
MACHINE LEARNING-DRIVEN PREMIUM ESTIMATION IN CROP INSURANCE: LEVERAGING CLIMATE AND COMMODITY MARKET BIG DATA

Marija Koprivica¹, Kristina Bradić², Mirjana Gligorijević³, Milica Kočović De Santo⁴

*Corresponding author E-mail: marija.koprivica@ekof.bg.ac.rs

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ABSTRACT

This study proposes a machine learning-driven framework for premium estimation in crop insurance against drought risk, integrating climatic and commodity market data. The methodology combines a Logistic Regression model for predicting drought probability with an Extreme Gradient Boosting model for forecasting commodity prices and crop yields, using regional datasets from Vojvodina and Šumadija. The results show strong predictive performance across regions and metrics. Findings confirm that drought occurrence, yield and price volatility are driven by climatic and spatial heterogeneity, underscoring the need for region-specific premium setting. The study demonstrates the potential of machine learning techniques to support more risk-sensitive and actuarially consistent pricing in agricultural insurance.

Introduction

Since the 1980s, the number of natural disasters with severe economic repercussions has tripled, while the expansion of settlements in risk-prone regions has magnified both the frequency and magnitude of losses associated with climate-induced events (Intergovernmental Panel on Climate Change, 2023). The resulting escalation

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- 1 Marija Koprivica, PhD, Full Professor, Faculty of Economics and Business, University of Belgrade, Kamenička 6, 11000 Beograd, Phone: +381641470084, E-mail: marija.koprivica@ekof.bg.ac.rs, ORCID ID (<https://orcid.org/0000-0003-4239-2252>)
 - 2 Kristina Bradić, MSc, Teaching Assistant, Faculty of Economics and Business, University of Belgrade, Kamenička 6, 11000 Beograd, Phone: +381691071999, E-mail: kristina.bradic@ekof.bg.ac.rs, ORCID ID (<https://orcid.org/0009-0008-9198-2770>)
 - 3 Mirjana Gligorijević, PhD, Full Professor, Faculty of Economics and Business, University of Belgrade, Kamenička 6, 11000 Beograd, Phone: +381658465005, E-mail: mirjana.gligorijevic@ekof.bg.ac.rs, ORCID ID (<https://orcid.org/0000-0002-1144-442X>)
 - 4 Milica Kočović De Santo, PhD, Senior Research Associate, Institute of Economic Sciences, Belgrade, Phone: +381603499333, E-mail: milica.kocovic@ien.bg.ac.rs, ORCID ID (<https://orcid.org/0000-0003-3304-7801>)

in exposure of assets and populations, compounded by the intensification of natural hazards, has placed agricultural landscapes under particular strain, notably through water deficits and the degradation of soil microbial biodiversity, ultimately threatening societal resilience and food availability (Botzen, 2016)"container-title": "Weather and Climate Extremes", "DOI": "10.1016/j.wace.2015.10.002", "ISSN": "2212-0947", "language": "en-US", "note": "publisher: Elsevier", "page": "70-79", "source": "www.sciencedirect.com", "title": "Trends in weather related disasters – Consequences for insurers and society", "volume": "11", "author": [{"family": "Botzen", "given": "W. J. Wouter"}], "issued": {"date-parts": ["2016", 3, 1]}}, "schema": "https://github.com/citation-style-language/schema/raw/master/csl-citation.json"}

An effective insurance system serves as a crucial risk-transfer and pooling mechanism, distributing losses across time and space and diversifying underwritten exposures across various sectors and hazard types. However, the growing severity and clustering of natural catastrophes increasingly undermine this stabilising function. Among climate-related risks, drought poses a particularly complex challenge for agricultural insurance due to its cumulative nature, spatial heterogeneity, and strong dependence on both climatic conditions and market dynamics. Drought-related losses are reflected not only through yield reductions but also through price fluctuations in commodity markets, which directly affect premium adequacy. This study aims to develop a region-specific, data-driven framework for drought insurance pricing in Serbia, thereby supporting premium accuracy and sustainability amid rising climate variability.

Contemporary frameworks, such as supply-side models (Aerts & Botzen, 2011; Brunette et al., 2015), demand-side models (Birghila et al., 2022; Islam et al., 2022) it is expected that climate change will alter future risks of natural disaster events considerably and, as a consequence...", "DOI": "10.1111/risa.13884", "language": "en", "source": "onlinelibrary.wiley.com", "title": "Risk-layering and optimal insurance uptake under ambiguity: With an application to farmers exposed to drought risk in Austria", "title-short": "Risk-layering and optimal insurance uptake under ambiguity", "URL": "https://onlinelibrary.wiley.com/doi/10.1111/risa.13884", "author": [{"family": "Birghila", "given": "Corina"}, {"family": "Pflug", "given": "Georg"}, {"family": "Hochrainer-Stigler", "given": "Stefan"}], "accessed": {"date-parts": ["2025", 10, 27]}}, {"id": "892", "uris": ["http://zotero.org/users/13081216/items/MKRRDSBU"], "itemData": {"id": "892", "type": "article-journal", "abstract": "This research attempted to develop a damage-based crop insurance model using satellite remote sensing imagery and field surveys of flash flood regions in Bangladesh. A normalized difference water index (NDWI, partial equilibrium model (Tesselaar et al., 2020) income inequalities imply that not all households can afford flood insurance. The uptake of flood insurance in voluntary markets may decline when flood risk increases as a result of climate change. This increase in flood risk may cause substantially higher risk-based insurance premiums, reduce the willingness to purchase flood insurance, and worsen problems with the unaffordability of coverage for low-income households. A socio-economic tipping-point can occur when the functioning of a formal flood insurance system is hampered

by diminishing demand for coverage. In this study, we examine whether such a tipping-point can occur in Europe for current flood insurance systems under different trends in future flood risk caused by climate and socio-economic change. This analysis gives insights into regional inequalities concerning the ability to continue to use flood insurance as an instrument to adapt to changing flood risk. For this study, we adapt the “Dynamic Integrated Flood and Insurance” (DIFI) and agent-based model (de Ruig et al., 2022; Dubbelboer et al., 2017) analyse insurance market responses to climate risk and policy uncertainty. However, their application has largely been confined to flood insurance. Existing research on crop drought insurance predominantly focuses on behavioural, policy, and conceptual aspects of insurance adoption, with limited emphasis on data-driven pricing. Studies such as Cabeza-Ramírez et al. (2024) explore farmers’ perception of climate change and drought insurance, emphasising the role of demand-side factors in determining insurance uptake. Similarly, Madaki et al. (2023) examine the key determinants of agricultural insurance adoption in Nigeria using a logit regression model. The literature also highlights the importance of marketing-related factors, such as product communication, distribution channels, and the adaptation of insurance products to farmers’ specific needs, for the broader acceptance of agricultural insurance schemes (Stojanović et al., 2012).

A more limited strand of the literature addresses drought risk from a pricing and actuarial perspective, often within the context of index-based and parametric insurance schemes. More broadly, climate change has important implications for the design and effectiveness of weather insurance contracts (Kapphan et al., 2012). Several studies focus on the selection and calibration of drought indicators for insurance design and risk assessment (e.g., Eze et al., 2020; Bucheli et al., 2021, Wu & Yang, 2024), highlighting the importance of spatial heterogeneity and index choice in effective risk transfer. Other contributions develop region-specific index-based insurance products and discuss implications for premium setting (Hohl et al., 2021, Barratt et al., 2025). In this context, Crane-Droesch (2019) argues that increasing climate variability requires more data-oriented approaches to regional risk assessment and insurance pricing. Koprivica et al. (2024) propose a premium-rating framework for index-based crop insurance covering both flood and drought risks, combining loss-cost and average-yield methods calibrated on Serbian crop data. Despite these contributions, machine learning-based frameworks that integrate climatic indicators and market variables for drought insurance pricing remain largely unexplored, particularly in Southeastern Europe.

This study addresses that gap by developing a machine learning-driven framework for premium estimation in crop drought insurance that integrates climatic and commodity market data. While much of the literature focuses on yield- or index-based insurance design, this study adopts a revenue-based pricing perspective that explicitly incorporates commodity price dynamics. Specifically, the research leverages high-resolution climate indicators, such as the aridity index and consecutive dry days, together with crop yield data, commodity market prices and exchange rate to quantify drought risk and enable actuarially consistent premium setting. By combining environmental and economic

datasets, the study addresses the challenge of accurately pricing climate-induced agricultural risks at a regional scale, with a focus on Serbia's main agricultural regions (Vojvodina and Šumadija). The proposed framework supports more risk-sensitive and adaptive premium setting, contributing to the robustness of agricultural insurance systems under evolving drought risk conditions.

Materials and methods

The methodological framework integrates climatic and economic datasets obtained from two data sources. Climatic data stem from the Digital Atlas of Serbia and include two drought-related indicators, the aridity index (AI) and consecutive dry days (CDD), covering the period 1950–2020 for Serbia's main agricultural regions, Vojvodina and Šumadija. The Statistical Office of the Republic of Serbia provides annual data on crop yields and market prices for wheat, soybeans and corn.

The CDD indicator quantifies the maximum number of consecutive days with precipitation below 1 mm, capturing short-term drought persistence. The forest aridity index (AI) is an aridity indicator originally developed for forest ecosystems. Following Führer et al. (2011), the index is calculated as:

$$AI = 100 \cdot \frac{T_{VII-VIII}}{(P_{V-VII} + P_{VII-VIII})}, \quad (1)$$

where $T_{VII-VIII}$ represents the mean temperature during the July-August period, while P_{V-VII} and $P_{VII-VIII}$ denote the accumulated precipitation from May to July and from July to August, respectively.

Climatic data from the Digital Atlas of Serbia were originally stored in NetCDF format. To facilitate subsequent analysis, these data were converted into a tabular structure comprising five attributes: *latitude*, *longitude*, *time*, *AI*, and *CDD*. The *time* variable was converted into an annual format. Climatic observations were then merged across indicators using common spatial and temporal coordinates (year, latitude, and longitude). Geographic coordinates were rounded to three decimal places to avoid potential floating-point inconsistencies.

To ensure spatial specificity and regional relevance, a regional filtering procedure was applied to climatic data. Grid points within the latitude range 44.7°–46.2° N and longitude range 18.8°–21.0° E were selected to represent the Vojvodina region. Similarly, grid points within 43.7°–44.6° N latitude and 19.5°–21.3° E longitude were used to delineate the Šumadija region.

For each region, observations were grouped by year to compute the annual mean aridity index, the mean number of consecutive dry days, and the standard deviation of consecutive dry days (σ_{CDD}). These summary indicators capture both the average intensity of drought conditions and their interannual variability within each region.

The proposed drought insurance pricing framework is grounded in fundamental actuarial principles of risk-based pricing, linking climatic variability to insurer expected financial exposure. In non-life insurance, the net premium is composed of two components: the expected loss $E(L)$ and a risk loading that accounts for uncertainty around expected outcomes. Following the standard-deviation principle of insurance premium calculation (Bühlmann, 1985), the risk loading is specified as proportional to the variability of drought conditions, measured by the standard deviation of consecutive dry days (). The resulting pricing specification is given by:

$$\text{Net premium} = E(L) + \lambda \times \sigma_{CDD}, \quad (2)$$

where $E(L)$ denotes the expected loss, λ is an exogenous risk-loading parameter reflecting the insurer's sensitivity to drought-related uncertainty, and σ_{CDD} measures the interannual variability of consecutive dry days.

The expected loss component $E(L)$ in (2) is derived through a two-stage statistical-actuarial procedure. In the first stage, the probability of drought occurrence is estimated. The second stage quantifies the financial severity of drought in terms of revenue losses, defined as the difference between expected and realised yields, valued at forecasted market prices and scaled by the insured land area. Thus, the expected loss is defined as:

$$E(L)_t = (Y_{exp} - Y_{drought})_t \times P(drought = 1)_t \times P_t \times A_t, \quad (3)$$

where Y_{exp} denotes the expected yield, $Y_{drought}$ denotes the yield under drought conditions, $P(drought=1)_t$ is the estimated probability of drought occurrence, P_t is the projected crop price, and A_t is the insured area.

Expected yields are generated using a separately developed Extreme Gradient Boosting (XGBoost) model for crop yield prediction (Chen & Guestrin, 2016; Radosavljević et al., 2025). The dataset is obtained from the Statistical Office of the Republic of Serbia, which reports crop yields measured in tons per hectare for the period from 1947 to 2025. The model incorporates the one-year lag of crop yields, the aridity index, cumulative dry days, and the variance of cumulative dry days as explanatory variables. The dataset is divided into training and testing samples using an 87-13% split. Yields under drought conditions are proxied by historical yield observations recorded during years identified as drought periods.

To quantify the probability of drought occurrence, this study employed a logistic regression model, a well-established statistical learning method widely used in hydrology, climatology, and environmental risk assessment. Logistic regression models the probability of a binary event. In our study, the probability of a drought is a function of a set of climatic explanatory variables. Specifically, the feature engineering provides the construction of the deviation of the annual aridity index from its long-term mean (defined as AI anomaly variable in logistic regression model), and the standard deviation of the consecutive dry days. Following a study on climate trend modelling (Vinnarasi et

al., 2023) the time-varying characteristics observed in the historical precipitation data questions the reliability of SPI and motivated the development of nonstationary SPI. To overcome some of the limitations in the existing nonstationary drought indices, a new framework for drought index is proposed, incorporating the temporal dynamics in the precipitation. The proposed drought index is developed by coupling the joint deficit index with the extended time sliding window-based nonstationary modeling (TSW-NSM, we include a trend variable and a quadratic trend to address potential nonlinear changes in drought probability over time. The trend variable is defined as the difference between the observation year and the first year in the sample.

Mathematically, the model expresses the conditional probability of drought occurrence as:

$$P(y_i = 1|X_i) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki})]} \quad (4)$$

where $P(y_i=1|X_i)$ denotes the probability of drought occurrence for observation i , x_{ji} are the climatic predictors, and $\beta_0, \beta_1, \dots, \beta_k$ are parameters estimated through maximum likelihood estimation (Hosmer et al., 2013). The coefficient β_j represents the change in the log-odds of drought occurrence associated with a one-unit increase in x_j , holding other predictors constant.

Drought conditions were defined using a composite drought indicator constructed as the sum of standardised anomalies of the forest aridity index and consecutive dry days ($DI = Z_{AI} + Z_{CDD}$). A drought year was identified when the drought indicator DI exceeded the 75th percentile of its historical distribution within the region. This approach ensures a stable classification of extreme climatic stress events while avoiding assumptions about the underlying distribution of the drought indicator.

In crop insurance, revenue-based policies indemnify income losses rather than physical losses alone, implying that commodity market prices are critical to both loss assessment and premium setting. The crop price, entering the expected loss component, is not treated as an exogenous variable but is endogenously forecasted using an Extreme Gradient Boosting (XGBoost) model. Gradient boosting approximates complex nonlinear functions by iteratively combining regression trees, thereby enabling the estimation of nonlinear and interaction effects without presupposing a specific functional form (Friedman, 2001). This flexibility is particularly advantageous for agricultural markets, where nonlinearities arise from supply constraints, weather shocks, and policy interventions.

The dataset on market prices is obtained from the Statistical Office of the Republic of Serbia and spans the period from 1994 to 2024. Given that agricultural commodity prices exhibit non-stationary and heteroskedastic dynamics, prices are modeled in logarithmic space in order to stabilise variance and reduce prediction error. Since commodity price formation is strongly influenced by macroeconomic and agro-climatic conditions, the XGBoost model incorporates the following explanatory variables: the Global Food Price Index, Agricultural Producer Price Index (specific to each crop), aridity index,

consecutive dry days (CDD), variance of CDD, and the mean annual EUR/RSD exchange rate. Additionally, feature engineering allows construction of lagged price variables, as predictors to ensure an ex-ante information set. The inclusion of autoregressive terms is well supported in the empirical literature on commodity markets, where prices exhibit strong serial dependence (Deaton & Laroque, 1992; Pindyck & Rotemberg, 1990). The dataset is divided into training and testing subsets, where the training sample covers the period from 1994 to 2018, while the testing sample includes the subsequent years.

Results

The logistic regression models were estimated separately for the Vojvodina and Šumadija regions. The estimated specification for Vojvodina is given by:

$$\text{logit}(p) = -3.44 + 0.566 \cdot AI_{anomaly} + 0.415 \cdot \sigma_{CDD} + 0.041 \cdot trend - 0.0006 \cdot trend^2$$

while the corresponding specification for the Šumadija region is:

$$\text{logit}(p) = 0.28 + 0.897 \cdot AI_{anomaly} - 0.028 \cdot \sigma_{CDD} - 0.162 \cdot trend - 0.0002 \cdot trend^2.$$

The logistic regression results indicate the model explains drought probability reasonably well in both regions. For Vojvodina, the model achieves a pseudo R^2 of 0.403 and is statistically significant according to the likelihood ratio test ($p < 0.001$), while for Šumadija, the model shows even stronger explanatory power with a pseudo R^2 of 0.564. The anomaly of the aridity index has a positive and highly significant coefficient. This result implies that years characterised by a higher aridity index relative to the long-term average are associated with a higher probability of drought. On the other hand, unlike the Šumadija model, in the Vojvodina model, the standard deviation of the consecutive dry days variable suggests that fluctuations in the dry days increase the probability of drought events. The time trend variables are insignificant in both models. (The detailed logistic regression results are provided in the Appendix).

Table 1. Logistic Regression Model Performance

Performance Metrics	Value
Accuracy	0.8667
Precision	0.7778
Recall	0.7778
F1-score	0.778
ROC-AUC	0.91

Source: Authors' calculations

Table 1 presents the performance results of the pooled sample model created using climate data from both the Šumadija and Vojvodina regions. The results imply that the logistic regression model demonstrates strong predictive performance in identifying drought events. The model achieves an accuracy of 0.87, meaning that approximately 87% of the observations in the test sample are correctly classified. Both precision and

recall equal 0.78. Additionally, the model strikes a good balance between correctly detecting drought events and avoiding misclassification with an F1-score of 0.78. Furthermore, the ROC–AUC value of 0.91 indicates that the model is highly effective at distinguishing drought from non-drought years.

In the second stage, XGBoost models were applied to forecast average annual yield and commodity prices for wheat, corn, and soybeans (tons/ha and RSD/kg respectively). Forecasting performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE), as shown in Table 2 and 3.

Table 2. XGBoost Log-Price Model Performance

Commodity	MAE	RMSE	SMAPE (%)
Wheat	0.197	0.232	6.41
Corn	0.196	0.257	6.47
Soybean	0.292	0.35	7.467

Note: MAE and RMSE are reported in logarithmic price units.

Source: Authors' calculations

Table 3. XGBoost Yield Model Performance

Commodity	MAE (t/ha)	RMSE (t/ha)	SMAPE (%)
Wheat	0.497	0.635	12.81
Corn	1.174	1.363	22.99
Soybean	0.57	0.691	23.23

Source: Authors' calculations

The XGBoost price model demonstrates strong predictive performance across all commodities, with SMAPE values below 8% for each crop. However, the yield prediction model shows higher forecasting errors. As agricultural yields are highly sensitive to climatic shocks and agronomic conditions, these SMAPE outcomes are expected and can be considered reasonable for the yield prediction model.

Together, the drought probability estimates derived from logistic regression and the projected commodity prices and yields generated through XGBoost constitute the key climatic and economic inputs required for region-specific, revenue-based crop insurance pricing.

Conclusions

This study demonstrates that the integration of temporal–spatial climatic data and machine learning techniques can significantly enhance net premium calculation for revenue-based crop insurance against drought risk. The main contribution of the research is threefold. First, the study provides a methodological contribution by combining logistic regression for probabilistic drought modelling with XGBoost algorithms for forecasting crop yields and commodity prices within an actuarial premium-calculation

framework. In the context of the Big Data revolution, this approach enables a dynamic, data-driven calculation of crop insurance premiums. By leveraging high-resolution indicators, such as the aridity index and consecutive dry days, the model captures the complex interactions between climate variability and drought risk, thus improving both predictive precision and regional specificity in premium determination.

Second, the research offers an empirical contribution by applying the proposed modelling framework to Serbia using long-term climatic and economic datasets. The results indicate that the selected climatic indicators provide a statistically coherent basis for estimating drought probabilities, while the machine learning models generate reliable forecasts of crop yields and market prices.

Third, the study provides a policy-relevant contribution by establishing a quantitative foundation for revenue-based crop insurance pricing in the Serbian agricultural sector. The proposed approach supports the development of more risk-sensitive and regionally differentiated insurance mechanisms that better reflect climatic exposure and market dynamics.

Although drought events are relatively infrequent in the analysed sample, the estimated logistic regression model demonstrates satisfactory predictive performance. Importantly, the primary objective of the logistic regression was not exact categorical classification, but the estimation of drought occurrence probabilities required for actuarial pricing, where probability calibration is more relevant than classification accuracy.

Empirical results show that the proposed model achieves high precision and recall in identifying drought events, consistent with the frequency and intensity patterns observed in the agricultural sector. Nevertheless, certain imbalances in class distribution, reflecting the rarity of extreme drought years, highlight the need for further methodological refinement. To address this issue, future research should incorporate class-imbalance mitigation techniques, such as Synthetic Minority Oversampling Technique (SMOTE) or One-Class Support Vector Machines (SVM).

Beyond technical improvements, actuarial modelling of agricultural insurance should also incorporate policy, behavioural, and marketing-related dimensions that influence farmers' insurance decisions. The effectiveness of insurance schemes depends not only on climatic risk assessment but also on farmers' risk perception, adoption behaviour, institutional settings, product communication, marketing strategies, and policy design. Incorporating these aspects would align agricultural insurance models more closely with real-world market dynamics and support the development of more effective and sustainable insurance solutions.

In this context, future research could benefit from integrating machine learning algorithms with system dynamics modelling. Such a hybrid modeling framework, implemented for example in VENSIM software, would enable the simulation of complex interactions among climatic, economic, and behavioural variables under alternative policy and climate scenarios.

In conclusion, this research contributes to the development of a resilient and data-driven crop insurance system for Serbia. By merging actuarial methods with machine learning, the proposed framework provides a foundation for evidence-based policy design, risk-informed pricing, and long-term sustainability in agricultural insurance markets.

Appendix

The following GitHub link provides the code for the models developed in this study, along with the corresponding results:

<https://github.com/bradickristina/ML-DRIVEN-CROP-INSURANCE.git>

Conflict of interests

The authors declare no conflict of interest.

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