (Yami and van Asten,

2017) established the global and theoretical framework, allowing local findings to be compared against established research. Population figures and physical characteristics were collected from administrative offices, detailing the socio-economic and non-climatic context of the study districts.

Long-term daily gridded rainfall and temperature records (1979–2010) were obtained for specific study sites from the Global Weather Data for SWAT (http://globalweather.tamu.edu/). The use of this gridded reanalysis meteorology product was strongly justified by the lack of long-term, consistent operational weather station records in the remote dissected gorges and highlands. This dataset overcomes issues of missing or inconsistent station data, providing a spatially continuous and representative time series essential for accurate drought analysis across the distinct AEZs (FAO, 2017).

2.5. Methods of Data Analysis

The collected data underwent a rigorous analytical process specifically tailored to the study's mixed-methods design and research objectives.

2.5.1. Descriptive and Climatic Analysis

To establish baseline findings, the quantitative data were analyzed using descriptive statistics (frequency, percentages, means, and indices) to quantify the characteristics of drought and the distribution of adaptation strategies before proceeding to further inferential analysis (Field, 2018).

To establish necessary climatic foundation, the Standardized Precipitation Index (SPI) (McKee et al., 1993) was applied to the 1979–2010 precipitation record to quantify historical drought characteristics (duration, magnitude, and intensity) across the three distinct AEZs.

2.5.2. Inferential Analysis (Binary Logistic Regression)

To address the primary inferential objective—identifying determinants that influence farmers' adoption of crop management strategies—Binary Logistic Regression (BLRM) was employed (Hosmer and Lemeshow, 2000; Greene, 2018). BLRM is the appropriate econometric model for analyzing a dichotomous dependent variable (Adoption: Yes/No) because it uses a logit link function to constrain the predicted probability of adoption to the required 0-to-1 range, a condition standard linear regression cannot meet. This makes the model ideal for describing the relationship between adoption and its predictor variables (Tarling, 2009).

$$\text{Logit}(y) = \text{In}(\text{odds}) = \text{In}\left(\frac{P}{1-P}\right) = B_0 + B_1x_{i1} + B_2x_{i2} \dots + B_px_{ip} \quad (3)$$

Where: y is the binary response variable (crop management options),

B_1 is the constant or the intercept of y,

$B_0 + B_1 x_{i1} + B_2 x_{i2}$ are regression coefficients,

P is the predicted probability to adopt (coded 1),

$1-P$ is predicted probability of the decision to adopt a particular adaptation option,

$x_{i1}+x_{i2}+x_{ip}$ are the predictor variables included in the model.

To provide precise, strategy-specific policy recommendations, seven independent Binary Logistic Regression Models were estimated to analyze the distinct, non-mutually exclusive crop management strategies. This approach successfully isolated the unique socio-economic, institutional, and environmental factors driving the choice for each specific adaptation and avoided the restrictive Independence of Irrelevant Alternatives (IIA) assumption associated with complex models like Multinomial Logit (Maddison, 2007). The resulting Odds Ratios (Exp(B)) are highly interpretable: a value greater than one indicates a positive relationship with adoption, and a value less than one indicates a negative relationship (SPSS 16), delivering precise, strategy-specific policy recommendations.

2.5.3. Variable description

The variables used in the model, categorized as dependent and explanatory, are defined and measured as follows.

Table 2: Definition and measurement of variables

Variable Type	Variable Name	Description and Measurement
Dependent Variables (Outcome)	Improved Seeds	Dummy:1 = Adopted; 0 = Did not adopt.
	Diversifying Crops	Dummy:1 =Diversifier (grows≥3 crops); 0 =Not a diversifier (grows<3 crops).
	Change Planting Dates	Dummy: 1 = Adopted; 0 = Did not adopt.
	Replanting Crops	Dummy: 1 = Adopted; 0 = Did not adopt.
	Agroforestry	Dummy: 1 = Adopted; 0 = Did not adopt.
	Organic Fertilizers	Dummy: 1 = Adopted; 0 = Did not adopt.
	Irrigation	Dummy: 1 = Adopted; 0 = Did not adopt.
	Water Harvesting	Dummy: 1 = Adopted; 0 = Did not adopt.
Explanatory variables (predictors)	Age of the household head	Continuous: Measured in years.
	Sex of the household head	Dummy: 1 = Male; 0 = Female.
	Family size in the household	Continuous: Number of people in the household.
	Education of the HH head	Dummy:1= Literate; 0 illiterate – no formal education attended
	Farmland fertility status	Dummy: 1 = Fertile; 0 = Otherwise (Less fertile/Infertile).
	Farm size of the households	Continuous: Measured in hectares (ha).
	Access to water for irrigation	Dummy: 1 = Yes (Access); 0 = No (No access).
	Livestock ownership	Continuous: Measured in Tropical Livestock Units (TLU).
	Annual farm income	Continuous: Measured in Ethiopian Birr (ETB).
	Non-farm income	Continuous: Measured in Ethiopian Birr (ETB).
	Access to credit	Dummy: 1 = Yes (Access); 0 = No (No access).
	Access to markets	Continuous: time taken to reach the nearest market (in hours).
	Number of relatives in a village	Continuous: The absolute number of relatives in the village.
	Farmer-to-farmer extension	Dummy: 1 = Yes (Participates); 0 = No (does not participate).
	Access to formal extension	Dummy: 1 = Yes (Access); 0 = No (No access).
	Access to training	Dummy: 1 = Yes (Access); 0 = No (No access).
	Access to weather information	Dummy: 1 = Yes (Access); 0 = No (No access).
	Perceived temperature change	Dummy: 1 = Yes (Perceived change); 0 = No (did not perceive change).
	Perceived rainfall change	Dummy: 1 = Yes (Perceived change); 0 = No (did not perceive change).
	Agroecology	Categorical: 1 = Highland; 2 = Midland; 3 = Lowland.

Note on Dummy Variables: For all dummy variables, the value 1 stands for 'Yes' or the presence of the attribute (e.g., Male, Adopted, Access), and 0 stands for 'No' or the absence of the attribute.

Source: The researcher's compilation

3.5.4. Model Diagnostics, Goodness-of-Fit, and Collinearity

Rigorous diagnostics were performed to confirm the stability of the parameter estimates and the adequacy of the model structure and fit.

(a) Model Structure and Justification: The study's structure required estimating seven independent Binary Logistic Regression Models (one for each distinct adaptation strategy) with all independent variables (listed in the table) included as covariates (Maddison, 2006). This approach was statistically necessary to isolate the unique determinants for each specific, non-mutually exclusive decision. The 95% confidence interval (CI) for the Odds Ratio was computed for interpretation.

(b) Goodness-of-Fit Assessment: Model adequacy was confirmed using the Hosmer-Lemeshow Goodness-of-Fit Test (Hosmer and Lemeshow, 2000), where an insignificant $p > 0.05$ confirmed the models adequately fit the observed data. This was supported by the Classification Table Analysis, which showed the full models significantly improved predictive accuracy over the null model (67.9% to 93.7% correct classification) compared to the constant-only model (58% to 92.6% correct classification).

(c) Collinearity Diagnostics: Collinearity was assessed using the Variance Inflation Factor (VIF). VIF is the preferred multivariate test as it accounts for the complex linear inter-correlation between a predictor and all other predictors. A parallel linear regression was run with the same independent variables to generate VIF values (Hosmer and Lemeshow, 2000). The results confirmed no multicollinearity problem in any of the seven models, as all VIF values consistently fell well below the common threshold of 10(ranging from 1.062 to 2.278), ensuring the stability of the coefficients.

Qualitative Analysis: Qualitative data from in-depth interviews (IDIs), focus group discussions (FGDs) and secondary information were subjected to thematic analysis (Braun and Clarke, 2006), involving systematic coding and interpretation to uncover recurring themes, patterns, and contextual factors.

3. Results and Discussion

3.1. Climate Characterization

Developing effective mitigation and adaptation strategies requires a comprehensive understanding of drought frequency, duration, magnitude, and severity. To assess these long-term patterns across the three agro-ecological zones from 1979 to 2010, the Standardized Precipitation Index (SPI) was utilized. The resulting data revealed distinct characteristics for each zone, demonstrating that prolonged duration does not inherently correlate with higher intensity (refer Table 3).

Table 3: Summary of drought duration, magnitude, and intensity by agro-ecological zone

Agro-ecology	Duration in year	Magnitude (−)	Intensity (−)	Span of time
Highland	18	12.16	0.68	1979−2010
Midland	12	12.54	1.05	1979−2010
Lowland	15	15.53	1.04	1979−2010

Source: Computed from Global Weather Data for SWAT[http://globalweather.tamu.edu/]

In the highland agro-ecological zone, drought persisted for the longest duration at 18 years, yet it recorded the lowest intensity at 0.68. In contrast, the midland and lowland zones faced more severe conditions over shorter periods; the midland zone reached the highest intensity of 1.05 over 12 years, while the lowland zone experienced the greatest magnitude of 15.53 over 15 years. These findings align with research by Gidey et al. (2024) and Daba et al. (2023), which asserts that the cumulative impact and magnitude of a drought can be more significant even when the event is shorter in duration.

This complex relationship between duration and severity is, further, supported by Otgonjargal (2012), who observed that shorter drought events often possess higher magnitudes than longer ones. For instance, the midland and lowland zones in this study exhibited significantly higher intensities despite their shorter time spans compared to the highland zone. Identifying these varied patterns is essential for tailoring climate-resilient strategies to the specific vulnerabilities and environmental stressors unique to each agro-ecological zone (Tilahun et al., 2022; Worku et al., 2021).

3.2. Descriptive Variation in Crop Management Strategy Usage by Agro-ecological Zone

The descriptive analysis of household data reveals a pronounced heterogeneity in strategy adoption across the three agro-ecological zones, with an overall average usage rate of 45.27% across all categories. A clear trend in adaptive effort emerges along an elevational and socioeconomic gradient; the highland zone exhibits the highest average usage at 51.22%, followed by the midland at 44.56%, while the lowland zone shows the lowest engagement at 40.02% (refer Table 4). Qualitative insights from focus group discussions and interviews suggest that this pattern is driven by a highland advantage characterized by superior access to financial services, infrastructure, and extension support, contrasting with the lowland barrier of remoteness and acute poverty (Worku et al., 2021).

Table 4: Percentage of households using crop management strategies by agroecology

Crop management options	Total(Average)	Highland	Midland	Lowland
Organic fertilizers	91.93	96.9	84.2	94.7
Improved seeds	53.67	77.5	75.9	7.6
Diversifying crops	68.13	69.8	68.4	66.2
Changing planting dates	74.13	94.6	67.7	60.1
Replanting crops	73.27	91.5	60.2	68.1
Irrigation	19.97	24.8	24.8	10.3
Water harvesting	7.6	3.9	3.0	16.0
Agroforestry	64.4	86.8	44.4	62.0
Average	45.27	51.22	44.56	40.02

Source: Household survey, March – Sept 2019, SPSS16 output using multiple response command

The adoption data further highlights a significant disparity between low-cost, accessible practices and capital-intensive technologies. Practices requiring minimal financial outlay, such as the use of organic fertilizers, are nearly universal, with an average adoption rate of 91.93% across all zones. This heavy reliance on manure represents a rational, risk-averse response to the high costs and logistical hurdles of chemical inputs (Gebremedhin and Placide, 2023). Similarly, crop diversification remains a consistent, low-cost risk management tool with uniform adoption across the region. However, more flexible adjustments like changing planting dates and replanting are significantly more prevalent in the highlands, reaching over 90% adoption, which suggests that farmers in this zone possess the necessary resources and information to make timely, responsive decisions.

In contrast, specialized and capital-intensive strategies expose severe institutional and resource constraints, particularly in the lowlands. For instance, the adoption of improved seeds is nearly 77% in the highland and midland zones but plummets to a mere 7.6% in the lowland zone, highlighting a dramatic failure of input markets and credit systems in remote areas (Worede et al., 2020). A similar trend is observed in water management; despite the extreme moisture stress of the lowlands, irrigation adoption there is only 10.3%, less than half the rate of the other zones, confirming that infrastructure and capital constraints often outweigh environmental necessity (Bryan et al., 2011).

Agroforestry presents a unique case where adoption is driven by a combination of ecological mandate and targeted intervention. While usage drops in the midlands, it remains high in the lowlands at 62%, largely due to the necessity of mitigating soil erosion and heat stress in degraded gorge ecosystems. Findings indicate that this sustained adoption is facilitated by non-governmental organizations that bundle soil and water conservation programs with direct economic incentives like food-for-work or cash-for-work. These programs encourage the establishment of contour bunds, living fences, and fodder woodlots, effectively offsetting the initial costs of tree-based systems. Ultimately, while the highlands benefit from systemic institutional support, the lowlands rely on specialized, incentive-based programming to overcome the barriers inherent in their fragile and resource-poor environment.

3.3. Determinants of Farmers’ Choice of Crop Management Strategies

The adoption of crop management measures is not uniform; its drivers vary based on the specific nature of each strategy. Consequently, this study utilizes seven independent Binary Logistic Regression Models (BLRM) rather than a single generalized model. This segmented approach, detailed in Table 5, prevents the masking of unique determinants and identifies the precise socio-economic, institutional, and environmental factors influencing choices such as improved seed use, organic fertilization, adjusted planting dates, replanting, crop diversification, agroforestry, and water management.

Table 5: Determinants of farmers' decision of crop management strategies to climate change

Independent variables	Improved seeds		diversify crops		Change planting dates		Replanting crops	
	Sig.	Exp(B)	Sig.	Exp(B)	Sig.	Exp(B)	Sig.	Exp(B)
Highland(1)	**.000**		**.001***		**.000***		**.000***	
Midland (2)	.130	.543	**.024***	.453	**.000***	.071	**.000***	.109
Lowland (3)	**.000**	.023	.125	1.598	**.000***	.085	**.046***	.454
Age of the HH	**.004**	.964	**.029***	.980	.133	.985	**.041***	.980
Gender_HH(1)	.735	1.140	.245	1.385	**.004***	2.264	**.034***	1.850
Family size	.076	1.520	.966	1.007	.217	1.240	.761	.950
Education	.769	.979	.405	1.047	**.005***	.853	.765	.982
weather info(1)	**.046**	1.826	**.040***	1.570	**.001***	.438	.463	1.191
Farm size	**.005**	1.895	**.002***	1.905	**.015***	1.655	.320	1.183
Land fertility(1)	.824	1.095	.289	1.324	.732	1.097	**.038***	1.791
TLU	.684	.966	.277	.936	**.009***	.842	**.022***	.868
Draught animal	.955	1.012	.724	1.059	**.017***	1.557	.188	1.249
Farm income	**.022**	1.000	**.000***	1.000	.066	1.000	**.000***	1.000
Non-farm inco	.349	1.000	.481	1.000	.183	1.000	.833	1.000
Far-far exten(1)	**.008**	2.464	**.034***	1.675	.905	1.031	**.001***	2.309
Exten_serv(1)	.842	1.062	**.015***	.562	.313	.774	.557	.865
Percept_ RF	**	**	**	**	.36.2	.1.480	.467	1.339
Constant	.920	1.084	.539	.695	**.000***	13.393	.156	2.561

Source: Households survey *significant at 0.05 ** not fitted to the model (1) stands for 'Yes'

Table 5: Determinants of farmers' adoption of crop management strategies (continued...)

Predictor variables	Organic fertilizers		Irrigation-water harvesting		Agro-forestry	
	Sig.	Exp(B)	Sig.	Exp(B)	Sig.	Exp(B)
Agroecology- highland(1)	**.000***		**.01***		**.000***	
Agroecology -midland(2)	**.000***	.032	.386	.651	**.000***	.06
Agroecology -lowland(3)	.442	.550	**.04***	2.24	**.003***	.35
Age _HH head	.903	1.002	.603	1.01	.922	1.00
Family size	**.000***	4.343	.785	.98	**.035***	1.31
Educational attainment	.949	1.008	.498	1.05	.116	1.11
Access to weather info(1)	**.023***	2.887	.428	1.28	.777	1.07
Farm size	.419	1.362	.808	1.05	**.033***	1.36
Access to water(1)	.767	1.246	**.00***	48.6	**.049***	2.53
Tropical livestock unit (TLU)	**.000***	1.780	.641	1.03	.24	1.06
Farm income	.864	1.000	.552	1.00	**.006***	1.00
Nonfarm income	.889	1.000	.621	1.00	.978	1.00
Farmer-to-farmer extension(1)	.080	2.271	.929	.971	**.019***	1.76
Extension service(1)	.926	1.047	**.00***	2.37	**.000***	2.30
Perception to temperature(1)	.534	1.595	.804	.886	.337	.70
Perception to rainfall(1)	.988	1.011	**.009***	2.296	.065	2.13
Constant	.214	.153	.056	.173	.452	.57

Source: Households survey, 2019; Note: The reference category is not adopt

Table 5 presents the logistic regression results, confirming that adaptation decisions are highly strategy-specific. The number of significant determinants varies across the seven models, ranging from four for organic fertilizers to seven for practices like agroforestry and changing planting dates. This variation proves that drivers are not uniform; for example, while family size significantly boosts the adoption of organic fertilizers and agroforestry due to labor needs, it remains irrelevant for improved seeds or shifting planting dates. These findings validate the use of separate binary models to capture precisely the unique decision-making processes behind each non-mutually exclusive adaptation choice.

3.3.1. Factors Influencing the Adoption of Improved Seeds

The model for improved seeds successfully identified six statistically significant determinants ($p<0.05$): agro-ecology, age of the household head, access to climate information, farm size, farm income, and farmer-to-farmer extension (Table 5).

The positive relationship between farm size (Exp(B)=1.895) and farm income (Exp(B)=1.000 - significant at p=0.022) and the adoption of improved seeds is well-documented. Larger farms and higher incomes provide the necessary capital and capacity to absorb the financial risks associated with purchasing new seed varieties and complementary inputs like fertilizers (Feige and Marr, 2012; Yesuf et al., 2008). Similarly, access to farmer-to-farmer extension Exp(B)=2.464) is a powerful positive driver, facilitating peer-to-peer learning which builds trust and is often more effective than formal approaches (Yohannes etal., 2020).

The study found that households in midland (Exp(B)=0.543) and lowland (Exp(B)=0.023) agroecological zones are less likely to adopt improved seeds compared to those in highland zones. This result strongly supports the idea that biophysical conditions significantly influence technology viability (Yesuf et al., 2008; Ayele et al., 2024), as distinct rainfall, temperature, and soil characteristics make certain improved seed varieties less suitable or profitable in lower altitudes.

Age of the household head shows a statistically significant negative relationship (Exp(B)=0.964), indicating that younger farmers are more likely to implement these strategies compared to their older counterparts. This is attributed to younger farmers' greater exposure to modern farming techniques, longer planning horizons, and higher willingness to accept risk (Yohannes et al., 2020; Ayele et al., 2024).

Although the study found that a farmer's perception of climate change was not a statistically strong predictor of improved seed use in this specific model, access to weather information (Exp(B)=1.826) was found to be a significant positive determinant. This aligns with research that emphasizes the importance of climate information services in driving the adoption of climate-smart agricultural practices (Gbetibouo, 2009; Yohannes et al., 2020).

3.3.2. Factors Influencing the Use of Organic Fertilizers (manure-compost)

Agroecology shows a significant difference in adoption likelihood. Households in the midland (Exp(B)=0.032) and lowland (Exp(B)=0.550) agro-ecological zones were less likely to adopt organic fertilizers compared to the highland zones. This divergence is justified by the key informants and FGD participants mostly attributed to the use of animal dung as a primary source of fuel in lower altitudes, diverting this resource from agricultural use.

This challenges the assumption that all degraded areas would see high fertilizer use. In contrast to the strategy-specific insignificance for improved seeds, family size is a crucial determinant, showing that an increase of one person in the family increases the odds of adopting organic fertilizers by a substantial factor of 4.343 (p<0.001). This highlights the labor-intensive nature of composting and manure application, which requires a large available labor force.

Households with access to weather information were 2.887 times more likely to adopt this crop management practice, as they understand that organic fertilizers can help crops withstand expected drought conditions. Similarly, livestock ownership (TLU) is a strong positive determinant, increasing the odds of adoption by a factor of 1.780, reflecting the fact that livestock is the primary source of manure for soil fertility management.

3.3.3. Factors Influencing the Crop Diversification

The model for crop diversification identified seven statistically significant factors (p<0.05): agroecology, age of the household head, access to weather information, farm size, farm income, farmer-to-farmer extension, and formal extension services (Table 5).

The model's results indicate a strong geographical influence, with households in the lowland agroecology found to be 1.598 times more likely to diversify than those of in the highland, while midland households were 0.453 times less likely. This aligns with the argument that farmers in vulnerable, dry land areas are more likely to adopt risk-mitigating strategies (Yohannes et al., 2020) due to heightened exposure to climatic shocks.

The positive relationship between farm size (Exp(B)=1.905) and crop diversification is well-established, as larger farms provide more land and capital opportunities for diversification (Yohannes et al., 2020). Access to weather information (Exp(B)=1.570) and farmer-to-farmer extension (Exp(B)=1.675) are consistently identified as key positive drivers.

In contrast, government extension services showed a statistically significant negative relationship (Exp(B)=0.562). This is a critical finding, suggesting that the formal extension approach in the study area may be counterproductive for promoting diversification, reinforcing the preference for trusted peer networks. The negative correlation with age (Exp(B)=0.980) is consistent with literature, showing younger farmers are more willing to experiment with new crops.

3.3.4. Factors Influencing Changing Planting Dates

The model for changing planting dates identified seven statistically significant determinants (p<0.05): elevation, gender, education, access to weather information, farm size, livestock ownership (TLU), and livestock ownership (Table 5). This unique set of variables further confirms that the decision process for this timing-based strategy is distinct from input-based or diversification practices.

The findings show that lowland (Exp(B)=0.071) and midland (Exp(B)=0.085) households were found to be significantly less likely to change planting dates than highland households. This negative relationship with lower elevation is supported by studies showing that the effective window for planting is often narrower in drier lowland areas, making the act of changing the date a riskier practice (Kassie et al., 2009).

The influence of farm size (Exp(B)=1.655) and livestock ownership(Exp(B)=1.557) is logical and widely accepted. These assets provide the necessary means to prepare land and plant crops quickly, allowing farmers to take advantage of short, unpredictable rainfall events. Furthermore, male-headed households were 2.264 times more likely to change planting dates than female-headed households, consistent with the literature noting that male farmers are often more involved in climate-sensitive field operations and have better access to information and heavy-duty resources.

Crucially, access to weather information showed a significant negative relationship (Exp(B)=0.438) with changing planting dates, which contradicts conventional expectations. This critical discrepancy suggests a fundamental failure in the delivery or trustworthiness of climate information in the specific study area. Farmers may receive information that is too generic, delayed, or inconsistent, leading them to disregard it and adhere to traditional signs, thereby reducing the likelihood of a planned change in planting. The negative relationship with education (Exp(B)=0.853) and livestock ownership (TLU) (Exp(B)=0.842) also points to older, perhaps more traditional, educated farmers being less reactive to climate signals and market fluctuations regarding planting windows.

3.3.5. Factors Influencing Replanting Crops

The model for replanting identified seven statistically significant factors ($p<0.05$): agroecology, age, gender, land fertility, livestock ownership (TLU), farm income, and farmer-to-farmer extension (Table 5).

Again, lower agroecology significantly inhibits adoption: midland (Exp(B)=0.109) and lowland (Exp(B)=0.454) households were significantly less likely to replant compared to the highlands. Replanting in moisture-stressed lowlands is a high-risk activity with low probability of success, directly discouraging its use (Tilahun and Simane, 2017).

Age shows a negative influence (Exp(B)=0.980), consistent with the risk-aversion of older farmers. Conversely, male-headed households were 1.85 times more likely to replant, reflecting greater access to labor and resources needed for this demanding activity.

The inverse relationship between livestock ownership (TLU) (Exp(B)=0.868) and replanting is a specific adaptive strategy unique to this high-risk decision. Farmers often view their livestock as a liquid form of climate-shock insurance. Instead of investing additional resources in a risky second planting, they may opt to sell animals to cope with the financial loss (Temesgen et al., 2009), shifting toward a livestock-based coping mechanism rather than crop recovery. In contrast, land fertility (Exp(B)=1.791) provides a strong incentive for replanting, as the probability of a successful second harvest is higher on healthier land.

3.3.6. Factors Influencing Irrigation and Water Harvesting

The model for Irrigation/Water Harvesting identified six statistically significant determinants ($p<0.05$): agroecology, access to water, formal extension services, perception of rainfall changes, perception of temperature changes, and access to water for irrigation (Table 5).

Access to water was found to be the single most significant determinant across all adaptation strategies in the study, increasing the probability of adopting irrigation by a massive factor of 48.649 ($p<0.001$). This self-explanatory necessity underscores the fundamental biophysical constraint.

Lowland households were 2.24 times more likely to adopt this strategy than highlands, justified by the necessity of water harvesting in areas characterized by frequent droughts and severe water shortages (Temesgen et al., 2009). The positive influence of formal government extension services (Exp(B)=2.37) on this strategy is a key counterpoint to the negative relationship observed in diversification, suggesting that complex, capital-intensive practices like irrigation require the structured technical support and training that formal services can provide (Yohannes et al., 2021).

Furthermore, a farmer's perception of climate change (rainfall) was found to be highly significant (Exp(B)=2.296). This highlights that when the threat of water scarcity is observed and internalized, it serves as a powerful psychological motivator to invest in expensive and labor-intensive water management technologies. The absence of other socio-economic factors like family size or farm income as significant drivers confirms that water availability and knowledge transfer are the primary bottlenecks for this specific practice.

3.3.7. Factors Influencing Agroforestry

The model on the adoption of agroforestry identified seven statistically significant determinants ($p<0.05$): agroecology, family size, farm size, access to water, farm income, farmer-to-farmer extension, and formal extension services (Table 5).

As with many other strategies, agroecology is critical: midland (Exp(B)=0.06) and lowland (Exp(B)=0.35) agro-ecological zones were less likely to practice agroforestry than the highlands. This confirms the critical requirement for reliable rainfall and cooler temperatures necessary for tree survival and long-term establishment (Tamene and Adimassu, 2019).

The positive influence of family size (Exp(B)=1.31) and farm size (Exp(B)=1.36) is consistent with the labor and land demands of this practice. Larger families provide the necessary labor force, and larger farms provide the space for the long-term allocation of land to tree crops (Temesgen et al., 2009). Both farm income (Exp(B)=1.00) and access to water (Exp(B)=2.53) also positively influence adoption, reflecting the upfront cost and necessary moisture for seedling establishment.

Finally, both farmer-to-farmer extension (Exp(B)=1.76) and formal expert services (Exp(B)=2.30) were significant positive determinants. This shows that agroforestry, being both technically complex and reliant on peer experience, benefits from a hybrid extension model, where both official training and trusted peer-to-peer demonstration are essential for successful uptake.

4. Conclusions and Policy Implications

This study concludes that climate change adaptation is a complex, heterogeneous process driven by a strategy-specific mix of biophysical, socio-economic, and institutional determinants. The analysis confirms that anticipatory adaptation is essential for reducing vulnerability, particularly in the environmentally fragile lowland and midland zones. Because determinants vary by strategy, such as credit driving seed adoption while weather information influences planting dates, the use of independent binary models is fully justified.

Despite this variability, agroecology and farmer-to-farmer extension emerged as the most consistent drivers of adaptation. These findings suggest that a one-size-fits-all approach is ineffective; instead, interventions must be tailored to local biophysical constraints and leverage peer-to-peer learning networks. Furthermore, the mixed impact of formal government services highlights a need to move away from rigid, top-down systems toward more participatory, bottom-up models.

To enhance regional resilience, policy must shift toward targeted interventions that formally support indigenous knowledge-sharing, reform extension services, and address structural barriers. Key priorities include improving localized weather forecasting, expanding credit access, and promoting sustainable land management to unlock the full adaptive potential of farming households across diverse landscapes.

References

Adger, W. N., Brown, K., and Huq, S. (2020). *Successful Adaptation to Climate Change: Linking Science and Policy in a Rapidly Changing World*. Routledge.

Alemayehu, M. (2022). Gender differences in the adoption of climate-smart agricultural practices in Ethiopia: A meta-analysis. *Journal of Agricultural and Environmental Ethics*, 35(3), 1-25.

Ayalew, M., Zeleke, G., and Kindie, B. (2023). Determinants of farmers' choice of climate change adaptation strategies in Simada district, South Gondar, Ethiopia. *Heliyon*, *9*(11), e21617.

Ayele, G., Teka, F., and Worede, M. (2024). Climate-smart agriculture adoption: The role of agroecological zones and technical suitability in Ethiopia. *Ethiopian Journal of Development Research*, *45*(1), 1-18.

Braun, V., and Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101.

Bryan, E., Ringler, C., Okoba, B., and Koo, J. (2011). Adaptation to climate change in Ethiopia and Kenya: Household perceptions, choice of strategies, and constraints. *Economic Development and Cultural Change*, *60*(1), 211-245.

Creswell, J. W., and Clark, V. L. P. (2017). *Designing and Conducting Mixed Methods Research* (3rd ed.). SAGE Publications.

Creswell, J. W., and Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Dawit, F., and Boka, N. A. (2025). Factors determining farmers' choice of climate-smart agriculture adaptation strategies: Evidence from Oromia Region, Ethiopia. *Heliyon*, 11(2), e13009.

Demissie, F., and Asfaw, Z. (2024). Smallholder farmers' perception and adaptation strategies to climate change in Ethiopia: A review. *Climate Risk Management*, 43, 100583.

Dillman, D. A., Smyth, J. D., and Christian, L. M. (2014). *Internet, phone, mail, and mixed-mode surveys: The tailored design method* (4th ed.). Wiley.

Food and Agriculture Organization (FAO). (2003). *Farming systems and poverty: Improving farmers' livelihoods in a changing world*. FAO and World Bank.

Food and Agriculture Organization (FAO). (2017). *Guidance on the use of the*

Standardized Precipitation Index in Agricultural Contexts. FAO.

Feige, A., and Marr, U. (2012). Sample Size Calculation and Recalculation in Clinical Trials. *Biometrical Journal*, *54*(3), 518–531.

Feige, J., and Marr, J. D. (2012). Determinants of sustainable intensification technology adoption among smallholder farmers. *Agricultural Systems*, *106*(1), 1-10.

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE Publications.

Fowler, F. J. (2014). *Survey research methods* (5th ed.). SAGE Publications.

Gashaw, T., Mekonnen, K., and Woldeamanuel, W. (2021). Determinants of crop diversification in Dabat District, Northwest Ethiopia. *Agriculture and Food Security*, *10*(1).

Gbetibouo, G. A. (2009). Understanding the determinants of farmers' adaptation to climate change in the Limpopo Basin, South Africa. *IFPRI Discussion Paper 00849*. International Food Policy Research Institute.

Gebremedhin, N., and Placide, M. (2023). The enduring reliance on organic inputs among East African smallholders: A response to market failures. *Journal of Agricultural Economics and Development*, *12*(4), 115-128.

Girma, T., Negash, M., and Tadesse, M. (2022). Determinants of climate-smart agricultural technology adoption in Ethiopia: A systematic review. *Journal of Agricultural Economics and Rural Development*, 8(2), 22-35.

Greene, W. H. (2018). *Econometric analysis* (8th ed.). Pearson Education.

Hosmer, D. W., Jr., and Lemeshow, S. (2000). *Applied logistic regression* (2nd ed.). John Wiley and Sons.

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). Wiley.

Intergovernmental Panel on Climate Change (IPCC). (2023). *Climate Change 2023: Synthesis Report*. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.

Kassie, M., Zikhali, P., Pender, J., and Waithaka, M. (2009). Determinants of climate change adaptation strategies in the rural areas of Ethiopia. *World Development*, *37*(4), 827-839.

Maddison, D. (2007). *The perception of and adaptation to climate change in Africa* (Vol. 4308). World Bank Publications.

McKee, T. B., Doesken, N. J., and Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Eighth Conference on Applied Climatology*. American Meteorological Society, 179–183.

Pison, G., Sarr, I., Bricas, S., and Bricas, P. (2012). Demographic dynamics in rural West Africa: A systematic review of population growth and its implications. *Global Health Action*, *5*(1).

Raune, P. (2012). *Mixed methods research for dummies*. John Wiley and Sons.

Shita, A., Zenebe, G., and Desta, H. (2022). Determinants of agricultural technology adoption in Amhara Region, Ethiopia: Evidence from improved maize variety. *Cogent Food and Agriculture*, 8(1), 2092194.

Simane, B., Zari, M. P., and Pfohl, K. D. (2023). Climate change, agriculture and sustainable development in Ethiopia: A review. *International Journal of Environmental Research and Public Health*, 20(2), 1642.

Tadesse, M., Beyene, B., and Mekonnen, Y. (2025). Impact of agro-ecology on farmers' choice of climate-smart agricultural practices: Evidence from West Arsi Zone, Ethiopia. *Environmental Management*, 75(1), 1-15.

Tamene, L., and Adimassu, Z. (2019). Adoption and impact of sustainable land management practices on soil erosion and productivity in the Ethiopian highlands. *Land Degradation & Development*, *30*(7), 801-812.

Tarling, R. (2009). *Statistical modeling for social researchers: Principles and practice*. Routledge.

Temesgen, B., Tola, B., and Mekonen, H. (2009). Determinants of households' adaptation decisions to climate change in rural Ethiopia. *Journal of Agricultural Science*, *147*(5), 629-641.

Temesgen, B., Tola, B., and Mekonen, H. (2010). Impacts of climate change on agriculture and food security in Ethiopia: An overview. *Journal of Environmental Science and Engineering*, *4*(2), 177-188.

Tilahun, A., & Simane, B. (2017). Determinants of farmers' choice of adaptation strategies to climate change in North Eastern Ethiopia. *International Journal of Environmental Protection and Policy*, *5*(3), 57-65.

Worede, S., Belay, A., and Kebede, M. (2020). Socioeconomic vulnerability and adaptive capacity to climate change in the Ethiopian Rift Valley. *Ecology and Society*, *25*(3), 44.

Worku, H., and Zeleke, M. (2021). Necessity-driven versus successful adaptation: Adoption paradox in arid and semi-arid Ethiopian agriculture. *International Journal of Environmental Research and Public Health, 18*(12), 6540.

World Meteorological Organization (WMO). (2024). *WMO Statement on the State of the Global Climate in 2024*. WMO-No. 1318.

Yami, M., an van Asten, P. (2017). *Climate change, agriculture and food security in Ethiopia*. Springer.

Yemane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper and Row.

Yesuf, M., Di Falco, S., Ringler, C., and Bryan, E. (2008). Drivers of adaptation to climate change in Ethiopia. *World Bank Policy Research Working Paper 4691*.

Yirga, F., Gebrehiwot, K., and Haile, A. (2022). Impact of credit access on agricultural technology adoption in Ethiopia: A systematic review and meta-analysis. *African Journal of Agricultural Research*, 18(6), 405-416.

Yohannes, Z., Teshome, M., and Belay, M. (2020). Adaptive capacity of mountain community to climate change: A case study in the Semien Mountains of Ethiopia. *Environment, Development and Sustainability*, *22*(4), 3051–3077. https://doi.org/10.1007/s10668-019-00334-3

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