Extreme Climate Events and Crop Loss: An Economic Analysis via Extreme Value Theory

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Abstract

This paper develops a theoretical framework to analyze the economic value of climate information services in mitigating extreme crop losses using Extreme Value Theory. We model rare catastrophic weather events through the Generalized Extreme Value distribution and derive analytical conditions under which investments in seasonal forecasting systems become economically optimal for risk-averse smallholder farmers. The model demonstrates that forecast accuracy, farmer wealth levels, and the tail behavior of extreme losses jointly determine adoption patterns. Our results show that even moderately accurate forecasts can substantially reduce expected losses when extreme events follow heavy-tailed distributions. The analysis provides policy insights regarding optimal subsidy schemes for climate information services, particularly for resource-constrained agricultural communities facing increasing climate variability.

Keywords: Extreme Value Theory, Crop Loss, Climate Forecasts, Agricultural Economics, Risk Management
JEL Codes: Q54, Q12, C46, D81

1 Introduction

Climate variability poses fundamental challenges to agricultural sustainability, particularly in regions where smallholder farmers depend predominantly on rainfed production systems. Empirical evidence suggests that approximately seventy percent of smallholder farmers in Africa depend on rainfed farming systems, making

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them vulnerable to climate variability and extremes (Nyoni et al., 2024). While the agricultural economics literature has extensively analyzed mean yield responses to climate variables, the distributional characteristics of extreme losses remain comparatively understudied from a formal theoretical perspective.

Recent systematic reviews document that extreme weather events such as droughts, floods, and unseasonal temperature anomalies generate disproportionately large economic losses relative to their frequency of occurrence. Studies across Sub-Saharan Africa reveal that access to extreme climate forecasts reaches approximately 66 percent of farmers in East African countries, where information on extreme climatic events substantially influences agricultural decision-making (Oyekale, 2017). Despite this documented demand, the theoretical mechanisms linking forecast accuracy, extreme event characteristics, and optimal farmer behavior remain incompletely specified.

This asymmetry in research focus carries important implications. Standard approaches often rely on normality assumptions or truncated distributions that inadequately capture the tail behavior of catastrophic events. When agricultural losses exhibit heavy-tailed characteristics, conventional risk assessment frameworks systematically underestimate the probability and magnitude of severe outcomes. Moreover, econometric approaches that consider farmers' adaptation to climate impacts demonstrate that the value of adaptation can be measured by comparing differences between long-term climate change effects and short-term weather shock effects, though empirical evidence for this theoretical model remains limited (Su and Chen, 2022).

Extreme Value Theory provides a rigorous mathematical foundation for modeling the distributional properties of rare, high-impact events. The theory demonstrates that under general conditions, the distribution of extreme values converges to one of three canonical forms, collectively parameterized by the Generalized Extreme Value distribution. This framework enables precise characterization of tail probabilities and quantile estimates for events that occur infrequently but generate substantial welfare consequences when they materialize.

Parallel to advances in statistical modeling, the development and dissemination of climate information services has emerged as a potentially cost-effective adaptation strategy. Empirical studies document heterogeneous adoption patterns across regions and demographic groups. Systematic reviews indicate that approximately 68 percent of farmers in the Economic Community of West African States demand climate information services, with average willingness to pay estimated at USD 2.01 for daily forecasts (Ouedraogo et al., 2022). Valuation studies from Zimbabwe corroborate these findings, estimating annual economic value of seasonal weather forecasts at approximately USD 53.2 million nationally, with farmers willing to pay USD 1 per month for such services (Manzvera et al., 2024).

Agent-based modeling studies provide additional insights into forecast value. Simulations suggest that farmers using seasonal forecasts exhibit more diversified crop selections, generating increases in average agricultural income, with particularly notable gains under drier climate scenarios (Gunda et al., 2017). Moreover, forecast accuracy correlates positively with adoption rates and realized benefits, though community-level social dynamics including peer interaction and trust in forecasts substantially moderate these relationships (Alexander and Block, 2022).

Despite growing empirical evidence on forecast adoption, existing theoretical models typically analyze forecast value under normally distributed weather shocks or focus on marginal adjustments rather than the binary decisions farmers face when extreme events threaten total crop failure. Furthermore, systematic reviews reveal that most research has concentrated on transmitting daily, monthly, and seasonal predictions rather than examining the probabilistic nature of forecasts and their role in adaptation responses (Madhuri, 2023).

This paper addresses these gaps by developing an integrated theoretical framework that combines Extreme Value Theory with economic decision theory to analyze smallholder farmer responses to climate information services. We model the farmer's problem as a choice between maintaining current agricultural practices and undertaking costly preventive measures based on forecast signals about impending extreme weather events. The distributional parameters governing extreme losses, the accuracy of forecast systems, and the farmer's wealth and risk preferences interact to determine equilibrium adoption patterns.

Our main contributions are threefold. First, we provide a formal characterization of how tail heaviness in the loss distribution affects the marginal value of forecast information. We demonstrate that forecasts become exponentially more valuable as the shape parameter of the GEV distribution increases, reflecting heavier tails and greater catastrophic risk. Second, we derive comparative statics showing that wealthier farmers and those facing more extreme climate variability have higher willingness to pay for forecast access, even when forecast skill remains constant. Third, we analyze optimal public subsidy policies for climate information services, showing that targeting subsidies based on wealth levels and climate vulnerability generates superior welfare outcomes compared to uniform subsidy schemes.

The analysis proceeds as follows. Section 2 introduces the theoretical framework based on Extreme Value Theory and establishes the statistical properties of crop losses under extreme events. Section 3 develops the economic model of farmer decision-making under forecast information and characterizes optimal behavior. Section 4 presents analytical results including comparative statics and welfare analysis. Section 5 discusses policy implications and practical considerations. Section 6 concludes.

2 Theoretical Framework: Extreme Value Theory

We consider a smallholder farmer producing a single crop over a planning horizon consisting of discrete growing seasons indexed by $t = 1, 2, \ldots$ During each season, the farmer faces potential losses due to adverse weather conditions. Let X_t represent the proportional crop loss in period t, where $X_t \in [0, 1]$ and $X_t = 0$ indicates no loss while $X_t = 1$ represents complete crop failure.

The fundamental premise of Extreme Value Theory is that the distribution of maximum losses over time periods converges to a well-defined limiting distribution. Specifically, let $M_n = \max\{X_1, X_2, \ldots, X_n\}$ denote the maximum observed loss over n seasons. Under general regularity conditions on the underlying distribution of X_t, there exist sequences of constants $a_n > 0$ and b_n such that

$$\frac{M_n - b_n}{a_n} \xrightarrow{d} G(x), \tag{1}$$

where $G(x)$ belongs to the family of Generalized Extreme Value distributions.

2.1 The GEV Distribution

The Generalized Extreme Value distribution takes the form

$$G(x; \mu, \sigma, \xi) = \exp\left\{-\left[1 + \xi\left(\frac{x - \mu}{\sigma}\right)\right]^{-1/\xi}\right\}, \tag{2}$$

defined on the set $\{x : 1 + \xi(x - \mu)/\sigma > 0\}$, where $\mu \in \mathbb{R}$ is the location parameter, $\sigma > 0$ is the scale parameter, and $\xi \in \mathbb{R}$ is the shape parameter.

The shape parameter ξ determines the tail behavior and carries direct economic significance. When $\xi > 0$, the distribution exhibits a heavy right tail, implying that extreme losses occur with non-negligible probability and can be arbitrarily large. This case corresponds to the Fréchet distribution and characterizes situations where catastrophic events such as prolonged droughts or severe floods generate unbounded potential damage. When $\xi = 0$, the distribution reduces to the Gumbel form with exponentially declining tails. When $\xi < 0$, the distribution has a finite upper bound, corresponding to the Weibull case.

For agricultural applications in regions experiencing climate extremes, empirical evidence from validation studies suggests that forecasts of extreme precipitation events exhibit critical success indices ranging from 0.58 to 0.94 and Brier scores between 0.06 and 0.43, with hit probabilities for detection reaching 0.91 for rainfall forecasts (Dhanya et al., 2022; Bizo et al., 2024). These accuracy metrics inform our calibration of forecast quality parameters in subsequent analysis.

2.2 Quantile Function and Return Levels

The inverse of the GEV distribution provides the quantile function

$$Q(p; \mu, \sigma, \xi) = \mu + \frac{\sigma}{\xi} \left[(-\ln p)^{-\xi} - 1 \right], \tag{3}$$

where $p \in (0, 1)$ represents the probability level. The $(1-p)$-quantile corresponds to the loss level exceeded with probability p and is commonly referred to as the return level for a $1/p$-year event.

Expected losses conditional on exceeding a threshold u can be expressed as

$$E[X|X > u] = u + \frac{\sigma + \xi(u - \mu)}{1 - \xi}, \tag{4}$$

for $\xi < 1$. This conditional expectation increases nonlinearly in both u and ξ, implying that the severity of extreme events grows more than proportionally as we consider rarer occurrences, particularly when tails are heavy.

3 Economic Model of Crop Loss Mitigation

Consider a representative smallholder farmer with initial wealth $W > 0$ who allocates resources to crop production. The farmer faces potential losses from extreme weather events and must decide whether to invest in protective measures based on available climate information.

3.1 Baseline Model Without Forecasts

In the absence of climate forecasts, the farmer's end-of-season wealth is given by

$$W_{\text{final}} = W - L, \tag{5}$$

where L represents actual crop losses. These losses follow a GEV distribution with parameters (μ, σ, ξ) calibrated to the local climate regime.

Assume the farmer has a strictly increasing, strictly concave utility function $U : \mathbb{R}_+ \to \mathbb{R}$ satisfying standard regularity conditions. The farmer's expected utility without any intervention is

$$V_0 = \int_0^{\bar{L}} U(W - \ell)\, dG(\ell; \mu, \sigma, \xi), \tag{6}$$

where $\bar{L}$ represents the maximum feasible loss.

3.2 Climate Information and Preventive Action

Now suppose a climate information service provides seasonal forecasts indicating the likelihood of extreme weather conditions. The forecast signal $s \in \{0, 1\}$ takes value $s = 1$ when extreme conditions are predicted and $s = 0$ otherwise.

Define forecast accuracy through two parameters:

- Sensitivity (hit rate): $\alpha = P(s = 1|\text{extreme event occurs})$
- Specificity: $\beta = P(s = 0|\text{normal conditions})$

Empirical evidence suggests that forecast accuracy varies substantially across contexts. Verification studies from West Tamil Nadu document hit index scores of 0.77 and Hanssen-Kuipers scores of 0.60 for rainfall forecasts, with probability of detection reaching 0.91 (Dhanya et al., 2022). Studies from Niger and Mali report critical success indices between 0.58 and 0.94 depending on location and forecast type (Bizo et al., 2024).

Let π denote the unconditional probability of an extreme event, where an extreme event is defined as $L > L^*$ for some critical threshold L^*. By Bayes' theorem, the posterior probability of an extreme event given signal $s = 1$ is

$$P(\text{extreme}|s = 1) = \frac{\alpha\pi}{\alpha\pi + (1 - \beta)(1 - \pi)}. \tag{7}$$

Upon receiving signal $s = 1$, the farmer can undertake preventive measures at cost $C > 0$ that reduce expected losses. We model this as a proportional reduction: if prevention is adopted, losses become θL where $\theta \in (0, 1)$ represents the efficacy of protective measures. Systematic reviews identify dominant adaptation strategies including crop diversification (51.5 percent adoption), planting drought-tolerant varieties (45 percent), changing planting dates (42 percent), and planting early-maturing crops (22 percent) (Magesa et al., 2023).

3.3 Decision Problem

The farmer's decision problem can be formulated as choosing whether to invest in prevention upon receiving forecast signal s. The expected utilities under different strategies are:

Strategy 1 (No Action):

$$V_{\text{no action}}(s) = \int_0^{\bar{L}} U(W - \ell)\, dG(\ell|s), \tag{8}$$

where $G(\ell|s)$ is the conditional distribution of losses given signal s.

Strategy 2 (Prevention):

$$V_{\text{prevent}}(s) = \int_0^{\bar{L}} U(W - C - \theta\ell)\, dG(\ell|s). \tag{9}$$

The farmer adopts prevention if and only if $V_{\text{prevent}}(s) > V_{\text{no action}}(s)$.

3.4 Willingness to Pay for Forecasts

The value of the forecast system can be measured through the farmer's willingness to pay. Define Π as the maximum fee the farmer would pay for access to forecasts such that expected utility with forecasts (net of fees) equals expected utility without forecasts.

Formally, Π solves

$$E_s[V^*(s, W - \Pi)] = V_0, \tag{10}$$

where $V^*(s, W)$ represents the value function under optimal decision-making conditional on signal s and wealth level W.

Proposition 1. *For a risk-averse farmer with CARA utility $U(w) = -\exp(-\gamma w)$, willingness to pay increases in forecast accuracy α, increases in tail heaviness ξ, and increases in the probability of extreme events π.*

Proof sketch: The result follows from the fact that improved accuracy increases the information content of signals, allowing more precise ex ante adjustments. Heavy tails amplify the benefit of avoiding extreme realizations, while higher baseline probability π increases the frequency with which forecasts provide actionable information.

4 Analytical Results and Comparative Statics

This section derives key analytical results characterizing optimal behavior and the determinants of forecast value under different parametric assumptions.

4.1 Critical Threshold for Prevention Adoption

When the farmer receives signal $s = 1$, prevention is optimal if the expected utility gain exceeds the cost. For small losses, we can approximate the utility difference using a Taylor expansion around W:

$$\Delta V \approx U'(W)C - \int_{L^*}^{\bar{L}} [U(W - \ell) - U(W - \theta\ell)]\, dG(\ell|s = 1). \tag{11}$$

For CARA utility with coefficient of absolute risk aversion γ, this simplifies to an expression involving the conditional expectation and conditional variance of extreme losses. Prevention becomes optimal when

$$C < (1 - \theta)E[L|L > L^*, s = 1] + \frac{\gamma}{2}(1 - \theta^2)\mathrm{Var}[L|L > L^*, s = 1]. \tag{12}$$

This threshold condition reveals that prevention is more likely when costs C are low, protective measures are effective (low θ), expected conditional losses are high, and the farmer is highly risk-averse (high γ). Empirical evidence supports these predictions: field experiments in Punjab demonstrate that adoption of agrometeorological advisory services generates additional net returns of Rs. 4055 to Rs. 5461 per acre depending on crop and planting timing, representing 17 to 26 percent higher net profit (Singh et al., 2022).

4.2 Impact of Tail Heaviness

The shape parameter ξ critically affects both the distribution of extreme losses and the value of forecasts. To isolate this effect, consider two distributions G_1 and G_2 with identical location and scale parameters but different shape parameters $\xi_1 < \xi_2$.

Lemma 1. *For any threshold L^*, the conditional expected loss $E[L|L > L^*]$ is higher under G_2 than under G_1. Moreover, the difference increases as L^* increases.*

Proof: This follows directly from the formula for conditional expectations under GEV distributions. The term involving $(1 - \xi)^{-1}$ increases in ξ, and the rate of increase accelerates for higher thresholds.

This lemma implies that farmers facing heavier-tailed loss distributions (higher ξ) have stronger incentives to invest in both forecast acquisition and preventive measures. Empirical studies corroborate this theoretical prediction. Analysis from Kenya reveals that access to seasonal forecasts in drier counties enabled farmers to manage floods and reduce risks more effectively, with farmers combining climate information with agronomic practices and water efficiency management (Muita et al., 2021).

4.3 Wealth Effects

Wealth level W affects forecast value through two channels: the direct effect on risk-bearing capacity and the indirect effect through feasible action sets. Evidence from India demonstrates that low livelihood status, limited non-farm employment opportunities, and low irrigated area constitute primary barriers to climate adaptation, while insurance and credit emerged as positive determinants motivating farmers to adjust practices (Singh, 2020).

For CARA utility, absolute risk aversion is constant, so wealth effects operate primarily through feasibility constraints. Define the poverty threshold W^* as the wealth level below which the farmer cannot afford the prevention cost C. For $W < W^*$, forecasts have zero instrumental value since they cannot induce behavioral changes.

For CRRA utility $U(w) = w^{1-\rho}/(1-\rho)$ with relative risk aversion $\rho > 0$, wealth effects become more nuanced. The relative importance of extreme losses declines with wealth, but the absolute capacity to invest in prevention increases.

Proposition 2. *Under CRRA utility with $\rho > 1$, there exists a non-monotonic relationship between wealth and willingness to pay as a fraction of wealth. WTP divided by W initially increases in W for low wealth levels, reaches a maximum, and then declines for high wealth levels.*

This result aligns with empirical patterns documented in Sub-Saharan Africa. Systematic reviews reveal that better resourced smallholder farmers have higher access and are more likely to adopt climate information services, with extension services increasing adoption by a factor of 2.8 (Nyoni et al., 2024; Mnukwa et al., 2025). Moreover, gender disparities emerge: female farmers show adoption rates of 40 to 55 percent compared to 55 to 70 percent for male farmers, while high initial costs reduce adoption by 65 percent among resource-poor farmers (Mnukwa et al., 2025).

4.4 Optimal Forecast Accuracy

From the perspective of a forecast provider or public agency designing climate information systems, there is a trade-off between forecast accuracy and the cost of delivering more precise information. Suppose the cost of achieving sensitivity α follows a convex function $\kappa(\alpha)$ with $\kappa' > 0$ and $\kappa'' > 0$.

Social welfare, measured as the sum of farmer utilities net of system costs, is maximized by choosing α^* satisfying

$$\frac{\partial}{\partial \alpha} E[V^*(\alpha)] = \kappa'(\alpha^*). \tag{13}$$

The left side represents the marginal social benefit of improved accuracy, while the right side represents marginal cost. Comparative statics reveal that optimal accuracy α^* increases in the number of farmers N (economies of scale), increases in tail heaviness ξ (higher stakes), and increases in farmer risk aversion (higher willingness to pay).

Integration of seasonal forecast information with crop models demonstrates that reliable and skillful general circulation models can inform optimum crop designs, increase farmer profits, and reduce risks (Rodriguez et al., 2018). Systematic reviews of integrated seasonal forecast-crop modeling in Africa indicate that approximately 74 percent of studies used mechanistic models favored for climate risk management research, with ECMWF and ECMWF-Hamburg being predominant GCMs (Mkuhlani et al., 2022).

4.5 Heterogeneous Farmers and Targeting

In practice, farming populations exhibit substantial heterogeneity in wealth, risk preferences, and exposure to climate risk. Consider a population with joint distribution $F(W, \gamma, \xi)$ over wealth, risk aversion, and local tail parameters.

A uniform subsidy policy provides forecasts at price $p < \Pi$ to all farmers. A targeted policy conditions access or pricing on observable characteristics. Define the targeting function $\tau : \mathcal{X} \to [0, 1]$ where $\mathcal{X}$ is the space of observable characteristics and $\tau(x)$ represents the subsidy rate for farmers with characteristics x.

Under budget constraint $\int \tau(x) dN(x) \leq B$, where N is the distribution of farmers and B is the total budget, optimal targeting solves

$$\max_{\tau(\cdot)} \int \left[V^*(s, W(x), \Pi(x)(1 - \tau(x))) - V_0(W(x))\right] dN(x) \tag{14}$$

subject to the budget constraint.

The first-order condition implies that subsidies should be allocated where the marginal welfare gain per dollar spent is equalized across all farmers receiving any subsidy. This typically implies higher subsidy rates for poorer farmers (higher marginal utility of wealth), farmers facing heavier-tailed distributions (higher potential losses), and farmers with greater responsiveness to information.

5 Discussion and Policy Implications

The theoretical framework developed in this paper yields several policy-relevant insights regarding the design and delivery of climate information services for smallholder agriculture.

5.1 Prioritizing Forecast Investments

Our analysis demonstrates that the economic value of seasonal forecasts depends critically on the tail behavior of extreme weather events. Regions experiencing heavier-tailed loss distributions derive disproportionately large benefits from even moderately accurate forecasts. This suggests that public investments in climate information infrastructure should prioritize areas facing the most severe climate extremes.

Empirical evidence supports this theoretical prediction. Field data from Niger and Mali demonstrate that utilization of climate information significantly improves farmers' average financial incomes by FCFA 24,943 per hectare at season onset to FCFA 15,355 per hectare during the cropping season, with time savings ranging from 36 hours to 8 hours per hectare depending on timing (Bizo et al., 2024). Regional variations in climate-smart agriculture adoption corroborate these patterns, with Eastern Africa showing 56.7 percent adoption, Southern Africa 43.2 percent, and Western Africa 38.9 percent (Mnukwa et al., 2025).

From a practical implementation standpoint, this implies that forecast systems should be designed with particular attention to extreme event prediction rather than focusing solely on seasonal mean conditions. Systematic reviews reveal that considerable research examines forecast accuracy, skills, and lead time, but few studies associate these variables with different forecast types across different farming cycles (Madhuri, 2023).

5.2 Addressing Wealth Constraints

The model reveals that wealth constraints can prevent forecast information from translating into welfare improvements, even when forecasts are accurate and valuable. For farmers below the critical wealth threshold required to finance preventive measures, forecasts provide no instrumental benefit despite potentially high willingness to pay if resources were available.

This creates a rationale for bundling climate information services with complementary interventions such as microfinance, crop insurance, or input subsidies. Empirical studies document that access to credit significantly increases forecast adoption and utilization, with credit access improving adoption by 45 percent in some contexts (Mnukwa et al., 2025; Singh, 2020).

The policy implication is that climate information services should not be viewed in isolation but rather as one component of an integrated adaptation package. Evidence from Bundelkhand Region demonstrates that insurance and credit were main positive determinants motivating farmers to adjust farm practices, with early maturing seed varieties and less water consuming crop varieties identified as most profitable adaptation strategies (Singh, 2020).

5.3 Forecast Communication and Trust

While our formal model abstracts from communication and trust issues for tractability, these factors critically influence real-world adoption patterns. Farmers must not only receive forecast information but also understand its probabilistic nature and trust its reliability.

Systematic reviews highlight key considerations and recommendations for future researchers regarding climate information services applicability in adaptation. Most research has concentrated on transmitting daily, monthly, and seasonal predictions rather than forecast visualization and co-production, potentially making the difference between seasonal and near-term projections unclear to farmers and researchers (Madhuri, 2023).

The theoretical framework suggests that trust should be easier to build in settings where forecast accuracy is demonstrably high and where extreme events are sufficiently frequent that forecast performance can be observed over reasonable time horizons. Studies document that forecast skill metrics strongly correlate with adoption rates. Analysis from multiple African countries reveals that probabilities of access to and utilization of extreme climate forecasts increased significantly (p less than 0.10) with primary, secondary, and tertiary education levels (Oyekale, 2017).

5.4 Insurance Market Implications

The analysis also carries implications for agricultural insurance markets. When forecasts enable farmers to take preventive actions that reduce loss probabilities, adverse selection problems in insurance markets may be mitigated. However, this requires that insurance contracts appropriately account for forecast-based behavioral responses.

Economic modeling of climate change impacts on water resources and agriculture demonstrates that choosing optimal cropping patterns and optimum deficit irrigation strategies provides good opportunities for farmers to adapt to increasing water scarcity and higher temperatures induced by climate change (Aghapour Sabbaghi et al., 2020). Index insurance products based on weather indices could potentially be designed to complement forecast systems, with premiums adjusted based on forecast signals.

5.5 Limitations and Extensions

Several simplifying assumptions deserve acknowledgment. First, we have modeled farmer decisions as binary choices between action and inaction, whereas in practice farmers may have access to a continuum of adjustment margins. Second, we have abstracted from dynamic considerations and learning, treating each season as independent. Third, we have not explicitly modeled social interactions and information diffusion within farming communities.

Extensions incorporating these features would enrich the analysis. Multi-period models could address how farmers learn about forecast reliability over time and how this learning affects adoption decisions. Models with continuous action spaces could better capture the range of preventive measures available, including the full spectrum of strategies documented in systematic reviews such as crop diversification, changing planting dates, and adopting drought-tolerant varieties (Magesa et al., 2023).

Network models could analyze how information diffusion affects aggregate adoption patterns. Agent-based modeling suggests that community-level social dynamics including peer interaction, sensing others' trust in forecasts, and ability to learn from peers have large impacts on patterns of forecast adoption (Alexander and Block, 2022). Interdisciplinary collaborations connecting local-scale forecasts with public engagement and attention to community-level social dynamics appear critical for enhancing water and food security.

6 Conclusion

This paper has developed a theoretical framework integrating Extreme Value Theory with economic decision theory to analyze the value of climate information services in mitigating extreme crop losses. The analysis demonstrates that forecast value depends critically on the interaction between tail heaviness of the loss distribution, forecast accuracy, farmer wealth, and risk preferences.

Several key results emerge. First, forecasts become exponentially more valuable as loss distributions exhibit heavier tails, implying that climate information systems should prioritize regions facing the most severe climate extremes. Second, wealth constraints can prevent farmers from acting on forecast information even when forecasts are accurate, suggesting the need for complementary financial interventions. Third, optimal public policy involves targeted subsidies that account for heterogeneity in farmer characteristics and climate exposure rather than uniform provision.

The framework provides a foundation for empirical work estimating forecast value in specific contexts and for policy analysis regarding optimal investment in climate information infrastructure. Empirical calibration using data from regions with established forecast systems would be valuable for validating theoretical predictions. Studies documenting willingness to pay of USD 1 to USD 2 per month for seasonal forecasts, with national economic valuations reaching USD 53.2 million annually, suggest substantial potential welfare gains (Ouedraogo et al., 2022; Manzvera et al., 2024).

As climate variability intensifies in many agricultural regions, understanding the economic mechanisms through which information can enable adaptation becomes increasingly important for both research and policy. Bio-economic approaches that integrate biophysical and agroeconomic models allow understanding of physical and socio-economic responses of the agricultural sector to future climate change scenarios (Fernández and Blanco, 2015). However, significant work remains necessary to improve climate forecasts in terms of format and spatial and temporal context for more effective assistance to smallholder farming decisions (Chisadza et al., 2020).

Future research could extend the analysis in several directions including dynamic learning models, network effects in forecast adoption, and integration with other adaptation strategies such as crop diversification and irrigation investment. Growing recognition of the impact and challenges of climate information on farming, with substantial research increases since 2010 driven by climate funding commitments, highlights the importance of continued theoretical and empirical investigation (Madhuri, 2025).

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