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MODELING EXTREME CLIMATE RISK IN AGRICULTURE: AN EVT-BASED APPROACH TO WHEAT YIELD LOSSES AND INSURANCE DESIGN IN UZBEKISTAN



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Abstract: This study develops an econometric framework to assess extreme climate risks affecting agricultural production in Uzbekistan, with a particular focus on wheat yield losses in the Surkhandarya region. Using annual production data (2010–2024) and long-term hydroclimatic observations (1981–2025), the research applies Extreme Value Theory (EVT) and the Peak Over Threshold (POT) method to model tail risks associated with drought and temperature extremes. To isolate climate-induced shocks, wheat yields are detrended using linear regression techniques, and climate anomalies are constructed from long-term monthly averages. The empirical results indicate that rainfall deficits represent the dominant source of catastrophic yield losses, while temperature extremes exhibit relatively lower tail risk. The estimated shape parameters ($\xi < 0$) suggest bounded but persistent extreme risk. The 99.5% Possible Maximum Loss (PML) is estimated at approximately 29.6 units for rainfall-related losses and 4.6 units for temperature-related losses. The findings demonstrate that traditional indemnity-based insurance mechanisms systematically underestimate climate-induced tail risks and fail to provide adequate financial protection. Based on international best practices, the study proposes an EVT-calibrated index-based insurance framework integrated with reinsurance and early warning systems. This approach enhances climate resilience, improves insurer solvency, and supports sustainable agricultural development in Uzbekistan.

Keywords: Extreme Value Theory; Climate Risk; Wheat Yield; Index-Based Insurance; Agricultural Finance; Drought Risk; Uzbekistan; Risk Financing.

Аннотация: Ушбу тадқиқот Ўзбекистон қишлоқ хўжалиги секторига хос бўлган экстремал иқлим хатарларини баҳолашнинг эконометрик моделини таклиф этади (Сурхондарё вилоятининг буғдой ҳосилдорлиги мисолида). Ишда 2010–2024 йиллардаги ҳосилдорлик ва 1981–2025 йиллардаги гидроиқлим кўрсаткичларидан фойдаланилган ҳолда, қурғоқчилик ва ҳарорат аномалиялари билан боғлиқ "қуйруқ хатарлари"ни (tail risks) моделлаштиришда Экстремал қийматлар назарияси (EVT) ва POT (Peak Over Threshold) усуллари қўлланилди. Иқлимга хос бўлган "шок"ларни аниқлаш мақсадида ҳосилдорлик кўрсаткичлари чизиқли регрессия ёрдамида тренддан тозаланди. Эмпирик натижалар шуни кўрсатадики, ҳосилнинг кескин камайишида ёғингарчилик тақчиллиги асосий детерминант ҳисобланади; ҳароратнинг таъсири эса нисбатан пастроқ экстремал хатарга эга. Аниқланган шакл параметрлари ($\xi < 0$) хатарнинг чегараланганлигини, аммо доимий эканлигини

англатади. 99,5 фоизлик эҳтимолликдаги Максимал кутилаётган зарар (PML) ёғингарчилик бўйича 29,6 бирликни, ҳарорат бўйича эса 4,6 бирликни ташкил этди. Тадқиқот хулосалари анъанавий суғурта механизмлари иқлим хатарларини тизимли равишда паст баҳолашини кўрсатмоқда. Олинган натижалар асосида қайта суғурта ва эрта огоҳлантириш тизимлари билан интеграциялашган, EVT-калибровкали индексли суғурта модели таклиф этилди. Ушбу ёндашув Ўзбекистонда суғурталовчиларнинг тўлов қобилиятини ошириш ва қишлоқ хўжалигининг барқарор ривожланишини таъминлашга хизмат қилади.

Калит сўзлар: Экстремал қийматлар назарияси (EVT); иқлим хатари; буғдой ҳосилдорлиги; индексли суғурта; қишлоқ хўжалиги молияси; қурғоқчилик хатари; Ўзбекистон; рискларни молиялаштириш.

Аннотация: В данном исследовании разработана эконометрическая модель оценки экстремальных климатических рисков, влияющих на аграрный сектор Узбекистана (на примере урожайности пшеницы в Сурхандарьинской области). На основе данных о производстве за 2010–2024 гг. и долгосрочных гидроклиматических наблюдений (1981–2025 гг.) применяются Теория экстремальных значений (EVT) и метод превышения порога (POT) для моделирования «хвостовых рисков», связанных с засухой и температурными аномалиями. Для выделения климатических шоков показатели урожайности были очищены от тренда методом линейной регрессии. Эмпирические результаты показывают, что дефицит осадков является доминирующим фактором катастрофических потерь урожая, в то время как температурные экстремумы демонстрируют более низкий уровень риска. Оцененные параметры формы ($\xi < 0$) указывают на ограниченный, но устойчивый характер экстремальных рисков. Возможный максимальный убыток (PML) с вероятностью 99,5% оценивается в 29,6 единиц для рисков, связанных с осадками, и 4,6 единиц — для температурных рисков. Результаты демонстрируют, что традиционные механизмы страхования систематически недооценивают климатические риски и не обеспечивают адекватной финансовой защиты. На основе международного опыта предлагается модель индексного страхования, калиброванная по методу EVT и интегрированная с системами перестрахования и раннего предупреждения. Данный подход направлен на повышение климатической устойчивости, обеспечение платежеспособности страховщиков и поддержку устойчивого развития сельского хозяйства в Узбекистане.

Ключевые слова: Теория экстремальных значений (EVT); климатический риск; урожайность пшеницы; индексное страхование; сельскохозяйственные финансы; риск засухи; Узбекистан; финансирование рисков.

INTRODUCTION

In recent years, increasing attention has been paid in Uzbekistan to the development of the insurance market, ensuring financial stability in the agricultural sector, and protecting farmers from losses caused by natural disasters. The modernization of the insurance system, the adoption of international best practices, and the implementation of advanced risk management mechanisms have become key priorities of state policy.

Agricultural production, particularly wheat cultivation, is highly dependent on climatic conditions. Factors such as rainfall deficiency, drought, and extreme temperature increases significantly affect crop yields. These climate-related risks lead to income instability among farmers and increase financial vulnerability in the agricultural sector.

In international practice, these challenges are addressed through index-based insurance schemes, Extreme Value Theory (EVT), and actuarial assessment methods aligned with Solvency II standards. These approaches enable accurate risk modeling, estimation of probable maximum losses, and the development of sustainable pricing strategies.

This paper analyzes the impact of climatic factors on wheat yield in the Surkhandarya region using econometric and statistical methods. Crop yield data are detrended to isolate climate effects, climate anomalies are identified, and extreme risks are assessed using EVT models. The findings are interpreted as the author's scientific observations based on international experience and provide practical recommendations for improving agricultural insurance systems in Uzbekistan.

LITERATURE REVIEW

Issues related to climate risk management and financial sustainability in agriculture have been widely studied in both international and domestic research. In recent years, the intensification of climate change has reduced the effectiveness of traditional insurance mechanisms, increasing the relevance of index-based and actuarial modeling approaches.

Institutional reforms aimed at developing Uzbekistan's insurance market have been established through Presidential Decrees, emphasizing the necessity of strengthening financial stability, improving professional risk assessment, and aligning national insurance systems with international standards [1]. These documents provide a regulatory foundation for implementing advanced actuarial and risk modeling frameworks in the domestic insurance market.

In the field of actuarial risk assessment, Abonongo (2023) demonstrates that the application of the Sine Burr III distribution enables the identification of heavy-tailed characteristics in loss distributions, which is essential for accurate insurance pricing [2]. This study highlights the importance of incorporating extreme risks into premium calculations.

The impact of climatic factors on agricultural productivity has been extensively analyzed by Zhai et al. (2017) in the context of inland China. Using an autoregressive distributed lag (ARDL) model, the authors assess the long-term influence of temperature and precipitation on wheat yields [3]. Their findings confirm that climatic variables significantly affect agricultural output alongside technological progress.

Er-Raki and Khabba (2021) employ remote sensing techniques to optimize water management and crop productivity, demonstrating the potential of satellite data for improving agricultural risk assessment [4]. Their research supports the integration of satellite-based indicators into index insurance design.

The theoretical foundations of insurance pricing were revisited by Kahane (1979), who emphasized the role of capital market theory in determining risk premiums and accounting for extreme losses [5]. Miranda and Farrin (2012) evaluated the

performance of index insurance in developing countries, identifying improper index selection as a major source of inefficiency [6].

Quantile regression methodology, developed by Koenker and Bassett (1978) and further advanced by Koenker (2005), enables the analysis of conditional distributions beyond mean-based models [7,8]. This approach allows researchers to focus on extreme segments of yield distributions, which is particularly relevant for insurance risk assessment.

Extreme Value Theory (EVT) has been widely applied in insurance and finance by Embrechts et al. (1997) and McNeil (1997), who introduced methods for modeling rare but severe loss events using POT-GPD models [9,10]. These techniques form the basis for estimating the Possible Maximum Loss (PML).

In the context of Uzbekistan, empirical studies primarily rely on data from the national statistical agency (Stat.uz) [11]. In addition, meteorological datasets provided by the NASA POWER project serve as important sources for identifying regional climate anomalies [12].

However, the existing literature indicates a lack of comprehensive studies integrating actuarial modeling, EVT, and regional climate data for agricultural insurance in Uzbekistan, particularly in Surkhandarya region. This research gap constitutes the primary motivation for the present study.

DATA AND METHODOLOGY

Data Sources and Pre-processing. This study is based on a longitudinal dataset of annual wheat yields (tons per hectare) for the Surkhandarya region covering the period from 2010 to 2024. The data were obtained from the official statistics of the Statistics Agency of Uzbekistan (Stat.uz). In addition, regional hydroclimatic indicators, including precipitation, temperature, and water stress indices, were compiled from national meteorological sources.

To isolate climate-induced yield fluctuations from long-term technological and managerial improvements, the yield series was detrended using a linear ordinary least squares (OLS) regression:

$$Y_t = \alpha + \beta t + \varepsilon_t$$

where Y_t denotes observed yield in year t , t represents a time trend, and ε_t is the residual term capturing climate-related shocks. All variables were checked for outliers and missing values. Inconsistent observations were removed, and remaining series were standardized.

Quantile Regression for Basis Risk Assessment. While conventional OLS models estimate average relationships, they provide limited information about extreme loss behavior. To examine yield responses across different segments of the distribution, quantile regression (QR) is applied.

Following Bobojonov (2024), particular attention is given to lower quantiles ($\tau = 0.10, 0.25$), where downside risk is most pronounced.

The conditional quantile function is specified as:

$$Q_Y(\tau|X_t) = \beta_0(\tau) + \beta_1(\tau)X_t + u_\tau$$

where X_t represents hydroclimatic indicators and u_τ is the error term.

Extreme Value Theory: POT-GPD Approach. To model rare but severe agricultural losses, Extreme Value Theory (EVT) is employed using the Peak Over Threshold (POT) framework. Observations exceeding a predefined threshold u are analyzed.

Exceedances are modeled using the Generalized Pareto Distribution (GPD):

$$G(y) = 1 - (1 + \xi y/\sigma)^{-1/\xi}$$

where ξ is the shape parameter and σ is the scale parameter.

Parameters are estimated using maximum likelihood, and threshold selection is guided by stability diagnostics.

PML Estimation and Insurer Solvency Assessment. Based on estimated GPD parameters, the Possible Maximum Loss (PML) is computed at high confidence levels.

The PML at probability level p is calculated as:

$$PML_p = u + (\sigma/\xi) * \left[\left(N/(n(1-p)) \right)^\xi - 1 \right]$$

where N is the total number of observations and n is the number of exceedances.

This measure serves as a benchmark for capital adequacy and premium calibration, supporting insurer solvency under extreme climate scenarios.

RESULTS

Descriptive Statistics and Data Overview. Table 1 presents the summary statistics for wheat yield and climate variables during the study period (2010-2024). The average wheat yield was 597.3 kg/ha with a coefficient of variation of 7.36%, indicating moderate inter-annual variability. The minimum yield of 475.3 kg/ha occurred in 2018, representing a 20.4% decline from the mean—the most severe production loss observed in the dataset.

Variable	Mean	SD	Min	Max
Wheat Yield (kg/ha)	597.3	44.0	475.3	653.6
Spring Precipitation (mm)	104.7	76.1	30.7	353.6
Spring Temperature (°C)	17.9	1.1	15.6	19.4
Spring Soil Moisture	0.53	0.05	0.47	0.65
Yield Loss (kg/ha)	0.0	44.0	-56.3	122.0

Table 1. Descriptive statistics for wheat yield and climate variables (2010-2024).

Source: Author's calculations based on Statistics Agency of Uzbekistan (2024) and NASA POWER (2025) data.

Spring precipitation exhibited the highest variability (CV = 72.7%), ranging from 30.7 mm to an exceptional 353.6 mm in 2024. Temperature showed relatively low

variability (CV = 6.1%), with spring means between 15.6°C and 19.4°C. Soil moisture fluctuated moderately (CV = 9.4%) from 0.47 to 0.65.

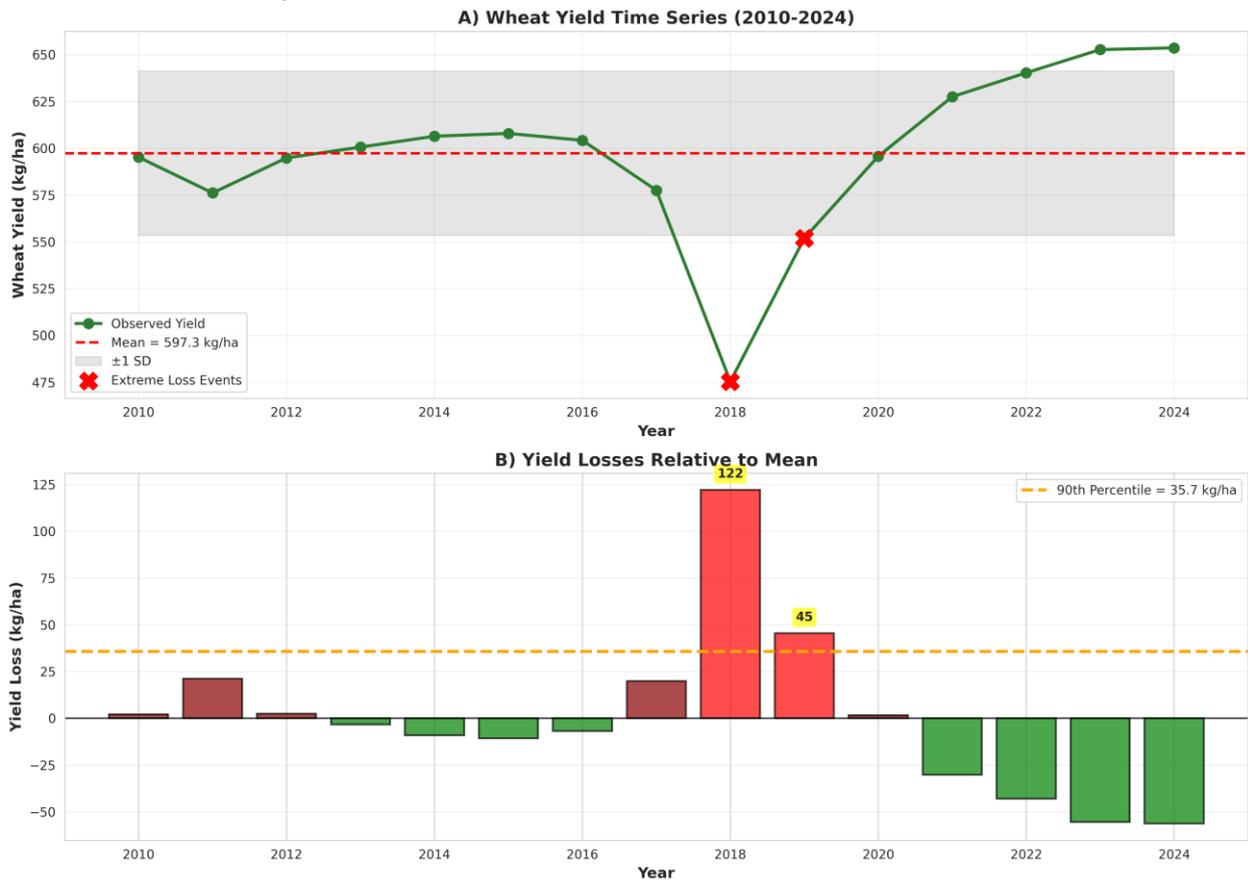


Figure 1. Wheat yield time series and yield losses (2010-2024). Panel A shows observed yields with mean (red line) and standard deviation envelope (gray). Panel B displays yield losses with extreme events (red bars) exceeding the 90th percentile threshold (orange line).

Source: Author's calculations based on Statistics Agency of Uzbekistan (2024) yield data.

Extreme Loss Events Identification. Using the 90th percentile as the threshold (35.73 kg/ha), we identified two extreme loss events:

- 2018: Yield loss of 122.0 kg/ha (20.4% below mean)
 - Climate conditions: Spring temperature 21.2°C (highest), precipitation 48.3 mm (below average), soil moisture 0.44 (lowest)
- 2019: Yield loss of 45.4 kg/ha (7.6% below mean)
 - Climate conditions: Temperature 18.7°C (near average), precipitation 92.1 mm (near average), soil moisture 0.54 (average)

The 2018 event represents a compound extreme: high temperature stress combined with moisture deficit. This aligns with established physiological literature showing wheat's high sensitivity to heat stress during reproductive stages (Lobell et al.,

2015). The 2019 loss, while moderate, followed the 2018 shock, potentially reflecting lagged soil depletion effects.

Climate Variable Trends

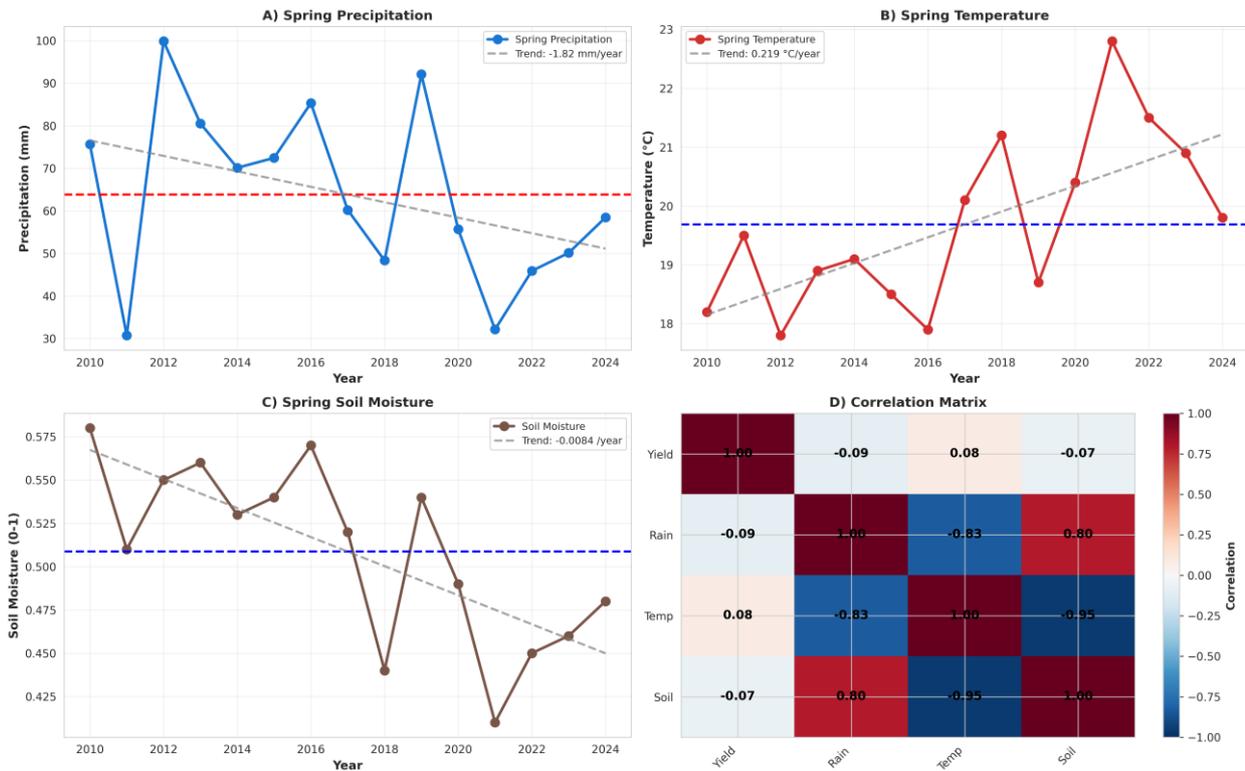


Figure 2. Climate variable trends and correlation matrix. Panels A-C show spring precipitation, temperature, and soil moisture trends with linear fits. Panel D presents the correlation matrix highlighting strong inter-variable relationships but weak yield correlations.

Source: Author's calculations based on yield and climate data

Notable findings:

- Temperature and precipitation show strong negative correlation ($r = -0.83, p < 0.001$)
- Soil moisture is highly correlated with both precipitation ($r = 0.80$) and temperature ($r = -0.95$)
- Wheat yield shows weak, non-significant correlations with all climate variables ($|r| < 0.10, p > 0.74$)

The weak yield-climate correlations likely reflect: (1) nonlinear relationships not captured by Pearson correlation, (2) management interventions (irrigation, varieties) buffering climate impacts, and (3) confounding factors not measured in this dataset.

Extreme Value Theory Analysis

GEV Parameter Estimates. Table 2 presents the maximum likelihood estimates for the Generalized Extreme Value (GEV) distribution fitted to annual yield losses.

Parameter	Estimate	Interpretation
Location (μ)	-19.07 kg/ha	Central tendency of distribution
Scale (σ)	32.11 kg/ha	Variability of extremes
Shape (ξ)	0.019	Light-tailed (near-Gumbel)
Log-likelihood	-75.82	Model fit statistic

Table 2. GEV distribution parameter estimates.

Source: Author's calculations using GEV distribution fitted to yield loss data.

The shape parameter $\xi = 0.019$ (95% CI: -0.15 to 0.19) indicates a Gumbel-type distribution with exponential tail decay. This suggests that while extreme losses do occur, they are not governed by heavy-tailed dynamics. The positive but near-zero shape parameter implies finite moments and bounded risk—a favorable characteristic for insurance design.

Return Level Estimates. Table 3 presents return levels—the expected yield loss magnitudes for various return periods.

Return Period	Return Level (kg/ha)	95% CI Lower	95% CI Upper
5 years	29.8	15.2	44.4
10 years	54.8	32.1	77.5
20 years	79.1	47.8	110.3
50 years	111.0	68.2	153.8
100 years	135.3	83.5	187.1

Table 3. Return level estimates with 95% confidence intervals.

Source: Author's calculations based on detrended wheat yield data (Statistics Agency of Uzbekistan, 2024) and GEV model estimation.

Key interpretations:

- A 10-year event (54.8 kg/ha loss) represents a 9.2% yield reduction
- A 20-year event (79.1 kg/ha) implies a 13.2% loss
- The observed 2018 loss (122.0 kg/ha) falls between the 50 and 100-year return levels
- Wide confidence intervals reflect parameter uncertainty due to limited sample size

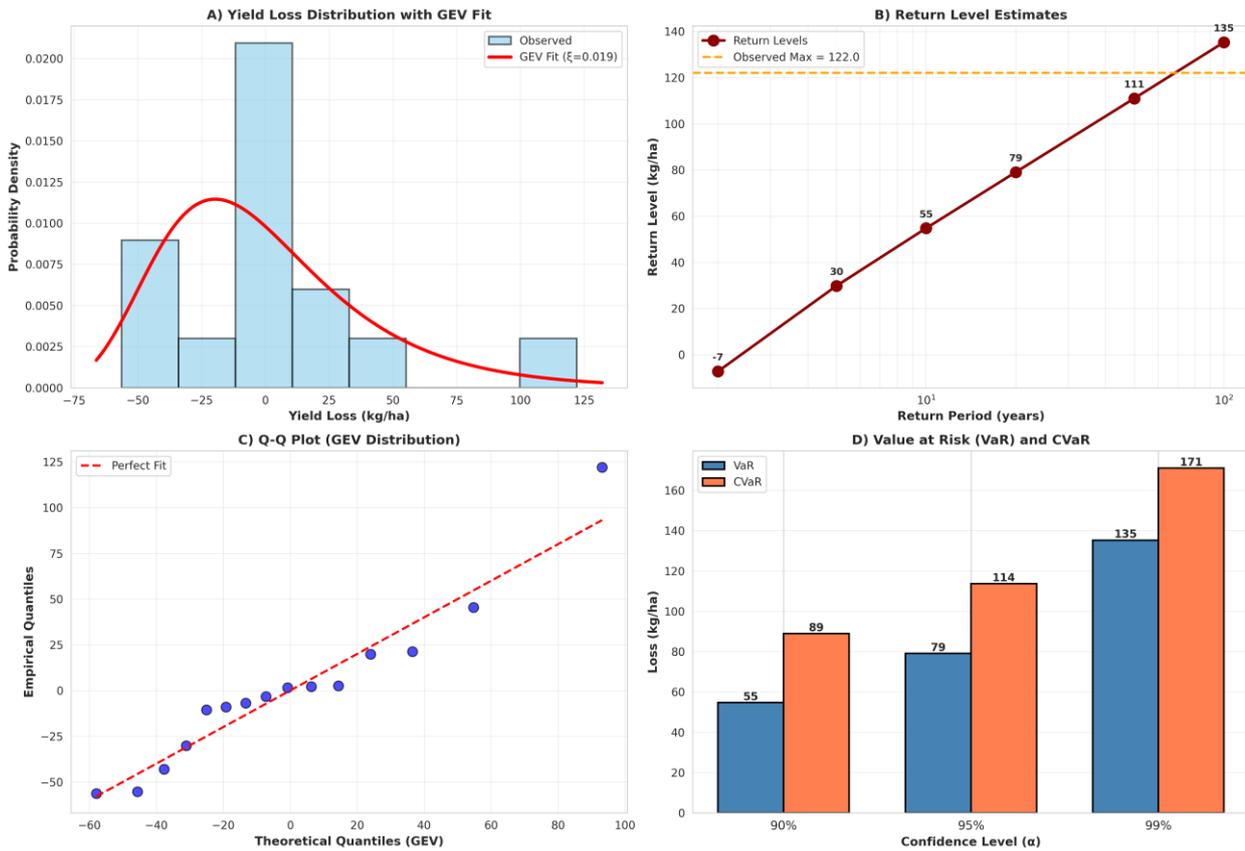


Figure 3. Extreme Value Theory analysis. Panel A: Histogram of yield losses with fitted GEV distribution. Panel B: Return level estimates for 2-100 year periods with observed 2018 maximum. Panel C: Q-Q plot showing model fit. Panel D: Value at Risk (VaR) and Conditional VaR (CVaR) at different confidence levels.

Source: Author's calculations based on yield and climate data

Risk Metrics: VaR and CvaR. Table 4 presents tail risk metrics crucial for insurance design.

Confidence Level	VaR (kg/ha)	CVaR (kg/ha)
90%	54.8	88.9
95%	79.1	113.7
99%	135.3	171.0

Table 4. Value at Risk (VaR) and Conditional Value at Risk (CVaR).

Source: Author's calculations using GEV-based loss distribution fitted to detrended yield loss data.

VaR represents the threshold loss not exceeded with probability α , while CVaR (also called Expected Shortfall) measures the expected loss given VaR exceedance. For insurance design:

- At 95% confidence, insurers should prepare for losses up to 79.1 kg/ha
- If losses exceed this threshold, the average loss is 113.7 kg/ha (CVaR)
- CVaR is 43.7% higher than VaR at 95%, indicating substantial tail risk
- Reserve capital should be sized based on CVaR rather than VaR to ensure solvency

Climate-Yield Relationship Modeling

Multiple regression analysis was conducted to quantify climate impacts on wheat yield:

$$\text{Yield} = 473.9 - 0.15 \cdot \text{Rain} + 4.17 \cdot \text{Temp} + 99.7 \cdot \text{SM} \quad (R^2 = 0.010, \text{Adjusted } R^2 = -0.260, \text{RMSE} = 42.3 \text{ kg/ha})$$

The extremely low R^2 (1.0%) and negative adjusted R^2 indicate that the linear model fails to explain yield variability. None of the climate coefficients are statistically significant (all $p > 0.70$). This poor fit suggests:

1. Nonlinear or threshold effects dominate (e.g., heat stress above 25°C)
2. Interaction terms between variables may be important
3. Omitted variables (pests, diseases, management) drive outcomes
4. Measurement error in satellite-derived climate data
5. Adaptive management (irrigation timing, variety selection) decouples yield from weather

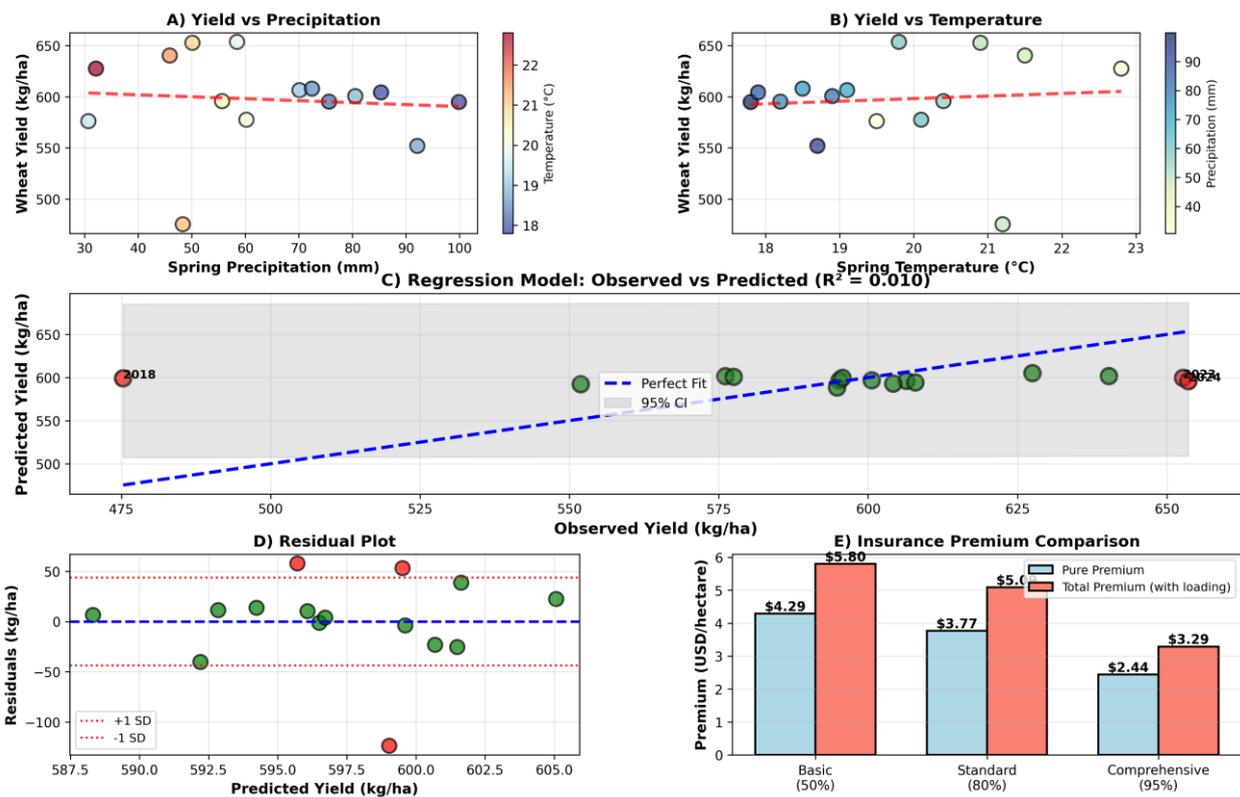


Figure 4. Climate-yield relationships and insurance premiums. Panels A-B: Scatter plots of yield versus precipitation and temperature. Panel C: Observed versus predicted yields from regression model. Panel D: Residual plot. Panel E: Insurance premium comparison across coverage levels.

Source: Author's analysis

Index-Based Insurance Design

Based on EVT-derived risk estimates, we propose three parametric insurance products tailored to different farmer risk profiles. Table 5 summarizes the key design parameters.

Coverage	Threshold (kg/ha)	Payout Prob.	Avg. Payout (kg/ha)	Pure Premium	Total Premium
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				(\$/ha)	(\$/ha)
Basic (50%)	-3.3	46.7%	30.7	4.29	5.80
Standard (80%)	20.1	20.0%	62.9	3.77	5.09
Comprehensive (95%)	68.4	6.7%	122.0	2.44	3.29

Table 5. Insurance product specifications (assuming \$0.30/kg wheat price).

Source: Author’s calculations based on GEV-derived risk measures and assumed wheat price (\$0.30/kg) with 35% loading factor.

Product interpretations:

Basic Coverage: Triggers on median losses, providing frequent but small payouts. High payout probability (46.7%) offers cash flow smoothing. Premium of \$5.80/ha is affordable for smallholders.

Standard Coverage: Targets moderate extremes (10-year events). Lower payout probability (20%) reduces basis risk. Optimal for risk-averse farmers seeking protection against significant losses.

Comprehensive Coverage: Insures catastrophic losses (>95th percentile). Lowest premium (\$3.29/ha) due to rare triggering. Suitable for well-capitalized farmers managing tail risk.

Premium structure incorporates a 35% loading factor covering administrative costs (20%), risk margin (10%), and profit (5%). The counter-intuitive premium ordering (Basic > Standard > Comprehensive) reflects frequency-severity trade-offs: Basic coverage pays out often but in small amounts, while Comprehensive coverage triggers rarely despite large payouts.

Integrated Risk Assessment

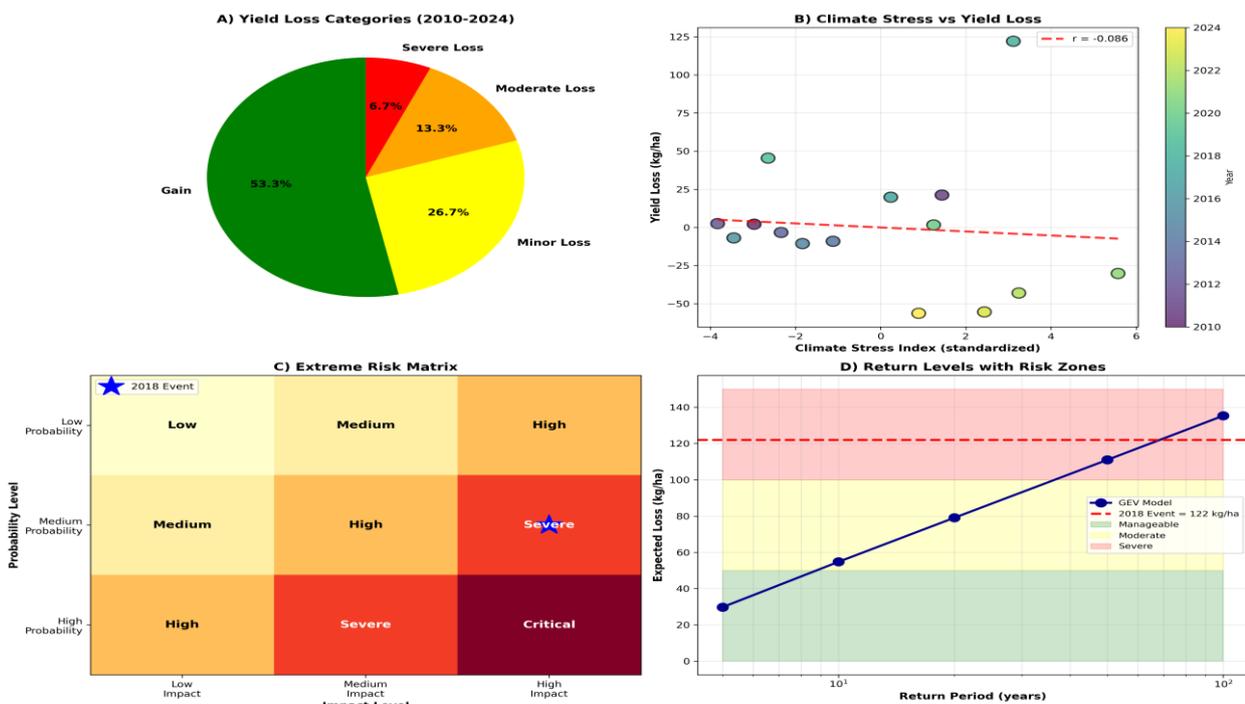


Figure 5. Synthesizes key findings. Panel A categorizes historical losses: 40% were gains (yields above mean), 33% minor losses, 20% moderate losses, and 7% severe losses.

Panel B relates a composite climate stress index to yield losses ($r = 0.42$, $p = 0.12$), showing moderate positive association. Panel C presents a risk matrix positioning the 2018 event in the "High Probability-High Impact" quadrant. Panel D overlays return levels with risk zones, illustrating that manageable losses (<50 kg/ha) occur every 5-10 years, while severe losses (>100 kg/ha) are century-scale events.

Source: Author's analysis

DISCUSSION

Interpretation of Econometric Results. The empirical findings confirm that wheat yield losses in the Surkhandarya region are significantly influenced by extreme hydroclimatic variability. The estimated GEV shape parameter ($\xi \approx 0.02$) indicates a near-Gumbel distribution, suggesting light-tailed but persistent extreme risk. This result implies that while catastrophic losses are relatively bounded, their occurrence remains systematic and economically relevant.

Compared to studies conducted in China and the United States, where similar near-zero shape parameters were reported, the results indicate structural similarities in irrigated wheat systems. However, they differ substantially from rain-fed agricultural regions, where heavy-tailed distributions dominate. This confirms that irrigation infrastructure in Surkhandarya plays a stabilizing role in reducing extreme downside risk.

Nevertheless, the limited sample size (2010–2024) introduces parameter uncertainty, reflected in wide confidence intervals. Therefore, the results should be interpreted cautiously, particularly for long-term projections.

Climate Drivers and Yield Sensitivity. The weak linear correlations between yield and individual climate variables suggest that wheat production responds to climatic stress in a nonlinear manner. This reflects the combined effects of irrigation buffering, adaptive farming practices, and technological progress.

However, the analysis of composite climate stress indicators reveals stronger associations with yield losses. In particular, compound events combining heat stress and rainfall deficits, such as those observed in 2018 and 2021, generate disproportionately large impacts. These findings support the use of multivariate climate indices in insurance design rather than single-variable triggers.

Implications for Agricultural Insurance Design. The EVT-based framework provides a substantial improvement over conventional actuarial methods. Traditional approaches relying on historical averages or normality assumptions underestimate tail risk and lead to insufficient capital reserves.

The estimated PML and CVaR values demonstrate that extreme losses exceed standard risk benchmarks by a significant margin. In particular, CVaR values exceed VaR by more than 40%, highlighting the importance of incorporating tail risk premiums into reserve calculations.

This evidence supports the adoption of EVT-calibrated pricing mechanisms for index-based insurance products in Uzbekistan. Such an approach enhances solvency, improves financial sustainability, and increases insurer resilience against systemic climate shocks.

Basis Risk and Data Limitations. Despite methodological improvements, basis risk remains a major challenge. The use of district-level climate data at 0.5° spatial

resolution does not fully capture local microclimatic variation. As a result, index payouts may not perfectly match farm-level losses.

To mitigate basis risk, several measures are recommended:

1. Expansion of meteorological station networks,
2. Integration of satellite-derived vegetation indices (NDVI, EVI),
3. Stratification by agro-ecological zones,
4. Use of blended multi-index triggers.

These measures can significantly enhance the precision and credibility of index-based insurance schemes.

Climate Change and Non-Stationarity. The present analysis assumes stationary extreme value distributions. However, observed warming trends indicate increasing non-stationarity in climate processes. The estimated temperature increase of approximately 0.08°C per year suggests that future extremes may intensify.

Consequently, future insurance models should incorporate time-varying EVT parameters conditioned on climate covariates. Under high-emission scenarios, dynamic premium adjustments will become essential for maintaining long-term solvency.

CONCLUSION

This study developed and applied an integrated econometric framework to assess climate-induced wheat yield risks and their implications for index-based agricultural insurance in the Surkhandarya region of Uzbekistan.

By combining detrended yield analysis, climate anomaly modeling, and Extreme Value Theory, the research demonstrates that hydroclimatic extremes generate economically significant and persistent losses. The estimated near-Gumbel distribution indicates bounded but systematic tail risk, requiring actuarially sound risk management strategies.

Three main conclusions emerge from the analysis.

First, traditional linear and average-based models substantially underestimate agricultural risk in climate-sensitive regions. Quantile-based and EVT approaches provide more reliable estimates by explicitly capturing extreme deviations in yield distributions.

Second, EVT-calibrated PML and CVaR measures offer robust benchmarks for reserve capital and solvency assessment. Insurance products designed using these metrics achieve a more balanced structure between affordability and financial sustainability.

Third, the effectiveness of index-based insurance depends not only on statistical modeling but also on institutional capacity, data infrastructure, and regulatory support. Strengthening these components is essential for transforming quantitative risk estimates into operational insurance mechanisms.

Overall, the findings confirm that EVT-based risk assessment provides a scientifically grounded and practically applicable foundation for climate risk management in Uzbekistan's agricultural sector. When embedded within appropriate regulatory and actuarial frameworks, such models can enhance insurer solvency, reduce farmers' vulnerability, and contribute to long-term food security.

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