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Weather Index Insurance and Input Intensification: Evidence from Smallholder Farmers in Kenya

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Abstract: Climate variability intensifies weather risks across smallholder rainfed farming systems in Africa. Farmers often respond by minimizing the use of modern inputs and opting for low-cost traditional practices, a strategy that decreases average yields and perpetuates poverty. While crop insurance could incentivize greater adoption of inputs, indemnity-based programs face market failures. Weather index insurance (WII), which utilizes objective weather data to trigger payouts while addressing traditional crop insurance market failures, is a viable solution. However, empirical evidence on the impact of WII remains limited, with most studies relying on controlled experiments or hypothetical scenarios that overlook real-world adoption dynamics. This study analyzed observational data from 400 smallholder farmers across diverse agroecological zones in Njoro Sub-County, Kenya, using instrumental variable regression to evaluate the impact of weather index insurance (WII) on input adoption and intensity of use. Findings indicated that WII significantly increased the adoption and intensification of improved inputs while displacing traditional practices, with effects moderated by gender, financial access, and infrastructure. Specifically, active WII users applied 28.7 kg/acre more chemical fertilizer and used 2.6 kg/acre more hybrid maize seeds while reducing manure and traditional seed usage by 27 kg/acre and 2.9 kg/acre, respectively. However, the effectiveness of WII was context-dependent, varying under extreme drought conditions and in high-fertility soils, which directly affected resilience outcomes. These findings suggest that policies should combine insurance with targeted agroecological practices and complementary measures, such as improved access to credit and gender-sensitive extension programs tailored to the specific needs of women farmers, to support sustainable agricultural transformation.

Keywords: weather index insurance; input intensification; smallholder farmers; climate resilience

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1. Background

Climate change has intensified weather risks in Sub-Saharan Africa, where extreme events such as droughts, floods, and storms have increased by 40% since 2000, resulting in annual agricultural losses exceeding CNY 15 billion [1]. Smallholder farmers, who contribute 60% of the region's food production and depend primarily on rainfed agriculture, are most affected [2]. In Kenya, where tropical climates exacerbate weather variability, 98% of agriculture is rainfed, and smallholders contribute over 70% of the country's food production, the impacts of weather risks are particularly severe [3,4]. Compounding these challenges, only 4% of arable land is irrigated, and less than 15% of smallholders can access formal credit, limiting their ability to mitigate losses [5]. These intersecting vulnerabilities

trap 10 million smallholder households in poverty [6], underscoring the urgency of scalable interventions to strengthen resilience and stabilize productivity.

Agricultural intensification has historically been linked to poverty reduction, as demonstrated by the Green Revolution in Asia and Latin America [7]. However, climate change has disrupted this model, particularly in rainfed systems. For instance, during droughts, farmers in Kenya typically reduce fertilizer use by 30–50%, forgoing yield gains of 4–6 tons per hectare [8]. This aligns with prospect theory, which suggests that smallholders prioritize avoiding losses over maximizing profits under uncertainty [9]. Although strategies such as crop diversification and distress sales provide short-term relief [10], they exacerbate long-term vulnerabilities. For instance, prolonged droughts lower agricultural wages by 40% and asset values by 60%, reinforcing cycles of poverty [11]. Institutional interventions should, therefore, address the fundamental linkage between climate risk and productivity declines.

Agricultural insurance could address this challenge, but traditional models face challenges in developing economies. Moral hazard and adverse selection increase operational costs by 30–50% [12], and covariate risks require costly reinsurance arrangements [13]. Fiscal limitations restrict coverage, with subsidized schemes reaching only 3% of farmers in Kenya [14]. Weather index insurance (WII) is a viable alternative. It utilizes objective weather data to trigger payouts, minimizing moral hazard while reducing administrative expenses by 60%, compared to traditional indemnity-based models [15]. Standardized premiums and indemnity terms across designated areas mitigate adverse selection, while the product's transparency facilitates access to global reinsurance markets for catastrophic risk coverage, strengthening insurer solvency [16,17].

Despite promising pilot results, the causal mechanisms linking weather index insurance (WII) to sustained agricultural productivity remain contested. While WII's role in mitigating climate risks is well-established [16], its secondary role in incentivizing productivity-enhancing inputs, critical for breaking low-yield equilibria, lacks consistent empirical support. Some studies demonstrate that WII reduces financial stress, promoting higher input use [18,19], while others report negligible effects without complementary interventions, such as credit or extension services [20,21]. This divergence reflects unresolved contextual factors, including local risk perceptions and institutional barriers, which current research has not addressed systematically.

Three key gaps undermine the policy relevance of existing WII research. First, reliance on controlled experiments and hypothetical scenarios [22,23] limits understanding of farmer decision-making dynamics and the contextual factors that moderate WII's effectiveness in real-world settings. Second, studies often focus on binary adoption decisions [24] rather than quantifying how WII influences input-use intensity (e.g., kg/acre), a critical metric for assessing sustainable intensification. Third, most evaluations overlook agroecological diversity, which includes factors such as biodiversity, soil types, and local climate conditions. For example, WII designs effective in humid highlands often fail in arid lowlands due to mismatches between index triggers and crop phenology [25].

This study addresses these gaps by evaluating the effectiveness of WII in promoting the adoption and intensification of modern agricultural inputs, such as chemical fertilizers and improved maize seeds, in Njoro Sub-County, Kenya. Using observational data from smallholders across multiple WII programs and agroecological zones, we bridged the divide between controlled experiments and real-world conditions, isolating how behavioral and environmental factors shape WII's effectiveness. Moving beyond binary adoption measures, we quantified WII's impact on input-use intensity for modern and traditional inputs, providing empirical evidence of its potential to drive sustainable agricultural intensification. Finally, we translated these findings into actionable recommendations

for improving WII design, ensuring scalability across diverse farming systems in Kenya and similar regions globally. Our results could inform Kenya's National Agricultural Insurance Program and refine theoretical frameworks at the intersection of climate-risk finance, behavioral economics, and resilient food systems.

2. Weather Index Insurance in Kenya

Weather index insurance (WII) has become a cornerstone of climate risk management for Kenyan smallholders, with operational schemes since the late 2000s [24]. The Kilimo Salama ("Safe Farming") Program, launched in 2009, is a model for WII in Sub-Saharan Africa, integrating mobile technology and input-linked coverage to reduce basis risk and administrative costs, which have hindered traditional insurance models [26,27]. Under this model, farmers who purchase insured inputs, such as hybrid maize seeds or fertilizers from approved suppliers, are automatically enrolled in WII, with premiums typically ranging from 10% to 20% of input costs, which raises retail prices proportionally [27].

Enrollment is facilitated via SMS with product-packaging codes or agro-dealer networks, ensuring geotagged plot alignment with nearby weather stations [24]. Payouts are triggered when rainfall, measured by automated weather stations, deviates from predefined thresholds during key crop growth phases. For example, a payout may occur if rainfall falls below 200 mm over an 8-week sowing period for maize. Claims are processed through mobile money (M-Pesa) within 14 days, enabling farmers to replant or smooth consumption in response to adverse weather [27].

Despite these advancements, WII uptake remains low, with only 12.7% of eligible smallholders enrolled as of 2022 [4]. Barriers to wider adoption include liquidity constraints and uneven weather station coverage, with only 62% of Kenya's agro-zones having reliable weather station density as of 2021 [28]. These constraints, along with other structural barriers, limit the effectiveness and reach of WII. Kenya's Agriculture Sector Transformation Strategy (ASTS) prioritizes WII expansion through partnerships involving insurers like APA, Jubilee, and the Kenya Agricultural Insurance Programme (KAIP) [29]. Despite policy efforts, the persistent low uptake of WII reflects systemic barriers. Integrating WII with targeted infrastructure and risk-contingent financing could bridge the gap between ambition and smallholder realities.

3. Methodology

3.1. Study Area

This study was conducted in Njoro Sub-County, Kenya (0°19′53″ S, 35°56′31″ E), a region that exemplifies the challenges of rainfed smallholder agriculture in climate-vulnerable areas. Over 70% of households rely on maize farming for subsistence and income, making food security closely linked to climatic variability. The sub-county spans 713 km^2 across six administrative wards: Mau-Narok, Mauche, Kihingo, Nesuit, Lare, and Njoro. With an altitude ranging from 1300 to 2000 m above sea level, the climate is characterized by temperatures between 25 °C and 30.5 °C and an annual rainfall of 850–1000 mm. However, recurrent droughts and erratic precipitation have reduced maize productivity by 30–50% since 2000 [30].

These declines are further compounded by structural constraints: median landholdings of 0.5–2 hectares limit economies of scale, while liquidity shortages hinder access to adaptive technologies, such as drought-resistant seeds. Fragmented extension services and delayed input subsidies further constrain adaptive capacity. Educational access is limited, with many farmers having only primary schooling, and healthcare and infrastructure services remain underdeveloped, compounding vulnerability. Land tenure is generally secure under customary law, with some legal protections in place; however, pressures exist

for land consolidation, and intergenerational transfer is often contested. Credit facilities are available primarily through informal channels, with limited legal safeguards. Economic pressures, particularly among young people, drive migration from rural to urban areas. Traditional community governance structures persist, influencing trust and risk perceptions in decision-making [30]. Our study, therefore, developed scalable resilience strategies tailored to Njoro's specific developmental, institutional, and infrastructural realities.

3.2. Sample Size Determination

This study used a multi-stage sampling approach to select 400 smallholder maize farmers across Njoro Sub-County, ensuring the sample reflected the area's agroecological and socioeconomic diversity while remaining logistically feasible for household surveys. The sampling method was chosen for its efficiency in capturing the hierarchical administrative and geographical structures of the sub-county while ensuring population representativeness. Kothari's formula for sample size (n) is as follows:

$$n = \frac{z^2 \times p \times q}{\varepsilon^2} \quad (1)$$

where:

Z = 1.96 (95% confidence level);
p = 0.5 (conservative estimate when population proportion is unknown);
ε = 0.05 (5% margin of error).

3.3. Sampling Procedure

The multistage sampling began with the purposeful selection of Njoro Sub-County due to its reliance on rainfall-dependent agriculture, which heightens vulnerability to climate variability. The sub-county was then stratified into six administrative wards, from which four, Kihingo, Lare, Nesuit, and Njoro, were selected based on the prevalence of maize-farming households according to the Ministry of Agriculture and Livestock Development and participation in weather index insurance (WII) programs (Figure 1). Within the selected wards, 20 villages were proportionally sampled based on their maize cultivation area. Respondents were randomly chosen within each selected village to ensure geographic representation. This approach ensured methodological rigor while reflecting agricultural relevance and spatial distribution.

3.4. Data Collection and Management

Ethical and logistical groundwork preceded fieldwork. Ethical approval was granted by Egerton University's Institutional Scientific and Ethics Review Committee, and a research license was issued by the National Commission for Science, Technology, and Innovation (NACOSTI), which oversees research initiatives in Kenya. A rigorous mixed-methods approach was employed to ensure validity and reliability of the findings. Primary data were collected through field observations and structured interviews, allowing real-time cross-verification of responses. Local key informants supported participant recruitment to promote trust and enhance response accuracy, mitigating common biases in farmer surveys.

Instrument reliability was assessed with a pilot study (n = 30) in Njoro Sub-County, which led to refinements for clarity and consistency. The questionnaire addressed adaptation practices (e.g., drought-resistant seeds, irrigation), risk perceptions, institutional engagement, and contextual barriers, including credit constraints and gendered knowledge gaps. Enumerators, trained in survey administration, adhered to protocols ensuring ethical compliance and measurement accuracy, achieving a 100% response rate.

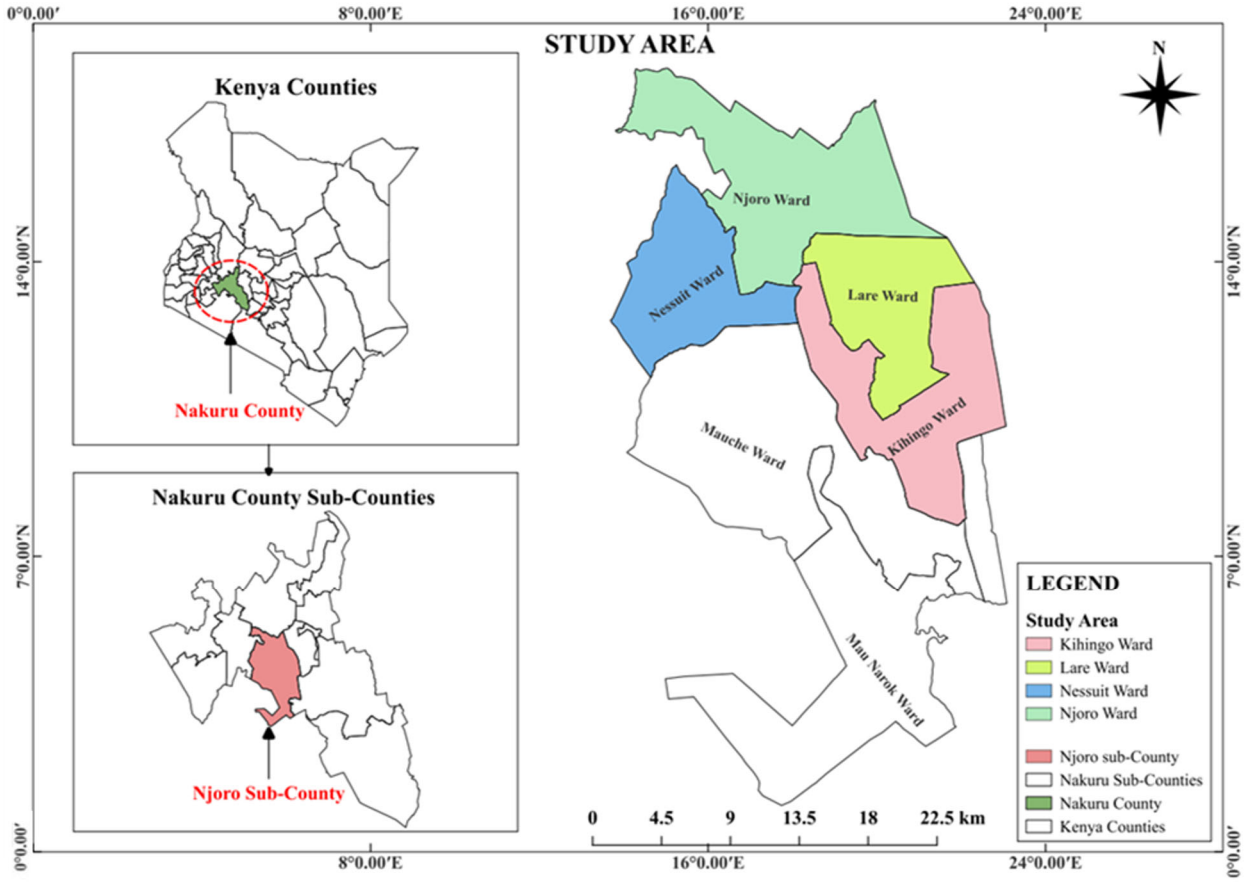


Figure 1. Map of Njoro Sub-County.

Quantitative analysis was performed using Stata 17, with hypothesis testing at a significance level of $\alpha = 0.05$. Empirical methods were supplemented by a systematic literature review of peer-reviewed journals and government reports, reinforcing the study's theoretical foundation and alignment with existing evidence.

3.5. Empirical Framework

The adoption of productivity-enhancing inputs by smallholder farmers is crucial for poverty reduction, yet underinvestment persists due to unmitigated weather risks. This study employed an IV-Probit model to investigate the impact of weather index insurance (WII) on input adoption in Njoro Sub-County, Kenya.

Unobserved factors, such as risk preferences or latent trust in institutions, may jointly influence farmers' decisions about WII adoption and input use, biasing standard probit estimates through endogeneity [31]. The IV-Probit model addresses endogeneity by using instrumental variables (IVs) that meet two conditions: relevance (a strong correlation with WII adoption) and exclusion (no direct effect on input use, except through WII) [32]. We used two instrumental variables (IVs), distance to the nearest weather station and participation in WII training programs, based on their theoretical and empirical relevance. Proximity to a weather station reduces basis risk, the gap between actual farm losses and insurance payouts, encouraging WII adoption [33]. Farmers farther from the station face higher basis risk, discouraging WII uptake. Since distance is geographically determined, it is unlikely to directly affect input use, except through its influence on WII adoption, which satisfies the exclusion restriction.

WII training programs enhance farmers' understanding of insurance, build trust, and increase WII uptake [34]. The random training assignment across villages ensured the

allocation was uncorrelated with unobserved farmer characteristics, further reinforcing the exclusion restriction. Statistical tests were conducted to confirm the strength and validity of the instrumental variables (IVs). A first-stage F-statistic exceeding the Stock–Yogo critical value of 10 for weak instruments indicated a robust relationship between the instrumental variables (IVs) and WII adoption, confirming their relevance. Additionally, the Sargan–Hansen over-identification test was applied to assess the validity of the exclusion restriction, ensuring that the instrumental variables did not directly affect input use and were homogeneous. The IV-Probit model was estimated in two stages as follows:

First-stage regression (endogenous variable equation)

The endogenous variable (WII adoption) was estimated using the exogenous variables and instruments.

$$Y_i = X_{1i}\Pi_1 + X_{2i}\Pi_2 + v_i \quad (2)$$

where Y_i is the endogenous variable from the first stage (WII adoption), X_{1i} is a vector of exogenous variables (e.g., farmer characteristics), X_{2i} is a vector of instrumental variables (distance to the weather station, training on insurance products), Π_1 and Π_2 are estimated parameter values, and v_i is the error term in the first-stage equation.

Second-stage regression (outcome equation)

The fitted values from the first stage (WII adoption) were used to estimate the effect on the outcome variable (input adoption).

$$Y_{1i}^{*} = \widehat{Y_{1i}}\beta + X_{1i}Y + u_i \quad (3)$$

where Y_{1i}^{*} is the latent dependent variable (input adoption), $\widehat{Y_{1i}}$ are the fitted values of the endogenous variable from the first stage (WII adoption), X_{1i} is the vector of exogenous covariates, β and Y are parameter estimates, and u_i is the error term.

4. Results and Discussion

4.1. Weather Index Insurance and Adoption of Agricultural Inputs

4.1.1. Descriptive Statistics of Insured and Non-Insured Smallholder Farmers

This section presents descriptive statistics comparing smallholder farmers who purchased weather index insurance (WII) with those who did not. Results in Table 1 highlight systematic differences between insured and non-insured farmers, showing how socio-economic, institutional, and behavioral factors influenced WII adoption. Insured farmers were generally older ($p < 0.05$), slightly more educated ($p = 0.081$), and had more farming experience ($p < 0.01$). These findings aligned with life-cycle technology adoption models, suggesting that accumulated knowledge facilitates the uptake of risk management tools [35]. However, the relatively low literacy levels among smallholders in Njoro, where tertiary schooling remains scarce, indicated that even marginal educational advantages significantly shape financial decision-making.

Economic capacity played a key role in WII adoption. Insured farmers reported 71% higher annual incomes ($p < 0.001$), consistent with global evidence showing that financial resources enable access to formal risk mechanisms [36]. In contrast, non-insured farmers faced significant financial constraints ($p < 0.05$), supporting the idea that even modest premiums can exclude the most vulnerable [37]. This economic disparity highlights the need for public–private partnerships to subsidize premiums or link WII to credit facilities, particularly given the insufficient legal frameworks for equitable lending practices in rural Kenya.

Table 1. Descriptive statistics of insured and non-insured smallholder farmers.

Variables	Total (n = 400) Mean (SD)	Insured (n = 166) Mean (SD)	Non-Insured (n = 234) Mean (SD)	p-Value
Socio-economic characteristics				
Age	49.38 (8.29)	50.60 (7.65)	48.52 (8.62)	0.013 **
Gender (%)	69.75 (45.93)	74.10 (43.81)	66.67 (47.14)	0.111
Schooling (years)	13.37 (4.20)	13.81 (4.47)	13.06 (3.99)	0.081 *
Household size	6.07 (2.47)	6.45 (2.55)	5.80 (2.37)	0.009 ***
Log of annual average income (ksh)	12.78 (0.63)	13.03 (0.58)	7.61 (0.62)	0.000 ***
Participation in lottery games (%)	34.50 (47.54)	62.05 (48.53)	14.96 (35.67)	0.000 ***
Experienced financial constraints (%)	95.50 (20.73)	92.77 (25.90)	97.44 (15.81)	0.027 **
Farm characteristics				
Maize farming (years)	14.66 (10.66)	16.51 (10.16)	13.35 (10.83)	0.003 ***
Total land owned (acres)	1.77 (1.38)	2.32 (1.59)	1.38 (1.05)	0.000 ***
Number of plots	1.34 (1.22)	1.41 (0.95)	1.41 (1.38)	0.565
Institutional characteristics				
Accessed loan (credit) (%)	39.00 (48.77)	39.16 (48.81)	38.89 (48.75)	0.957
Farmer group membership (%)	50.75 (50.00)	59.04 (49.18)	44.87 (49.74)	0.005 ***
Distance to nearest market (km)	2.61 (0.97)	2.47 (0.93)	2.72 (0.99)	0.010 **
Distance to financial institution (km)	2.93 (1.54)	1.47 (0.54)	3.97 (1.12)	0.000 ***
Distance to weather station (km)	2.86 (1.28)	1.80 (0.58)	3.61 (1.11)	0.000 ***
Weather index insurance training (%)	23.25 (42.24)	43.37 (49.56)	8.97 (2.86)	0.000 ***
Weather/Weather-shock-related characteristics				
Experienced weather shocks (%)	77.75 (41.59)	50.00 (50.00)	97.44 (15.81)	0.000 ***
Access to weather information (%)	98.75 (11.11)	99.40 (7.74)	98.29 (12.96)	0.326
Average yield loss to weather shocks	83.78 (36.86)	75.51 (43.00)	87.88 (32.64)	0.017 ***

Notes: Means and standard deviations (SD) are shown in parentheses for each variable. ***, **, and * indicate that the difference in means between sub-groups is statistically significant at 1%, 5%, and 10%, respectively; km denotes kilometers.

Household dynamics further distinguished the two groups. Insured farmers tended to have larger families ($p < 0.01$), suggesting that labor pooling facilitates premium payments, and they also owned larger landholdings ($p < 0.001$), reinforcing the idea that asset ownership incentivizes insurance uptake [10]. However, the lack of policy pressure to consolidate landholdings or secure inter-generational tenure may perpetuate inequalities in access to insurance. Behaviorally, insured farmers exhibited higher risk tolerance (62.05% vs. 14.96% engaged in lottery games; $p < 0.001$), underscoring the relationship between risk appetite and insurance participation [38].

Institutional access disparities further underscored systemic barriers to adoption. Insured farmers resided closer to financial services ($p < 0.001$) and weather stations ($p < 0.001$), highlighting the crucial role of physical infrastructure in facilitating financial inclusion. Their greater participation in farmer groups ($p < 0.01$) and insurance training ($p < 0.001$) illustrates how social networks reduce information asymmetries. A slight advantage in market proximity ($p < 0.05$) may provide indirect incentives for adoption by improving access to information. While mobile money platforms facilitate premium payments, disparities in network coverage, digital literacy, and device ownership can limit equitable access to WII among smallholders in Njoro Sub-County. This highlights the need for targeted collaborations among insurers, telecom firms, and local farmer cooperatives to bridge the last-mile connectivity gaps.

Weather-related experiences revealed insightful paradoxes. Despite reporting fewer yield losses ($p < 0.05$), insured farmers experienced fewer weather shocks ($p < 0.001$), suggesting better ex ante risk management or different perceptions of shocks. With nearly universal access to weather information (98.75%), these findings suggest that awareness alone is insufficient for WII adoption, supporting calls for complementary interventions [22]. The residual influence of community-based governance, where traditional risk-sharing mechanisms persist, may also explain these discrepancies, although such ethnographic insights were not captured in the survey data.

These results suggest that economic capacity, physical access, behavioral factors, and institutional linkages significantly impact WII adoption. The lower yield losses among insured farmers suggest that WII mitigates productivity losses from climate shocks. However, the paradox of insured farmers reporting fewer losses despite fewer shocks raises critical questions. This could reflect differences in risk perceptions, with insured farmers potentially downplaying the severity of shocks due to enhanced risk management or awareness. Alternatively, biases in self-reported data may influence the findings, and the residual effect of community-based governance and traditional risk-sharing mechanisms, unaccounted for in the survey, could also explain these discrepancies. Further investigation is needed to clarify these factors. To scale WII's benefits, financial and infrastructural investments, along with targeted behavioral and institutional interventions, are essential to addressing adoption disparities.

4.1.2. Descriptive Statistics of General Input Use Patterns Among Insured and Non-Insured Farmers

Table 2 presents descriptive statistics comparing input utilizations between smallholder farmers who purchased weather index insurance (WII) and those who did not, illustrating input use patterns. The results highlight clear differences in input use, risk management strategies, and intensification practices. Insured farmers applied 58.98 kg/acre of chemical fertilizer, nearly ten times the rate of non-insured farmers (6.13 kg/acre, $p < 0.001$), aligning closely with agronomic recommendations for maize in Njoro Sub-County's acidic soils [8]. This suggests that WII mitigates risk aversion and liquidity constraints, enabling more efficient input use [16]. However, it also raises concerns about equitable access to agrochemicals, especially in the context of input subsidies and agribusiness marketing pressures in rural Kenya, where smallholders often face challenges adopting synthetic inputs amidst cost volatility.

A substitution effect was evident in the use of organic inputs. Insured farmers applied less manure ($p < 0.05$) and in smaller quantities ($p < 0.001$), likely due to increased access to synthetic fertilizers and the labor-intensive nature of manure application, which disproportionately burdens women and elderly household members, a nuance absent from the quantitative data. The lower standard deviation in manure use among insured farmers (19.28 vs. 36.61) suggests more standardized practices, but ethnographic research could clarify whether this reflects true precision or a shift away from traditional methods due to time constraints.

Seed selection patterns further differentiated the groups. Insured farmers predominantly adopted improved maize varieties ($p < 0.001$) and used three times as much seed ($p < 0.001$), leveraging drought-tolerant genetics to mitigate germination risks [39]. In contrast, non-insured farmers used traditional seeds and over-seed (7.69 kg/acre vs. 2.69 kg/acre, $p < 0.001$), which depleted seed reserves and exacerbated intergenerational knowledge loss. These contrasts highlight how WII's financial security drives technology adoption while exposing smallholder reliance on global agribusiness through commercial seed dependencies, a dynamic Shiva [40] warns may undermine food sovereignty by replacing locally adapted seeds with patented varieties requiring recurring purchases.

Table 2. Descriptive statistics of general input use patterns among insured and non-insured farmers.

Variables	Total (n = 400) Mean (SD)	Insured (n = 166) Mean (SD)	Non-Insured (n = 234) Mean (SD)	p-Value
Used chemical fertilizer (%)	46.50 (49.94)	86.75 (34.01)	17.95 (38.46)	0.000 ***
Chemical fertilizer quantity (kg/acre)	28.06 (35.80)	58.98 (33.47)	6.13 (15.39)	0.000 ***
Used manure (%)	49.00 (50.05)	42.77 (49.62)	53.42 (49.88)	0.036 **
Manure quantity (kg/acre)	25.97 (31.92)	15.21 (19.28)	33.60 (36.61)	0.000 ***
Used improved maize seeds (%)	59.50 (49.15)	89.76 (30.41)	38.03 (48.65)	0.000 ***
Improved maize seeds (kg/acre)	6.04 (5.59)	10.23 (4.24)	3.07 (4.41)	0.000 ***
Used traditional maize seeds (%)	69.75 (45.99)	46.99 (50.06)	85.90 (34.88)	0.000 ***
Traditional maize seeds (kg/acre)	5.62 (4.81)	2.69 (3.46)	7.69 (4.56)	0.000 ***
Hired labor (%)	83.00 (37.61)	95.78 (20.16)	73.93 (43.99)	0.000 ***
Labor (person-days/acre)	23.64 (15.37)	32.36 (13.63)	17.45 (13.42)	0.000 ***
Average maize yield (bags/acre)	12.05 (5.56)	16.44 (5.26)	8.94 (3.15)	0.000 ***
Cultivated maize (acres)	1.16 (0.67)	1.49 (0.67)	0.92 (0.56)	0.000 ***
Number of maize plots	1.39 (1.22)	1.34 (0.95)	1.41 (1.38)	0.565

Notes: Each variable is presented with its mean and standard deviation (SD) (in parentheses). ***, ** denote statistically significant mean differences between sub-groups at the 1%, 5% significance levels; 'acre' refers to the unit of land measurement, and 'kg' signifies kilograms.

Labor allocation patterns reinforced the transformative impact of WII. Insured farmers hired more labor ($p < 0.001$) and used nearly twice as many person-days (32.36 vs. 17.45, $p < 0.001$), reflecting intensified cultivation. This was reflected in their 84% yield advantage (16.44 vs. 8.94 bags/acre, $p < 0.001$), demonstrating synergistic effects from combined inputs. However, the similar number of plots ($p = 0.565$) suggests that insured farmers focused on optimizing existing holdings rather than expanding spatially, an important consideration for land-tenure policies in Njoro, where subdivision pressures and inheritance disputes often limit operational scale.

These findings collectively illustrate how WII encourages smallholders to adopt capital- and knowledge-intensive production practices, moving away from traditional risk-coping mechanisms while fostering high-productivity, resilient systems. They also highlight WII's transformative potential as a financial safety net and a catalyst for sustainable intensification.

4.1.3. Descriptive Statistics of Input Use Patterns for Active Users Among Insured and Non-Insured Farmers

Building on the previous analysis of general input use patterns, this section examines input quantities used by farmers who actively engage with them, comparing insured and non-insured groups. The analysis in Table 3 illustrates how weather index insurance (WII) transformed production intensity among smallholders in Njoro Sub-County, with insured farmers applying nearly double the amount of chemical fertilizer (67.99 kg/acre vs. 34.14 kg/acre, $p < 0.001$). This finding aligns with risk-mitigation frameworks [41], but the 99% disparity also highlights broader disparities in access to input. Insured farmers in Kenya's highlands often benefit from bundled services, such as the Kenya Cereal Enhancement Programme (KCEP), which links participants to agro-dealers offering input loans [42]. While KCEP's rollout in Njoro remains uneven, its presence may exacerbate existing inequalities in access to inputs.

Table 3. Descriptive analysis of input use among active users for insured and non-insured farmers.

	Total		Insured		Not Insured		*p*-Value
	No. of Users	Mean Usage	No. of Users	Mean Usage	No. of Users	Mean Usage	
Chemical fertilizer quantity (kg/acre)	186	60.35	144	67.99	42	34.14	0.000 ***
Manure quantity (kg/acre)	196	53.00	71	35.56	125	62.90	0.000 ***
Improved maize seed quantity (kg/acre)	238	10.16	149	11.40	89	8.08	0.000 ***
Traditional maize seed quantity (kg/acre)	279	8.05	78	5.73	201	8.95	0.000 ***

Notes: Each variable is presented with its mean and number of farmers (in parentheses). *** denote statistically significant mean differences between sub-groups at the 1% significance levels; 'acre' denotes the unit of land measurement, and 'kg' denotes kilograms.

The gap in organic input use was equally telling. Non-insured farmers applied 77% more manure (62.90 kg/acre vs. 35.56 kg/acre, $p < 0.001$), a practice deeply embedded in Njoro's agroecological traditions, but were increasingly constrained by labor shortages as youth migrated to urban areas [8]. This divergence suggests that WII accelerates the shift from knowledge-intensive soil management.

Seed adoption trends further reflected WII's modernizing influence: insured farmers used 41% more improved seeds (11.40 kg/acre vs. 8.08 kg/acre, $p < 0.001$), particularly drought-tolerant varieties promoted by Njoro's extension services. In contrast, non-insured farmers continued to rely on traditional seeds (8.95 kg/acre vs. 5.73 kg/acre, $p < 0.001$), which may reflect limited access to formal seed systems, as observed in other Kenyan smallholder communities where liquidity constraints hinder the purchase of certified seeds. Qualitative studies in Nakuru County further highlight farmer hesitancy toward hybrid seeds due to mismatches between vendor promises and actual drought performance [43].

4.1.4. The Effectiveness of Weather Index Insurance in Promoting Input Adoption

This section builds on the descriptive analysis of input use patterns among insured and uninsured farmers, using robust inferential methods to assess the effects of weather index insurance (WII) on input adoption (Table 4). The IV-Probit model addressed endogeneity by using distance to the nearest weather station and training on insurance as instruments for WII uptake, ensuring they satisfied exclusion restrictions (see the empirical framework for details). The primary focus was on the second-stage regression, where the fitted values from the first stage (WII adoption) were used to estimate input adoption. The first stage confirmed the relevance of the instrumental variables, ensuring exogenous variation for unbiased estimation in the second stage. The outcome variable in this stage was modeled as a binary input, where '1' indicates adoption of modern inputs (chemical fertilizer and improved seeds) or traditional inputs (manure and traditional seeds), and '0' indicates non-adoption.

IV-Probit results in Table 4 showed significant treatment effects. Marginal effects at the sample means indicated that WII adoption increased chemical fertilizer use by 123 percentage points ($p < 0.01$) and improved seed adoption by 10.01 percentage points (coefficient = 1.001, $p < 0.01$). While the adoption of manure remained statistically insignificant ($p = 0.208$), insured farmers replaced traditional seeds with modern, insured alternatives ($p < 0.01$). This shift aligns with agricultural transformation theory, which suggests that financial products like WII alter the risk–return tradeoff, promoting technology adoption [41].

Table 4. Regression analyses of the role of weather index insurance in promoting input adoption.

Variables	First-Stage Regression		Second-Stage Regression							
	WII Uptake		Chemical Fertilizer		Manure		Improved Maize Seeds		Traditional Maize Seeds	
	Coefficients (Robust S.E.)	*p*-Value	Coefficients (Robust S.E.)	*p*-Value	Coefficients (Robust S.E.)	*p*-Value	Coefficients (Robust S.E.)	*p*-Value	Coefficients (Robust S.E.)	*p*-Value
Distance to the nearest weather station	−3.731 (0.622)	0.000 ***	-	-	-	-	-	-	-	-
Training on insurance products	2.977 (0.512)	0.000 ***	-	-	-	-	-	-	-	-
WII uptake	-	-	1.230 (0.366)	0.001 ***	−0.383 (0.304)	0.208	1.001 (0.327)	0.002 ***	−1.249 (0.330)	0.000 ***
Age	0.189 (0.185)	0.306	−0.083 (0.098)	0.401	0.041 (0.088)	0.64	0.038 (0.098)	0.697	−0.127 (0.093)	0.171
Age squared	−0.002 (0.002)	0.267	0.001 (0.001)	0.472	0.000 (0.001)	0.819	0.000 (0.001)	0.720	0.001 (0.001)	0.149
Gender	0.514 (0.348)	0.139 *	0.030 (0.172)	0.86	0.298 (0.148)	0.044 **	−0.100 (0.165)	0.544	0.046 (0.171)	0.787
Schooling	−0.143 (0.048)	0.003 ***	−0.019 (0.024)	0.446	−0.013 (0.019)	0.494	−0.004 (0.023)	0.858	−0.036 (0.020)	0.073 *
Training on agri-production technology	−0.926 (0.476)	0.052 *	0.476 (0.202)	0.019 **	0.006 (0.182)	0.976	−0.017 (0.228)	0.939	0.232 (0.200)	0.246
Total land owned	−0.490 (0.186)	0.009 ***	0.288 (0.126)	0.022 **	−0.023 (0.097)	0.816	0.176 (0.138)	0.200	−0.034 (0.102)	0.74
Land leased out	−0.756 (0.248)	0.002 ***	0.058 (0.120)	0.63	0.074 (0.099)	0.455	0.192 (0.138)	0.164	0.000 (0.100)	0.996
Wealth	0.445 (0.153)	0.004 ***	0.194 (0.076)	0.010 ***	−0.056 (0.065)	0.392	0.299 (0.077)	0.000 ***	−0.189 (0.069)	0.006 ***
Household off-farm labor members	−0.157 (0.074)	0.034 **	0.023 (0.040)	0.566	0.019 (0.035)	0.589	0.086 (0.042)	0.043 **	−0.004 (0.039)	0.927
Household farm labor members	−0.189 (0.192)	0.325	−0.088 (0.088)	0.315	0.023 (0.068)	0.732	0.033 (0.080)	0.681	0.054 (0.086)	0.532
Rear livestock	1.322 (0.388)	0.001 ***	0.004 (0.192)	0.983	0.116 (0.154)	0.448	−0.207 (0.185)	0.263	0.073 (0.176)	0.681
Distance to nearest market (km)	−0.863 (0.245)	0.000 ***	−0.077 (0.103)	0.453	−0.020 (0.085)	0.813	−0.118 (0.095)	0.211	−0.059 (0.099)	0.555
Road condition	−0.497 (0.262)	0.058 *	0.299 (0.121)	0.013 **	−0.197 (0.108)	0.068 *	0.058 (0.124)	0.637	−0.166 (0.118)	0.159
Size of the largest maize plot (acres)	2.327 (0.608)	0.000 ***	−0.365 (0.252)	0.147	−0.042 (0.197)	0.831	−0.223 (0.265)	0.401	0.257 (0.214)	0.231
Land leased in	0.470 (0.578)	0.416	0.363 (0.229)	0.114	−0.188 (0.217)	0.386	−0.025 (0.248)	0.919	0.086 (0.237)	0.716
Soil fertility	0.427 (0.361)	0.237	−0.342 (0.203)	0.091 *	0.129 (0.148)	0.384	0.482 (0.163)	0.003 ***	−0.155 (0.167)	0.354
Financial constraints	0.432 (0.647)	0.505	−0.764 (0.411)	0.063 *	−0.087 (0.333)	0.794	−0.376 (0.413)	0.362	−0.335 (0.359)	0.352
Drought in 2022	−0.557 (0.609)	0.361	0.218 (0.253)	0.389	−0.589 (0.220)	0.008 ***	0.262 (0.262)	0.317	−0.708 (0.286)	0.013 **
Drought in 2023	−2.016 (0.595)	0.001 ***	−1.434 (0.323)	0.000 ***	0.153 (0.215)	0.477	−1.429 (0.475)	0.003 ***	0.082 (0.237)	0.73
High-yield—weather-sensitive	0.328 (0.444)	0.46	0.071 (0.180)	0.694	−0.307 (0.166)	0.065 *	0.125 (0.197)	0.523	−0.317 (0.177)	0.073 *
Weather Information	−2.301 (0.987)	0.020 ***	−0.385 (0.823)	0.64	0.568 (0.537)	0.29	−1.443 (0.745)	0.053 *	0.252 (0.703)	0.72
Constant	10.168 (5.581)	0.068 *	3.437 (2.710)	0.205	−0.996 (2.266)	0.66	0.447 (2.603)	0.864	6.052 (2.424)	0.013 **
Wald Chi-squared	100.21 ***		130.1 ***		46.43 ***		129.51 ***		98.83 ***	
Wald test of exogeneity	-		7.58 ***		0.77		0.29 **		0.08	

Notes: Coefficients are shown with robust standard errors (S.E.) in parentheses; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; "km" stands for kilometers, and "acres" denotes the unit of land measurement.

A comparative analysis revealed that WII adoption had a stronger impact on chemical fertilizer use than on the adoption of improved maize seeds ($p < 0.01$). This supports Carter's capital constraint hypothesis, which suggests that WII alleviates liquidity barriers for high-cost inputs like fertilizers [44], which typically require three to five times the seasonal expenditure of seeds. Farmers prioritized inputs with the greatest financial constraints when risk was mitigated. In contrast, WII adoption reduced traditional seed use ($p < 0.01$), consistent with the study by Karlan et al. [41], who found that insured farmers shifted toward modern inputs to reduce downside risk. The negligible effect on manure ($p = 0.208$) suggests that WII does not uniformly promote all inputs, highlighting the role of input-specific economic characteristics, such as cost and substitutability, in shaping adoption patterns [45]. These findings underscore that WII's impact is context-dependent, with farmers allocating resources toward higher-return, capital-intensive technologies when risk is mitigated.

While the quantitative analysis provides robust evidence of WII's effects, an ethnographic perspective offers deeper insights into the socio-cultural dynamics influencing input adoption in Njoro Sub-County. The use of manure is not merely an economic decision but is embedded in local knowledge systems, cultural practices, and labor dynamics. Although manure application is rooted in Njoro's agroecological traditions, migration patterns have exacerbated labor shortages, threatening the sustainability of this practice. The preference for manure among non-insured farmers, despite its lower efficiency, reflects a broader socio-economic context where traditional methods persist, even when more efficient alternatives exist.

Moreover, the shift toward modern seeds, while enhancing productivity, underscores the intersection of financial security and cultural trust in new technologies. In Njoro, as elsewhere in Kenya, the adoption of improved seeds is influenced by experiences with commercial seed markets, which have been characterized by the presence of counterfeit products [46]. These local dynamics, though not captured by quantitative data, highlight the importance of trust in the seed market, which can either facilitate or hinder the adoption of modern inputs, such as improved seeds.

Gender significantly influenced input adoption. Women were 29.8 percentage points more likely to use manure ($p < 0.05$), aligning with findings by Feliciano [47] on gendered agroecological practices, where women's roles in resource management and livestock care led them to favor organic inputs. However, this preference may also stem from structural constraints, as women often face barriers to accessing credit, land, and markets for modern inputs [48]. In contrast, education showed a marginally significant negative association with traditional seed adoption ($p < 0.1$), supporting human capital theory, which suggests educated farmers use networks and market access to adopt improved varieties [49]. These patterns highlight the complex relationship between social stratification and agricultural modernization.

Wealth strongly influenced input adoption. A one-unit increase in wealth raised the probability of using chemical fertilizers by 19.4 percentage points ($p < 0.01$) and adopting improved seeds by 29.9 percentage points ($p < 0.001$) while reducing traditional seed use by 18.9 percentage points ($p < 0.01$). This supports the risk-coping hypothesis, which suggests that wealthier farmers, with greater liquidity and assets, exhibit higher risk tolerance for adopting productivity-enhancing technologies [50]. However, this wealth-driven intensification may pose sustainability challenges. A heavy reliance on chemical fertilizers poses a risk to long-term soil health and may exacerbate productivity gaps between farmers with access to abundant resources and those with limited resources [51].

The effectiveness of weather index insurance (WII) depends on complementary institutional support. Agricultural training boosted chemical fertilizer adoption by

47.6 percentage points ($p < 0.05$), demonstrating that technical knowledge complements financial risk mitigation. This finding supports the dual constraint framework, where WII alleviates liquidity barriers while extension services fill agronomic knowledge gaps [52]. Notably, training had no significant effect on traditional inputs, suggesting that extension programs are more effective in promoting complex, knowledge-intensive technologies like fertilizers rather than simpler inputs like seeds, consistent with trends in Sub-Saharan Africa [53]. This differential impact suggests that combining insurance with input-specific training may be more effective than standalone programs, particularly for capital-intensive technologies requiring financial security and technical expertise.

The allocation of household labor to off-farm activities affected agricultural input decisions through opportunity cost factors. Households engaged in off-farm work were 2.21 percentage points less likely to use chemical fertilizers ($p < 0.10$), supporting Ellis's (2000) [54] theory that labor markets compete for time-sensitive farm operations, such as fertilizer application. However, this labor substitution effect does not extend to improved seed adoption ($p > 0.10$), consistent with Suri's [55] hypothesis that labor-constrained farmers prioritize labor-saving technologies. Similar patterns were observed in India's National Rural Employment Guarantee Scheme, where off-farm income increased fertilizer opportunity costs but did not affect hybrid seed uptake [56]. These findings suggest that labor market integration shifts input choices toward less labor-intensive technologies.

Farm scale also played a key role in input adoption. Larger farms were 28.8 percentage points more likely to use chemical fertilizers than smallholdings ($p < 0.05$), supporting the minimum efficient scale hypothesis [57], where bulk procurement and mechanized application make fertilizers economically viable only above certain operational thresholds. This effect mirrors Brazil's agricultural transformation, where fertilizer application rates tripled on farms over 10 hectares [58]. In contrast, manure adoption remained unaffected by scale ($p > 0.10$), indicating that manure, a labor-intensive yet low-capital input, is still viable for smallholders. Its low cost and no scale requirements allow its continued use despite agricultural modernization [59].

Transport infrastructure reshaped input adoption by reducing costs and facilitating market integration. Improved road conditions increased chemical fertilizer use by 29.9 percentage points ($p < 0.05$) while reducing manure use by 19.7 percentage points ($p < 0.05$), demonstrating infrastructure's polarizing effect. This aligns with global evidence that road development lowers fertilizer costs while accelerating the abandonment of labor-intensive organic practices [60]. The lack of a significant effect on seed adoption ($p = 0.15$) highlighted that infrastructure impacts inputs differently; transport improvements primarily affected fertilizer use, while labor opportunity costs drove the adoption of manure. These polarizing effects present sustainability trade-offs. Fertilizer use boosts short-term yields but may undermine long-term soil health in vulnerable agroecosystems [61]. This underscores the need for policies that balance productivity gains with soil preservation, offering a Pareto improvement over blanket subsidies.

Farmers demonstrated complex soil fertility management strategies that challenged the one-size-fits-all approach to input use. High-fertility soils increased the adoption of improved seeds by 48.2 percentage points ($p < 0.01$) while reducing synthetic fertilizer use by 34.2 percentage points ($p < 0.10$), revealing a substitution effect where natural soil fertility reduced reliance on purchased inputs. This supports findings by Marenya and Barrett [62] in western Kenya, where smallholders selectively applied fertilizer to marginal soils, leveraging natural fertility when crop responses plateaued. This contradicts the complementarity assumed in many WII programs, which often rely on uniform input recommendations. These results underscore the limitations of blanket input prescriptions in WII policies, suggesting that incorporating soil test-based targeting could enhance

nutrient use efficiency and better align input recommendations with actual soil conditions, as demonstrated in Zimbabwe [63].

Financial constraints were the primary barrier to the adoption of modern inputs. Capital-constrained households were 76.4 percentage points less likely to use fertilizer ($p < 0.10$), nearly double the positive impact of WII participation. This confirms liquidity constraints as the critical adoption bottleneck, supporting observations by Sheahan et al. [8] that input timing and credit access outweigh risk mitigation. While WII addresses risk-related barriers, its effectiveness is limited by capital scarcity, as seen in Ethiopia [64]. These findings underline the need for complementary financial instruments, such as input credit or harvest-contingent repayment, to fully unlock WII's potential, in line with the framework by Karlan et al. [41] on liquidity's role in agricultural technology adoption.

The relationship between drought severity and WII efficacy followed a nonlinear threshold pattern. During the moderate 2022 drought, traditional inputs (manure: −58.9 percentage points; traditional seeds: −70.8 percentage points) collapsed, while modern inputs remained stable among insured farmers, confirming WII's ability to sustain adoption under moderate stress. However, the extreme 2023 drought overwhelmed WII's protective mechanisms, causing sharp declines in modern input use. This bifurcated response aligns with the threshold models by Carter et al. [44], highlighting a vulnerability in index-based insurance systems. These findings emphasize the urgent need to redesign WII to maintain effectiveness under escalating climate extremes, especially with the projected increase in drought frequency and severity [65].

4.1.5. Effect of Weather Index Insurance on Agricultural Input Quantities for Active Users

This analysis extended beyond binary adoption metrics by quantifying the impact of weather index insurance (WII) on input intensification under climate risk. We employed a two-stage instrumental variables (IV) approach, ensuring causal identification with strong first-stage validity ($p < 0.001$) and confirming the exclusion restriction through Wu–Hausman tests. Heteroscedasticity-robust standard errors and endogeneity tests supported the robustness of our estimates, mitigating potential biases (Table 5).

Results in Table 5 show that WII induced asymmetric input substitution, consistent with the loss-aversion framework of the prospect theory [66]. Farmers increased high-yield inputs and fertilizers (+28.7 kg/acre, $p < 0.001$) and improved seeds (+2.6 kg/acre, $p < 0.05$) while reducing traditional risk-mitigating practices like manure (−27.0 kg/acre, $p < 0.001$) and traditional seeds (−2.9 kg/acre, $p < 0.05$). This aligns with the liquidity hypothesis by Karlan et al. [41], where WII payouts alleviate credit constraints, enabling the adoption of productivity-enhancing technologies. However, the near-symmetric trade-off between fertilizer and manure adoption suggests the existence of competing risk-management strategies. While WII promotes short-term yield maximization, this may come at the cost of long-term agroecological resilience, potentially reducing soil fertility and biodiversity and increasing susceptibility to pests and diseases. These effects echo concerns about "technological lock-in" [67]. These findings extend the findings by Sibiko and Qaim [24] by quantifying input-level trade-offs, revealing unintended consequences where WII boosts immediate productivity but may exacerbate soil degradation and compromise long-term sustainability [61].

Table 5. Analysis of the impact of weather index insurance on agricultural input quantities for active users.

Variables	First Stage		Chemical Fertilizer (kg/acre)		Manure (kg/acre)		Improved Maize Seeds (kg/acre)		Traditional Maize Seeds (kg/acre)	
	Coefficient (Robust S.E.)	*p*-Value	Coefficient (Robust S.E.)	*p*-Value	Coefficient (Robust S.E.)	*p*-Value	Coefficient (Robust S.E.)	*p*-Value	Coefficient (Robust S.E.)	*p*-Value
Distance to the nearest weather station	−3.731 (0.622)	0.000 ***								
Training on insurance products	2.977 (0.512)	0.000 ***								
WII uptake	-		28.767 (5.736)	0.000 ***	−27.072 (4.350)	0.000 ***	2.549 (0.539)	0.000 ***	−2.851 (0.637)	0.000 ***
Age	0.189 (0.185)	0.306	5.511 (2.677)	0.041 **	1.456 (1.998)	0.467	0.455 (0.263)	0.086 *	−0.063 (0.288)	0.827
Age squared	−0.002 (0.002)	0.267	−0.055 (0.026)	0.038 **	−0.015 (0.019)	0.449	−0.004 (0.003)	0.113	0.001 (0.003)	0.823
Gender	0.514 (0.348)	0.139	8.987 (4.441)	0.045 **	1.276 (4.189)	0.761	0.493 (0.428)	0.251	−0.784 (0.450)	0.082 *
Schooling	−0.143 (0.048)	0.003 ***	−0.393 (0.527)	0.457	0.711 (0.508)	0.163	0.073 (0.051)	0.154	0.020 (0.050)	0.689
Training on Agri-production technology	−0.926 (0.476)	0.052 *	−2.060 (4.019)	0.609	−1.090 (3.471)	0.754	0.275 (0.398)	0.49	0.357 (0.619)	0.565
Total land owned	−0.490 (0.186)	0.009 ***	−0.133 (2.236)	0.953	0.101 (1.949)	0.959	0.280 (0.224)	0.213	0.127 (0.265)	0.633
Land leased out	−0.756 (0.248)	0.002 ***	−1.449 (2.435)	0.553	0.373 (2.075)	0.857	−0.255 (0.230)	0.268	0.178 (0.348)	0.609
Wealth	0.445 (0.153)	0.004 ***	0.439 (1.842)	0.812	0.163 (1.722)	0.925	0.215 (0.168)	0.203	−0.169 (0.210)	0.42
Household off-farm labor members	−0.157 (0.074)	0.034 **	−0.498 (0.861)	0.564	0.384 (0.642)	0.55	0.063 (0.083)	0.453	−0.044 (0.103)	0.671
Household farm labor members	−0.189 (0.192)	0.325	−0.824 (2.018)	0.684	−3.581 (1.608)	0.027 **	−0.370 (0.177)	0.037 **	−0.225 (0.205)	0.275
Rear livestock	1.322 (0.388)	0.001 ***	0.526 (4.494)	0.907	−1.646 (3.939)	0.677	0.249 (0.408)	0.542	0.611 (0.477)	0.202
Distance to nearest market (km)	−0.863 (0.245)	0.000 ***	2.219 (2.381)	0.353	2.602 (1.944)	0.182	−0.132 (0.211)	0.532	0.367 (0.245)	0.134
Road condition	−0.497 (0.262)	0.058 *	1.846 (3.394)	0.587	2.872 (2.666)	0.283	0.087 (0.299)	0.772	0.171 (0.315)	0.588
Size of the largest maize plot (acres)	2.327 (0.608)	0.000 ***	3.519 (3.793)	0.355	1.993 (4.674)	0.67	−0.331 (0.444)	0.457	0.431 (0.603)	0.475
Land leased in	0.470 (0.578)	0.416	1.469 (6.191)	0.813	0.087 (6.108)	0.989	0.823 (0.608)	0.178	0.000 (0.679)	0.988
Soil fertility	0.427 (0.361)	0.237	1.825 (4.136)	0.66	−0.814 (3.619)	0.822	0.408 (0.406)	0.316	−0.626 (0.426)	0.143
Financial constraints	0.432 (0.647)	0.505	−16.677 (6.096)	0.007 ***	8.180 (4.484)	0.070 *	0.510 (0.615)	0.408	0.937 (0.800)	0.243
Drought 2022	−0.557 (0.609)	0.361	0.716 (5.511)	0.897	2.831 (3.862)	0.464	0.563 (0.529)	0.288	0.533 (0.629)	0.397
Drought 2023	−2.016 (0.595)	0.001 ***	−1.183 (4.395)	0.788	−6.593 (3.859)	0.089 *	−1.106 (0.447)	0.014 **	0.683 (0.615)	0.268
High-yield—weather-sensitive	0.328 (0.444)	0.46	4.256 (4.218)	0.314	4.203 (3.736)	0.262	−0.288 (0.412)	0.485	−0.471 (0.532)	0.376
Weather Information	−2.301 (0.987)	0.020 **	10.772 (7.164)	0.135	11.122 (5.673)	0.052 *	0.697 (0.939)	0.459	1.154 (1.578)	0.465
Constant	10.168 (5.581)	0.068 *	−108.060 (73.545)	0.144	−9.880 (53.265)	0.853	−6.560 (6.539)	0.317	6.881 (7.670)	0.37
Endogeneity test [a]			$\chi^2 = 0.987$		$\chi^2 = 0.653$		$\chi^2 = 0.819$		$\chi^2 = 0.534$	
Heteroscedasticity test [b]			$\chi^2 = 2.75$ *		$\chi^2 = 2.84$ *		$\chi^2 = 26.88$ ***		$\chi^2 = 7.64$ **	

Notes: Coefficients are shown with robust standard errors (S.E.) in parentheses; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; "km" stands for kilometers, and "acres" denotes the unit of land measurement. [a] Durbin–Wu–Hausman test statistic; [b] Pagan–Hall test statistic.

Age also mediated input use, challenging conventional adoption narratives. Older farmers applied 5.5 kg/acre more fertilizer ($p < 0.01$) and 0.5 kg/acre more improved seeds ($p < 0.05$) for each additional year of age. This suggests a long-term risk–return calculus where experience outweighs initial risk aversion. This finding resonates with broader sociocultural patterns in rural communities in Kenya, where older farmers may have accumulated not only practical farming knowledge but also social capital within their communities, influencing their decision-making. In contrast, younger farmers' slower adoption reflects liquidity constraints or shorter planning horizons, despite their presumed adaptability [68]. These generational differences highlight the limitations of one-size-fits-all programs. Integrating the experiential knowledge of older farmers with targeted techno-financial support for younger farmers could help better balance productivity and sustainability.

Gender significantly shaped agricultural input allocation. Female-managed plots applied 8.99 kg/acre more chemical fertilizer ($p < 0.01$) but 0.78 kg/acre less traditional seed ($p < 0.05$) than male-managed plots. These differences reflect deeper socio-cultural dynamics in labor roles, where women's dual responsibilities for both farming and household tasks shape their input choices. Women's preference for labor-saving inputs, such as chemical fertilizers, reduces planting and maintenance demands, compared to traditional seeds [69]. Additionally, women's greater responsibility for household food security leads to a preference for yield-stabilizing strategies, with chemical fertilizers offering more predictable harvests than traditional seeds, which are vulnerable to pests and climate variability [69]. These findings underscore how structural gender disparities, beyond access, shape input decisions, with implications for designing labor-efficient and risk-contingent agricultural technologies.

Liquidity constraints further influenced input use. Financial scarcity reduced chemical fertilizer application by 16.7 kg/acre ($p < 0.01$) and increased manure use by 8.18 kg/acre ($p < 0.05$). This substitution effect is particularly pronounced in regions where formal credit systems are underdeveloped, and farmers often rely on informal financial mechanisms, such as savings groups or community-based insurance. This trend reflects a broader pattern where cash-limited farmers prioritize affordability over agronomic efficiency, especially in regions with underdeveloped input markets [64]. Manure is a soil amendment and a liquidity buffer, requiring no upfront cash and often sourced from on-farm biomass [59]. This highlights the limitations of input promotion programs that overlook household capital constraints, suggesting that financial instruments, such as input credit, are essential for enabling fertilizer adoption among resource-poor farmers.

Climate shocks also shaped input decisions. While the 2022 drought had no detectable effect, the prolonged 2023 drought reduced manure use by 6.59 kg/acre ($p < 0.05$) and increased the adoption of improved maize seeds by 1.11 kg/acre ($p < 0.1$). This shift aligns with models of sequential climate shocks, where short-term droughts are buffered by savings or informal insurance, but prolonged exposure depletes adaptive reserves [70]. These findings are consistent with the adaptive strategies employed by rural communities in East Africa, where farmers often rely on informal insurance systems, such as family networks or community solidarity, to cope with short-term shocks. The increased adoption of drought-tolerant seeds and reduced manure use reflect a risk-avoidance strategy typical of smallholders facing recurrent climate stress [39]. The nonlinear nature of these effects underscores the need for climate adaptation policies to account for the duration of shocks, as single-year interventions may overlook the cumulative erosion of resilience resulting from consecutive droughts.

Access to weather forecasts increased manure application by 11.12 kg per acre ($p < 0.05$), demonstrating how climate information supports adaptive input optimization. This highlights how access to digital infrastructure, such as weather forecasting

systems, can bridge knowledge gaps and enable farmers to make more informed, context-specific decisions. Manure's dual benefits, as a drought-resistant soil amendment and a low-risk investment during rainfall uncertainty [59], explain this effect. Weather-informed farmers prioritize low-capital, locally adaptable inputs over volatile, capital-intensive ones, particularly in rainfed systems where climate forecasts improve organic input efficacy [71].

These findings highlight the complex interplay of financial, gendered, and agroecological factors in shaping input decisions under climate extremes. Weather index insurance (WII) alleviates liquidity and risk constraints, prompting farmers to adopt yield-enhancing practices consistent with risk-averse behavior under climate uncertainty. Nevertheless, the interaction between WII adoption and socio-economic factors underscores the importance of context-specific interventions. Notably, input substitution follows nonlinear thresholds. Short-term climate shocks prompt minimal change, but prolonged droughts shift adoption toward modern inputs. These shifts emphasize the need for more comprehensive, multi-level support systems that integrate financial instruments, gender-responsive policies, and digital tools to ensure equitable and sustainable adaptation to climate risks. This observation, absent from traditional adoption models, demonstrates how farmers' decisions evolve in response to cumulative climate stress.

5. Conclusions and Policy Recommendations

Agricultural intensification is crucial for poverty reduction and food security. However, climate-induced weather shocks often discourage smallholder farmers from investing in yield-enhancing inputs. Weather index insurance (WII) has emerged as a promising solution to mitigate these risks, but its ability to promote sustained input use remains debated. This study shows that WII accelerates the adoption of key inputs, specifically chemical fertilizers (+28.7 kg/acre) and improved maize seeds (+2.6 kg/acre), while replacing traditional alternatives, such as manure (−27 kg/acre) and local seeds (−2.9 kg/acre). However, this dual effect reveals a dilemma: while insurance is designed to mitigate risk, it may inadvertently encourage over-reliance on a narrow set of inputs, potentially reducing agricultural system diversity and its ability to adapt to long-term environmental changes.

The effectiveness of WII is shaped by a complex interplay of socio-economic and environmental factors, such as gender disparities, financial constraints, and infrastructure gaps. Our findings reinforce existing research on the positive effects of WII and reveal significant non-linearities in its impact. For example, female-headed households retain manure despite using WII, likely due to manure's drought resilience or exclusion from formal input markets. This finding challenges standard adoption models, which often overlook such nuanced decision-making. In contrast, households with off-farm income tend to use WII to invest more in high-yield inputs, reflecting broader financial inequalities within rural communities. These socio-economic disparities underscore the need for context-sensitive policies that recognize the varying adaptive capacities of households. Spatial disparities further underscore the importance of infrastructure: improved roads are associated with higher chemical fertilizer use but lower manure use, indicating the need for geographically tailored insurance systems to mitigate exacerbating inequalities in underserved regions.

WII demonstrated resilience during the moderate drought of 2022; however, its effectiveness weakened significantly during the severe drought of 2023, revealing its threshold-dependent nature, which aligns with climate adaptation models. Farmers deviated from standardized risk models by substituting inputs based on localized risk perceptions. For example, in drought-prone areas, farmers retained traditional seeds, despite having insurance coverage. Furthermore, in regions with high-fertility soils, WII's influence diminished, emphasizing how agroecological conditions shape the effectiveness of financial tools. These

findings challenge the assumption that all farmers will respond uniformly to climate risks, underscoring the need for policies that account for biophysical thresholds and local adaptation strategies.

This study makes significant contributions to existing theories in three key areas. First, WII's impact on input use is influenced by risk–liquidity interdependence, where liquidity constraints often outweigh the benefits of risk reduction, particularly in marginal environments. Second, socio-economic and agroecological factors drive diverse responses to WII, challenging the one-size-fits-all approach to resilience. Third, the 2022–2023 drought dichotomy illustrates that WII's stabilizing effect diminishes beyond certain climate thresholds, underscoring the nonlinear nature of climate resilience and the necessity for policy redesign to address extreme climate events.

Given these insights, we argue that WII must evolve from a standalone risk-transfer tool into an integral component of climate-resilient agricultural systems. Policies should prioritize context-sensitive designs addressing local infrastructure gaps, gendered access barriers, and diverse agroecological conditions. For instance, pairing WII with agroecological safeguards in semi-arid regions, such as offering premium discounts for maintaining soil organic matter or providing bundled credit for organic fertilizers, could help preserve traditional, resilient practices like manure use. In areas dominated by female-headed households, gender-responsive delivery models, such as targeted agricultural extension programs specifically designed for women farmers and flexible repayment schedules aligned with seasonal cash flows, can effectively address gender-specific barriers.

Moreover, recognizing WII's threshold-dependent nature, policymakers should integrate it within layered resilience strategies to manage extreme climate shocks effectively. For example, in drought-prone areas, integrating WII with shock-responsive social protection and community seed banks can mitigate input collapse during severe drought conditions, as experienced in 2023. In underserved, remote areas, public–private partnerships that leverage digital infrastructure, such as mobile-based insurance platforms, can enhance last-mile delivery and improve insurance literacy among farmers. Tailoring these interventions explicitly to varied local contexts can help policymakers better align WII initiatives with long-term sustainability goals and the Sustainable Development Goals (SDGs) on zero hunger and climate action.

Despite the valuable insights of this study, several important questions remain. For instance, why do female farmers retain manure under WII—due to risk aversion, cultural factors, or adaptive strategies, and how does WII influence long-term soil carbon? Additionally, the reluctance of younger farmers to adopt modern inputs, despite having higher education levels, warrants further investigation. The cross-sectional design limits causal inference, and reliance on self-reported data may introduce bias. Future research should employ mixed methods, including behavioral experiments, soil monitoring, and the integration of remote sensing data, alongside quasi-experimental and longitudinal designs, to assess causality and quantify the hidden costs associated with the loss of agroecological practices. Expanding studies to agroecological transition zones, such as semi-arid irrigated regions, and testing the scalability of WII across diverse farming systems would further enhance understanding of its adaptability and impact.

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References

1. FAO. *The Impact of Disasters on Agriculture and Food Security: Avoiding and Reducing Losses Through Investment in Resilience*; FAO: Rome, Italy, 2023.
2. World Bank. *Climate Shocks and Agriculture: A Review of Losses and Adaptation in Sub-Saharan Africa*; World Bank: Washington, DC, USA, 2023.
3. IPCC. Climate Change 2023: Synthesis Report. In *Contribution of Working Groups I, II, and III to the Sixth Assessment Report (AR6)*; IPCC: Geneva, Switzerland, 2023.
4. *Kenya National Bureau of Statistics, Economic Survey 2022*; Kenya National Bureau of Statistics: Nairobi, Kenya, 2022.
5. World Bank. *Kenya Secures $250 Million to Help 500,000 Smallholder Farmers Enhance Value Addition and Access Markets*; World Bank: Washington, DC, USA, 2022.
6. Government of Kenya. *National Climate Risk Assessment Report 2023: Impacts on Agriculture and Food Security*; Government of Kenya: Nairobi, Kenya, 2023.
7. Pingali, P.; Sunder, N. Transitioning Toward Nutrition-Sensitive Food Systems in Developing Countries. *Annu. Rev. Resour. Econ.* **2017**, *9*, 439–459. [CrossRef]
8. Sheahan, M.; Black, R.; Jayne, T. Are Kenyan farmers under-utilizing fertilizer? Implications for input intensification strategies and research. *Food Policy* **2013**, *41*, 39–52. [CrossRef]
9. Schröder, D.; Freedman, G.G. Decision making under uncertainty: The relation between economic preferences and psychological personality traits. *Theory Decis.* **2020**, *89*, 61–83. [CrossRef]
10. Janzen, S.A.; Carter, M.R. After the Drought: The Impact of Microinsurance on Consumption Smoothing and Asset Protection. *Am. J. Agric. Econ.* **2019**, *101*, 651–671. [CrossRef]
11. Meza, I.; Rezaei, E.E.; Siebert, S.; Ghazaryan, G.; Nouri, H.; Dubovyk, O.; Gerdener, H.; Herbert, C.; Kusche, J.; Popat, E.; et al. Drought risk for agricultural systems in South Africa: Drivers, spatial patterns, and implications for drought risk management. *Sci. Total Environ.* **2021**, *799*, 149505. [CrossRef] [PubMed]
12. Powell, D.; Goldman, D. Disentangling moral hazard and adverse selection in private health insurance. *J. Econ.* **2021**, *222*, 141–160. [CrossRef]
13. Kuhn, S.; Hazell, P.; Hess, U. Innovations and Emerging Trends in Agricultural Insurance. 2016. Available online: https://www.researchgate.net/profile/Peter-Hazell/publication/283089244_Innovations_and_emerging_Trends_in_Agricultural_Insurance/links/567ebcdd08ae051f9ae657d2/Innovations-and-emerging-Trends-in-Agricultural-Insurance.pdf (accessed on 10 February 2025).
14. Central Bank of Kenya. *Report on the Agriculture Sector Survey—September 2023*; Central Bank of Kenya: Nairobi, Kenya, 2023.
15. World Bank. Weather index insurance for agriculture: Guidance for development practitioners. In *Agriculture and Rural Development Discussion Paper 50*; World Bank: Washington, DC, USA, 2011.
16. Benso, M.R.; Gesualdo, G.C.; Silva, R.F.; Silva, G.J.; Rápalo, L.M.C.; Navarro, F.A.R.; Marques, P.A.A.; Marengo, J.A.; Mendiondo, E.M. Review article: Design and evaluation of weather index insurance for multi-hazard resilience and food insecurity. *Nat. Hazards Earth Syst. Sci.* **2023**, *23*, 1335–1354. [CrossRef]
17. Sun, Y. Enhanced Weather-Based Index Insurance Design for Hedging Crop Yield Risk. *Front. Plant Sci.* **2022**, *13*, 895183. [CrossRef]
18. Isaboke, H.; Qiao, Z.; Nyarindo, W. The effect of weather index based micro-insurance on food security status of smallholders. *Agric. Resour. Econ. Int. Sci. E-Journal* **2016**, *2*, 5–21. [CrossRef]
19. Belissa, T.K. Effects of weather index insurance adoption on household food consumption and investment in agricultural inputs in Ethiopia. *J. Agric. Food Res.* **2024**, *16*, 101043. [CrossRef]
20. Mobarak, A.M.; Rosenzweig, M.R. Informal Risk Sharing, Index Insurance, and Risk Taking in Developing Countries. *Am. Econ. Rev.* **2013**, *103*, 375–380. [CrossRef]

21. Castaing, P.; Gazeaud, J. Do Index Insurance Programs Live up to their Promises? *Aggregating Evid. Mult. Exp.* **2022**, *175*. [CrossRef]
22. Aizaki, H.; Furuya, J.; Sakurai, T.; Mar, S.S. Measuring farmers' preferences for weather index insurance in the Ayeyarwady Delta, Myanmar: A discrete choice experiment approach. *Paddy Water Environ.* **2021**, *19*, 307–317. [CrossRef]
23. Tang, Y.; Cai, H.; Liu, R. Farmers' Demand for Informal Risk Management Strategy and Weather Index Insurance: Evidence from China. *Int. J. Disaster Risk Sci.* **2021**, *12*, 281–297. [CrossRef]
24. Sibiko, K.W.; Qaim, M. Weather index insurance, agricultural input use, and crop productivity in Kenya. *Food Secur.* **2020**, *12*, 151–167. [CrossRef]
25. Dalhaus, T.; Musshoff, O.; Finger, R. Phenology Information Contributes to Reduce Temporal Basis Risk in Agricultural Weather Index Insurance. *Sci. Rep.* **2018**, *8*, 46. [CrossRef]
26. International Finance Corporation. *Agriculture and Climate Risk Enterprise (ACRE)—Kilimo Salama—Kenya, Rwanda, Tanzania*; International Finance Corporation: Washington, DC, USA, 2015.
27. Seuret, E. Kilimo Salama: Micro Crop Insurance Through Mobile. 2010. Available online: http://kilimosalama.wordpress.com/ (accessed on 12 February 2025).
28. Kenya Meteorological Department (KMD). *State of Kenya's Climate 2023*; Kenya Meteorological Department (KMD): Nairobi, Kenya, 2023.
29. Government of Kenya; Government of Kenya (GoK). *Agriculture Sector Transformation and Growth Strategy (ASTS) 2019–2029*; Ministry of Agriculture, Livestock, Fisheries, and Cooperatives: Nairobi, Kenya, 2019.
30. Government of Kenya. *Nakuru County First County Integrated Development Plan (2018–2022): Kenya Vision 2030—Towards a Globally Competitive and Prosperous Nation*; Government of Kenya: Nairobi, Kenya, 2022.
31. Sande, J.B.; Ghosh, M. Endogeneity in survey research. *Int. J. Res. Mark.* **2018**, *35*, 185–204. [CrossRef]
32. Bastardoz, N.; Matthews, M.J.; Sajons, G.B.; Ransom, T.; Kelemen, T.K.; Matthews, S.H. Instrumental variables estimation: Assumptions, pitfalls, and guidelines. *Leadersh. Q.* **2023**, *34*, 101673. [CrossRef]
33. Jensen, N.D.; Mude, A.G.; Barrett, C.B. How basis risk and spatiotemporal adverse selection influence demand for index insurance: Evidence from northern Kenya. *Food Policy* **2018**, *74*, 172–198. [CrossRef]
34. Fonta, W.M.; Sanfo, S.; Kedir, A.M.; Thiam, D.R. Estimating farmers' willingness to pay for weather index-based crop insurance uptake in West Africa: Insight from a pilot initiative in Southwestern Burkina Faso. *Agric. Food Econ.* **2018**, *6*, 11. [CrossRef]
35. Taherdoost, H. A review of technology acceptance and adoption models and theories. *Procedia Manuf.* **2018**, *22*, 960–967. [CrossRef]
36. World Bank. *Financial Inclusion Overview*; World Bank: Washington, DC, USA, 2025.
37. IFA. *The Hidden Risks of Being Poor: The Poverty Premium in Insurance*; IFA: Tokyo, Japan, 2021.
38. Maccheroni, F.; Marinacci, M.; Wang, R.; Wu, Q. Risk Aversion and Insurance Propensity. *Am. Econ. Rev.* **2025**, *115*, 1597–1649. [CrossRef]
39. Cacho, O.J.; Moss, J.; Thornton, P.K.; Herrero, M.; Henderson, B.; Bodirsky, B.L.; Humpenöder, F.; Popp, A.; Lipper, L. The value of climate-resilient seeds for smallholder adaptation in sub-Saharan Africa. *Clim. Change* **2020**, *162*, 1213–1229. [CrossRef]
40. Shiva, V. The Seed Emergency: The Threat to Food and Democracy. 2015. Available online: https://www.aljazeera.com/opinions/2012/2/6/the-seed-emergency-the-threat-to-food-and-democracy/ (accessed on 10 March 2025).
41. Karlan, D.; Osei, R.; Osei-Akoto, I.; Udry, C. Agricultural Decisions after Relaxing Credit and Risk Constraints *. *Q. J. Econ.* **2014**, *129*, 597–652. [CrossRef]
42. Government of Kenya. *Kenya Cereal Enhancement Programme (KCEP): Climate Resilient Agricultural Livelihoods Annual Report 2020–2021*; Government of Kenya: Nairobi, Kenya, 2021.
43. Njora, B.; Yılmaz, H. Analysis of The Impact of Agricultural Policies on Food Security in Kenya. *Eurasian J. Agric. Res.* **2021**, *5*, 66–83.
44. Carter, M.R.; Cheng, L.; Sarris, A. Where and how index insurance can boost the adoption of improved agricultural technologies. *J. Dev. Econ.* **2016**, *118*, 59–71. [CrossRef]
45. Emerick, K.; De Janvry, A.; Sadoulet, E.; Dar, M.H. Technological Innovations, Downside Risk, and the Modernization of Agriculture. *Am. Econ. Rev.* **2016**, *106*, 1537–1561. [CrossRef]
46. Kenya Markets Trust. *Scratch-Off Labels for Seed: KMT Agri-Inputs Case Study*; Kenya Markets Trust: Nairobi, Kenya, 2012.
47. Feliciano, D. A review on the contribution of crop diversification to Sustainable Development Goal 1 "No poverty" in different world regions. *Sustain. Dev.* **2019**, *27*, 795–808. [CrossRef]
48. Agarwal, B. Gender and Land Rights Revisited: Exploring New Prospects via the State, Family and Market. *J. Agrar. Change* **2003**, *3*, 184–224. [CrossRef]
49. Wossen, T.; Berger, T.; Di Falco, S. Social capital, risk preference and adoption of improved farm land management practices in Ethiopia. *Agric. Econ.* **2015**, *46*, 81–97. [CrossRef]

50. Dercon, S.; Christiaensen, L. Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *J. Dev. Econ.* **2011**, *96*, 159–173. [CrossRef]
51. Ficiciyan, A.; Loos, J.; Sievers-Glotzbach, S.; Tscharntke, T. More than Yield: Ecosystem Services of Traditional versus Modern Crop Varieties Revisited. *Sustainability* **2018**, *10*, 2834. [CrossRef]
52. Lei, X.; Yang, D. Cultivating Green Champions: The Role of High-Quality Farmer Training in Sustainable Agriculture. *J. Knowl. Econ.* **2024**, *16*, 2016–2046. [CrossRef]
53. Anderson, C.L.; Reynolds, T.W.; Biscaye, P.; Patwardhan, V.; Schmidt, C. Economic Benefits of Empowering Women in Agriculture: Assumptions and Evidence. *J. Dev. Stud.* **2020**, *57*, 193–208. [CrossRef]
54. Ellis, F. *Rural Livelihoods and Diversity in Developing Countries*; Oxford University Press: Oxford, UK, 2000. [CrossRef]
55. Suri, T. Selection and Comparative Advantage in Technology Adoption. *Econometrica* **2011**, *79*, 159–209. [CrossRef]
56. Nandy, A.; Tiwari, C.; Kundu, S. India's Rural Employment Guarantee Scheme—How does it influence seasonal rural out-migration decisions? *J. Policy Model.* **2021**, *43*, 1181–1203. [CrossRef]
57. McAuliffe, R.E. Minimum Efficient Scale. In *Wiley Encyclopedia of Management*; Cooper, C.L., McAuliffe, R.E., Eds.; Wiley: Hoboken, NJ, USA, 2015. [CrossRef]
58. Assunção, J.J.; Braido, L.H.B. Testing Household-Specific Explanations for the Inverse Productivity Relationship. *Am. J. Agric. Econ.* **2007**, *89*, 980–990. [CrossRef]
59. Sadeghpour, A.; Afshar, R.K. Livestock manure: From waste to resource in a circular economy. *J. Agric. Food Res.* **2024**, *17*, 101255. [CrossRef]
60. Shamdasani, Y. Rural road infrastructure & agricultural production: Evidence from India. *J. Dev. Econ.* **2021**, *152*, 102686. [CrossRef]
61. Gao, R.; Duan, Y.; Zhang, J.; Ren, Y.; Li, H.; Liu, X.; Zhao, P.; Jing, Y. Effects of long-term application of organic manure and chemical fertilizer on soil properties and microbial communities in the agro-pastoral ecotone of North China. *Front. Environ. Sci.* **2022**, *10*, 993973. [CrossRef]
62. Marenya, P.P.; Barrett, C.B. Soil quality and fertilizer use rates among smallholder farmers in western Kenya. *Agric. Econ.* **2009**, *40*, 561–572. [CrossRef]
63. Phiri, K.; Nhliziyo, M.; Madzivire, S.I.; Sithole, M.; Nyathi, D. Understanding climate smart agriculture and the resilience of smallholder farmers in Umguza district, Zimbabwe. *Cogent Soc. Sci.* **2021**, *7*, 1970425. [CrossRef]
64. Tofu, D.A.; Woldeamanuel, T.; Haile, F. Smallholder farmers' vulnerability and adaptation to climate change induced shocks: The case of Northern Ethiopia highlands. *J. Agric. Food Res.* **2022**, *8*, 100312. [CrossRef]
65. IPCC. *Climate Change 2022: Impacts, Adaptation, and Vulnerability*; IPCC: Geneva, Switzerland, 2022.
66. Shin, S.; Magnan, N.; Mullally, C.; Janzen, S. Demand for Weather Index Insurance among Smallholder Farmers under Prospect Theory. *J. Econ. Behav. Organ.* **2022**, *202*, 82–104. [CrossRef]
67. Magrini, M.-B.; Béfort, N.; Nieddu, M. Technological lock-in and pathways for crop diversification in the bio-economy. In *Agroecosystem Diversity*; Academic Press: Cambridge, MA, USA, 2019; pp. 375–388.
68. Rizzo, G.; Migliore, G.; Schifani, G.; Vecchio, R. Key factors influencing farmers' adoption of sustainable innovations: A systematic literature review and research agenda. *Org. Agric.* **2024**, *14*, 57–84. [CrossRef]
69. Doss, C.R. Women and Agricultural Productivity: What Does the Evidence Tell Us? Yale University Economic Growth Center Discussion Paper, (1051). 2015. Available online: https://ageconsearch.umn.edu/record/212153?v=pdf (accessed on 10 March 2025).
70. Touch, V.; Tan, D.K.; Cook, B.R.; Li Liu, D.; Cross, R.; Tran, T.A.; Utomo, A.; Yous, S.; Grunbuhel, C.; Cowie, A. Smallholder farmers' challenges and opportunities: Implications for agricultural production, environment and food security. *J. Environ. Manag.* **2024**, *370*, 122536. [CrossRef]
71. Guido, Z.; Zimmer, A.; Lopus, S.; Hannah, C.; Gower, D.; Waldman, K.; Krell, N.; Sheffield, J.; Caylor, K.; Evans, T. Farmer forecasts: Impacts of seasonal rainfall expectations on agricultural decision-making in Sub-Saharan Africa. *Clim. Risk Manag.* **2020**, *30*, 100247. [CrossRef]

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