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Stakeholder priorities in model selection for managing basis risk in soybean index insurance in Paraná Brazil

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Abstract

Crop production systems that rely solely on rain-fed water face high uncertainty from extreme weather shocks. While index insurance can transfer this risk to insurance markets, its design depends on yield models that minimise basis risk, a challenge inadequately addressed in key agricultural regions like South America. This study introduces a stakeholder-weighted framework for index insurance model evaluation that examines how alternative yield-modelling approaches perform when farmers and insurers attach different importance to negative basis risk (uncompensated losses) and positive basis risk (unnecessary payouts). Using municipal soybean yield and gridded weather-derived extreme climate indices data, we estimate panel fixed-effects, quantile, and weighted model aggregation specifications for early and late maturity windows. Their out-of-sample performance is evaluated by decomposing total basis risk into negative and positive basis components. We then apply a stakeholder-weighted loss function to examine how the preferred model changes with the relative weight assigned to these two components. Results show that no model is universally superior. Quantile models generally reduce negative basis risk and therefore offer greater protection against uncompensated losses, whereas panel fixed-effects models generally limit positive basis risk. Weighted model aggregation does not consistently outperform the individual models. Model selection depends on stakeholder priorities, agroclimatic clusters, and soybean maturity windows. These findings demonstrate that index insurance model selection is a policy-dependent decision rather than a purely predictive exercise. The framework provides a transparent basis for balancing farmer protection and insurer costs in climate risk transfer design.

Keywords: Index insurance; Basis risk decomposition; Soybean; Model selection; Policy-scenarios; Extreme weather

JEL Classification: Q19; Q54; C31; C33; C52; C53;G22

1. Introduction

In rainfed farming systems, index crop insurance has emerged as a scalable instrument for assessing and mitigating weather risk by tying payouts to objective, exogenous indices rather than farm-level loss adjustment (Belhsen et al., 2025). In addition, it has been championed as an emerging low-cost risk transfer tool alternative to traditional indemnity insurance, especially in data-scarce environments. Its promise is multifold. For example, it provides quick compensation to farmers and, when well-designed, stabilise income when adverse weather conditions strike (Nguyen et al., 2025). Yet when payouts diverge from realised losses (basis risk), its effectiveness erodes, undermining adoption and welfare gains (Wijesena & Pradhan, 2025). Contextualised index crop insurance designs are urgently needed in macro-critical agricultural regions like Brazil, where rising weather variability threatens key rainfed crops and coverage is limited (Souza et al., 2023). For example,

less than 10% of the total losses following the 2024 floods in the Rio Grande do Sul were insured (Musselwhite, 2024).

Over the past decade, methodological advances have expanded how we model the yield-weather relationship. Traditional regression and panel approaches remain common, while machine learning methods (neural networks, random forests) are increasingly used to capture complex nonlinearities (Schmidt et al., 2022). Meanwhile, hybrid or optimization-based designs aim to link these models directly into index contract design to reduce basis risk (Sun, 2022). The integration of satellite, remote sensing, and gridded climate products provides additional leverage when ground weather station networks are sparse: comprehensive reviews show growing use of NDVI, soil moisture, and hybrid indices in insurance design (Abdi et al., 2022; Nguyen et al., 2025). These approaches help alleviate basis risk where weather data are coarse or uneven (Eltazarov et al., 2023).

Despite advances in index insurance modelling, three related problems remain. First, empirical evidence from South America remains limited (Abdi et al., 2022; Vyas et al., 2021), even though soybean production in the region is highly exposed to weather variability and represents more than 50% of global supply (Colussi et al., 2025). Second, model comparison frequently emphasises predictive accuracy without assessing whether prediction errors generate uncompensated agricultural losses or unnecessary insurance payouts (Stigler & Lobell, 2024). These two basis risk components have different consequences: negative basis risk weakens farmer protection, whereas positive basis risk increases insurer costs (Palwishah et al., 2023). Third, the selection of an index model is often treated as a purely statistical problem, although the preferred model may depend on the relative policy importance assigned to these competing errors. Consequently, a model with the lowest conventional prediction error may not necessarily provide the most appropriate insurance design for a particular stakeholder objective.

To address these gaps, this study investigates how the selection of a soybean index insurance model changes across location, maturity windows and stakeholder priorities in Paraná, Brazil. We first identify relevant relationships between municipal soybean yields and a comprehensive set of gridded extreme climate indices. We then compare panel fixed-effects, quantile regression, Lasso quantile regression and weighted model aggregation using expanding window out-of-sample forecasts. For each model specification, basis risk profile is decomposed into false negative and false positive components. A stakeholder-weighted loss function is subsequently used to determine whether the preferred model changes when greater importance is assigned to protecting farmers against uncompensated losses or to limiting unnecessary insurer payouts. We answer the following questions:

1. Which extreme climate indices are associated with soybean yield loss across early and late maturity windows in Paraná?
2. How do alternative yield models compare in terms of out-of-sample negative and positive basis risks across agroclimatic clusters?

3. How does the preferred index model change when different relative importance is assigned to uncompensated losses and unnecessary payouts?

The study makes three contributions. First, it provides evidence on soybean index insurance design in Paraná, extending the empirical literature to an agriculturally important but comparatively underexamined South American setting. The analysis incorporates extreme climate indicators across different weather dimensions and distinguishes between early and late maturity windows. Second, it compares established yield-modelling approaches according to the insurance consequences of their out-of-sample prediction errors rather than relying exclusively on conventional measures of predictive accuracy. This reveals whether a model primarily reduces uncompensated losses or avoids unnecessary payouts. Third, the study introduces a transparent decision criterion that assigns different relative importance to negative and positive basis risks. The criterion is not intended to replace empirical evidence on stakeholder preferences or commercial contract evaluation. Instead, it shows how model selection changes under alternative policy priorities and identifies the trade-offs that decision makers would need to consider when designing an index insurance product.

The paper proceeds as follows. Section 2 reviews the literature concerning weather–yield modelling, index insurance, basis risk and stakeholder trade-offs in contract design. Section 3 describes the study area, data, modelling framework, out-of-sample evaluation and basis risk decision criterion. Section 4 reports the results of the weather–yield model specifications, basis risk evaluation and sensitivity analysis. Section 5 discusses the implications for soybean yield modelling, model selection, and index insurance design. Section 6 concludes by identifying the contribution, limitations, and priorities for further validation.

2. Literature review

2.1 Modelling weather and crop yields for index insurance design

Extreme weather conditions such as droughts (Kaur et al., 2021; Y. Li et al., 2019; Madadgar et al., 2017; Schmitt et al., 2022), rising temperatures (Hamed et al., 2021; H. Zhang et al., 2022), frost (W. Guo et al., 2024; Nuttall et al., 2019; Y. Zhao et al., 2024), rainfall deficit (Lauffenburger et al., 2023; Martinez-Feria & Basso, 2020; Zachariah et al., 2020), excessive rainfall (Iizumi et al., 2024; Kim et al., 2024; Y. Li et al., 2019), weakening solar radiation (L. Guo et al., 2024; Javed et al., 2024; Y.-C. Li et al., 2022), strong winds (Bhandari et al., 2023; Bundy et al., 2023; Hosseini et al., 2020), and low humidity (Ting et al., 2023; Xu et al., 2023) influence crop development and yields. However, their effects are not necessarily homogeneous across crops, locations, and growing periods. Weather conditions that are beneficial during one phenological stage may become damaging during another, while differences in soil, crop type, crop varieties, and cropping season can modify the observed yield response (P. Feng et al., 2018; Lesk et al., 2020; Schmitt et al.,

2022; Tappi et al., 2023; Zachariah et al., 2020). Given the uncertainty surrounding the impacts of extreme weather, two issues are fundamental. First, understanding the effects of extreme weather conditions on crop yields, and second, developing effective climate risk management solutions to improve farmers' resilience against weather shocks. Consequently, understanding how weather variability translates into yield outcomes remains a central challenge for agricultural risk assessment and index insurance design.

The relationship between crop yield and weather risk has been assessed through a variety of models reflecting varying degrees of complexity. First, statistical models are widely used because of their transparency and modest data requirements. Examples include classical regression (Satpathi et al., 2023; Thimmegowda et al., 2023), time-series (Ji et al., 2019; Matsui & Mochida, 2024; Sjulgård et al., 2023), panel (Zhai et al., 2022; H. Zhao et al., 2024), and Bayesian spatial (Ramsey, 2020; Roth et al., 2024). Second, machine learning models such as artificial neural networks (Satpathi et al., 2023; Thimmegowda et al., 2023), deep neural networks (Crane-Droesch, 2018), convolutional neural networks (Srivastava et al., 2022), boosted regression trees (Sidhu et al., 2023), least absolute shrinkage and selection operator (Lasso) regression (Heilemann et al., 2024), extreme gradient boosting (Roznik et al., 2023), random forest (Yu et al., 2023), and support vector regression (Bouras et al., 2021), can capture linear and non-linear complex relationships between crop yield and weather risk. Third, process-based crop models or crop simulation models simulate crop yields and growth by incorporating soil, phenological, physiological, and weather dynamics (Xiao et al., 2022). Typically, the Decision Support System for Agrotechnology Transfer (DSSAT), Agricultural Production Systems sIMulator (APSIM), WO^{RLD} FO^{OD} STudies (WOFOST), and Environmental Policy Integrated Climate (EPIC) are commonly used for crop yield simulation (Ajilogba & Walker, 2023; Choruma et al., 2019; Kulig et al., 2020; Vogel et al., 2020). Fourth, hybrid and ensemble models seek to integrate multiple approaches and capitalise on their strengths to improve crop yield prediction (Rajasivaranjan et al., 2022; Satpathi et al., 2023; Shahhosseini et al., 2021; Wallach et al., 2018).

No modelling approach is uniformly preferable for insurance design. Statistical models are relatively transparent and can be estimated using historical yield and weather observations, but their performance may be affected by assumptions regarding functional form, multicollinearity, omitted variables and limited extrapolation beyond the observed climate range (X. Feng et al., 2023). Machine learning models can represent complex relationships, but may require large training datasets and can overestimate model performance when temporal or spatial dependence is not handled appropriately (Filippi et al., 2025; Hu et al., 2024; Islam et al., 2023). Process-based models provide an agronomic representation of crop development but require detailed calibration data that may not be available at the spatial and temporal scale required for insurance implementation (Ammar & Davies, 2019; Kim et al., 2024; Zampieri et al., 2018). Hybrid and ensemble models are not exempt from the same challenges faced by other approaches (Cao et al., 2022;

N. Zhang et al., 2023).

For index insurance, model quality should not be assessed solely by predictive accuracy. Payouts are triggered from model-based representations of crop losses, meaning that model error can transform into differences between realised and insured losses. Different modelling approaches may therefore produce different insurance outcomes even when their predictive performance appears similar. Consequently, model selection should be evaluated using out-of-sample measures that reflect the insurance objectives of the contract rather than forecasting performance alone.

2.2 Weather indices and the sources of basis risk

Index crop insurance replaces individual loss assessment with a predetermined indicator that is expected to represent insured agricultural losses. Common indicators include cumulative rainfall, standardised precipitation index (SPI), standardised precipitation evapotranspiration index (SPEI), evaporative stress index (ESI), normalised difference vegetation index (NDVI), soil moisture index (SMI), Palmer drought severity index (PDSI), growing degree days (GDD), cooling degree days (CDD), heating degree days (HDD), and frost index (Bucheli et al., 2021; Cirone et al., 2024; Eze et al., 2020; Ghahari et al., 2019; Haro-Monteagudo et al., 2018; Kath et al., 2018; Murthy et al., 2024; Sun, 2022; Vroege et al., 2021; Williams & Travis, 2019; J. Zhang et al., 2017). Few specialised designs have incorporated wind thresholds, solar radiation, relative humidity and climate signals such as the El Niño–Southern Oscillation (Khalil et al., 2007; Pan et al., 2022; Perondi et al., 2023; Prokopchuk et al., 2020; Shi & Jiang, 2016; Tack & Ubilava, 2015; Tsiboe et al., 2023).

The suitability of an indicator depends on its relationship with the insured loss, its spatial and temporal resolution, the quality and continuity of the underlying data and its transparency to prospective users (Dalhaus & Finger, 2016; Tappi & Santeramo, 2022; Vroege et al., 2021). An index based on a single weather variable may be readily understood but may fail to capture losses generated by multiple or interacting weather conditions (Benso et al., 2023; Mazviona & Sølvsten, 2025). A more complex multivariate index may improve predictive performance but can become difficult to communicate, validate and administer. Index construction therefore involves a trade-off between predictive representation, operational simplicity and transparency (Dalhaus & Finger, 2016; Williams & Travis, 2019).

The major problem of index insurance is basis risk: the difference between the payout generated by the index and the actual insured loss (Bucheli et al., 2021). Basis risk can arise from several sources. Spatial or geographic basis risk occurs when the weather measurement or gridded observation does not represent conditions at the insured location (Leppert et al., 2021). Temporal basis risk arises when the measurement period is inconsistent with the timing of crop exposure (Dalhaus & Finger, 2016). Design basis risk describes an index’s failure to capture all necessary information required for crop yield

prediction or model misspecification (Dalhaus et al., 2018; Leppert et al., 2021).

The consequences of basis risk can be separated into two components. Negative basis risk occurs when the contract payment is below the payment implied by the realised loss (Palwishah et al., 2023). This is particularly consequential for farmers because the insurance provides insufficient compensation when protection is needed. Positive basis risk occurs when the contract payout exceeds the payment implied by the realised loss. Although such a payment may benefit the recipient in a particular period, it represents an additional cost to the insurer and may affect pricing and product sustainability. These components are sometimes described as false negative and false positive basis risk, respectively (Sun, 2022).

A single aggregate basis risk measure can conceal these asymmetrical outcomes. Two models may produce similar total discrepancies while distributing them differently between farmers and insurers. A model that substantially reduces payout shortfalls may appear equivalent to one that primarily reduces excess payments, even though the two models serve different decision objectives. Basis risk decomposition is therefore necessary for evaluating how model errors affect the parties to an insurance contract.

2.3 Evaluating index insurance performance

Index insurance studies evaluate contract performance using different approaches. Some assess the index’s ability to predict yields or losses using traditional statistical performance metrics such as root mean squared errors (RMSE), coefficient of determination, and correlation coefficients (He et al., 2022; Sun, 2022, 2025). Others use expected utility approaches to assess whether insurance improves farmer welfare under an assumed utility function and level of risk aversion (Biffis & Chavez, 2017; Chen et al., 2024; Conradt, Finger & Spörri, 2015; Dalhaus & Finger, 2016; Tan & Zhang, 2024; Zou et al., 2023). Common measures used include expected utility, certainty equivalent, income, and risk premium.

A third approach examines the contract’s ability to reduce income variability and mitigate downside risk. Metrics include variance (Zou et al., 2023), standard deviation (Chen et al., 2024), mean semi-deviation (Miquelluti et al., 2022), downside variance, downside loss or semi-variance (Conradt, Finger & Spörri, 2015; Eltzazarov et al., 2023; Kanchai et al., 2024; Vedenov & Barnett, 2004), tail risk or value at risk (VaR) (Chen et al., 2024), false negative and positive (Sun, 2022), expected shortfall, conditional value at risk or conditional tail expectation (Kath et al., 2018), spectral risk measure (Miquelluti et al., 2022), coefficient of variation, and lower partial moment (Tsiboe et al., 2023). These approaches answer different questions. Because the objective of index insurance is to align payouts with realised losses, basis risk measures provide a direct assessment of contract performance. Unlike prediction metrics, which evaluate forecasting accuracy, basis risk measures evaluate the extent to which model errors affect insurance payments and therefore provide a more relevant criterion for model selection in insurance applications.

2.4 Stakeholder priorities and model selection

Farmers, insurers and policymakers may evaluate basis risk outcomes differently. From the farmer’s perspective, a payout shortfall leaves part of an insured loss uncompensated and reduces the reliability of the contract as a financial protection mechanism. Repeated payout failures may also weaken confidence in index insurance and reduce willingness to participate. From the insurer’s perspective, excess payouts increase claims costs relative to represented losses and may need to be reflected in premiums, reserves or reinsurance arrangements. Policymakers may attach value to farmer protection while also considering affordability, continuity of provision and the use of public premium subsidies.

Previous studies have recognised that negative and positive basis risk create different consequences and that index design can depend on the objective being minimised (Janzen et al., 2021; Stigler & Lobell, 2024; Sun, 2022, 2025). When using expected utility models, farmers’ preferences are formalised through a utility function, while risk minimisation models select contract parameters according to a specified downside risk measure. These approaches are valuable when the necessary information on preferences, wealth, premiums and contract terms is available. In many empirical applications, however, stakeholder preferences are not directly observed.

A transparent alternative is to treat the relative importance assigned to the two basis risk components as a policy scenario. A stakeholder-weighted loss function can place weights on negative and positive basis risks to reflect different policy priorities. Although changing weights does not estimate the actual preferences of farmers or insurers, it reveals whether the preferred model is robust to alternative priorities and identifies the points at which the model selection decision changes. This distinction is important: the resulting weight is a decision parameter, not an empirically estimated behavioural coefficient.

2.5 Evidence from Brazil and research gap

South and Central America remain underrepresented in the index insurance literature relative to other regions. Vyas et al. (2021) identify limited evidence for major agricultural producers in South America, while Abdi et al. (2022) report that only 7% of the studies included in their review originated from South and Central America. This limitation is important because insurance indices calibrated in other climatic and institutional settings may not transfer directly to Brazilian production systems.

Existing Brazilian studies demonstrate both the relevance and feasibility of agricultural index insurance. Patt et al. (2009) used an experimental setting in Ceará to investigate understanding and decision making in an index insurance market. Alves et al. (2015) examined the potential role of weather insurance for Brazilian crops exposed to drought, flooding, heat and cold stress. Miquelluti et al. (2022) designed and evaluated a precipitation-based soybean insurance product for Paraná, while Lavorato & Braga (2023) examined index insurance performance for beans and maize in Brazil’s semiarid region

using gridded precipitation and temperature data.

This literature establishes the importance of the Brazilian setting but leaves three connected questions insufficiently resolved. First, limited evidence considers a broad range of extreme climate indicators across soybean maturity windows. Second, few comparisons determine whether alternative statistical models generate materially different negative and positive basis risk outcomes. Third, the preferred model is seldom examined across alternative relative weights assigned to farmer protection and insurer cost objectives.

The present study addresses these gaps by combining multiple dimensions of gridded extreme climate information with maturity-specific soybean yield models for Paraná. It compares four established modelling approaches according to their out-of-sample basis risk consequences across agroclimatic clusters. It then evaluates whether model selection changes when alternative relative policy costs are assigned to payout shortfalls and excess payouts. The intended contribution is to provide a more transparent assessment of how established models perform under different index insurance objectives.

3. Materials and methods

3.1 Analytical framework

Index insurance is designed to address covariate risks that affect multiple policyholders within a geographical area (Belova & Sannikova, 2019; Benami et al., 2021). The credibility of this instrument depends on how closely the index corresponds to the risk exposures of the target population, how the candidate yield model is selected, and the relative importance assigned to negative and positive basis risk. Figure 1 presents the analytical framework used in this study.

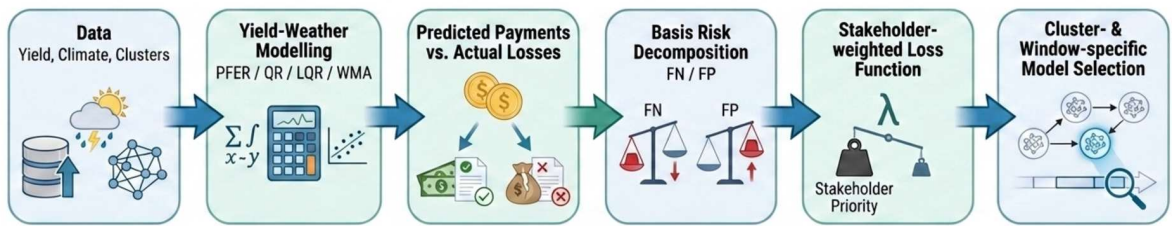


Figure 1: Analytical framework for stakeholder-sensitive model selection

Municipal yield observations and gridded extreme climate indices are first processed for two soybean maturity windows. Panel fixed-effects regression, quantile regression and Lasso quantile regression are then used to generate temporally ordered out-of-sample yield predictions, while weighted model aggregation combines the component model forecasts. The predicted yields are converted into index generated payments and compared with payments implied by observed yields. The resulting discrepancies are decomposed into negative and positive basis risk. Finally, a stakeholder-weighted loss function evaluates

how the preferred model changes across agroclimatic clusters, maturity windows and alternative relative policy weights. The framework evaluates the basis risk implications of alternative yield models. It does not estimate premiums, insurance demand, farmer welfare, income stabilisation or insurer solvency.

3.2 Study area

This study focuses on Brazil, the largest producer of soybeans, accounting for 40% of global production (Silva et al., 2025). Our study area is Paraná, which is marked by a purple colour as shown in Figure 2. Paraná State, which is divided into 399 municipalities, has an estimated area coverage of 199,315 km² and is located in the southern part of Brazil, lying between 22°–26° latitude south and 48°–54° longitude west. It is the second major contributor of soybean production, following Mato Grosso State. About 74% of the land in Paraná is used for agricultural activities (Dudas et al., 2023). This makes agriculture activities in Paraná of primary importance for economic growth of Brazil, creation of employment opportunities, and global food security (Kureski et al., 2022; Oliveira et al., 2023). Soybean production takes place mainly under rainfed conditions. In addition, climate variations in Paraná increase the uncertainty of sowing and harvesting times (Gasparin et al., 2024).

The Brazilian government developed a risk management tool, Zoneamento Agrícola de Risco Climático (ZARC), for the purpose of informing farmers on the optimal sowing dates. The ZARC is jointly managed by the Ministry of Agriculture, Livestock, and Supply (MAPA) and Empresa Brasileira de Pesquisa Agropecuária (EMBRAPA), a Brazilian Agricultural Research Corporation. The ZARC contributes to reducing crop production losses caused by extreme weather conditions such as droughts, frosts, and excessive rainfall. Compliance with the ZARC tool qualifies farmers to benefit from government subsidised loan arrangements such as the Programa de Garantia da Atividade Agropecuária (PROAGRO) and a rural insurance subsidised program, the Programa de Subvenção ao Prêmio do Seguro Rural (PSR). ZARC also promotes sustainability through efficient soil, water, and environmental management. As a standard, ZARC recommends a sowing window of October 10 – December 15 for soybean. Although ZARC specifies recommended sowing periods, changing temperature and precipitation conditions can affect the suitability of historically established production windows (Toffoli, 2022). These climatic and institutional characteristics make Paraná an appropriate setting for evaluating how alternative yield–weather models perform when used to inform soybean index insurance payments. The study evaluates candidate models and their basis risk implications rather than a fully priced commercial insurance product.

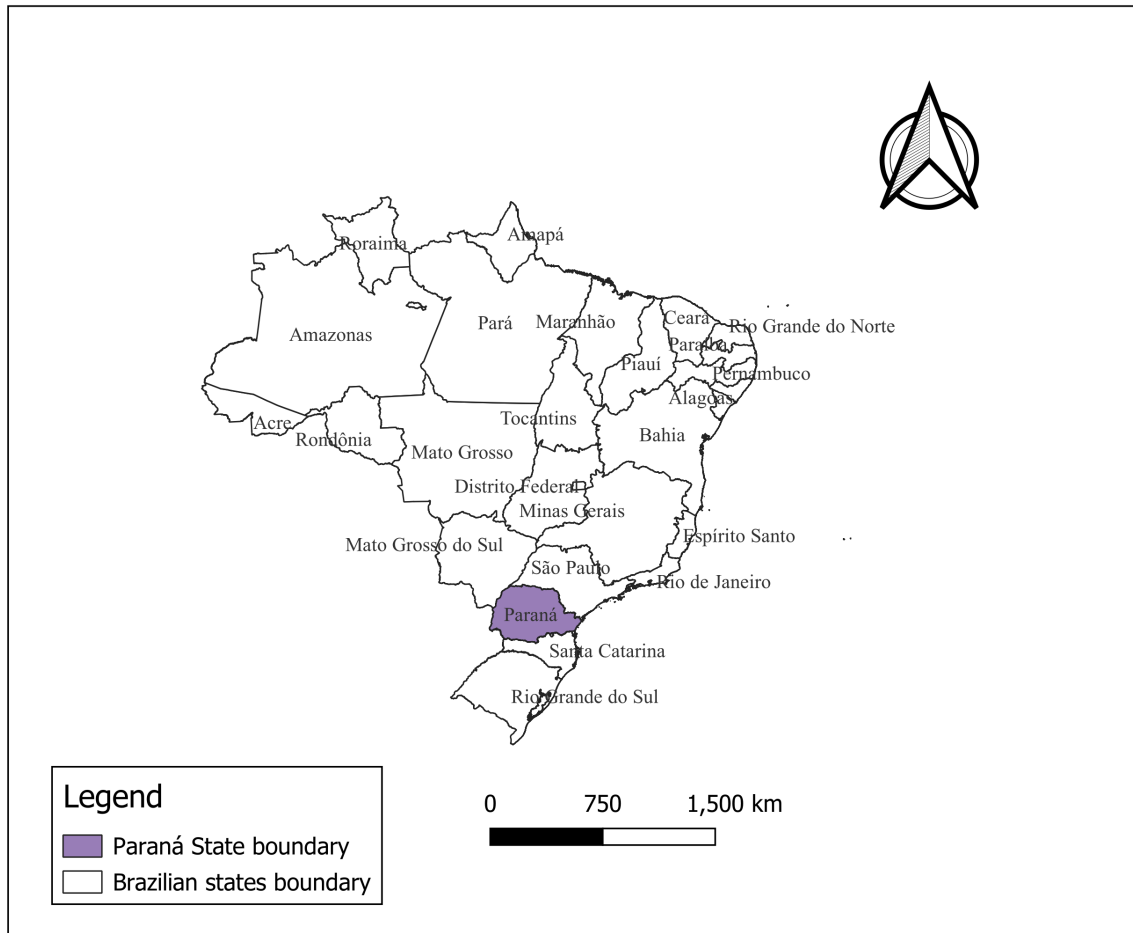


Figure 2: Map of Brazil showing state boundaries and highlighting Paraná as the study area.

3.3 Data

3.3.1 Yield data

Municipal soybean yield data for the 2008–2022 agricultural seasons were obtained from IRB(Re) for 399 municipalities in Paraná State. Because raw yields reflect both weather-driven variation and non-weather influences (improved crop varieties, farming practices, pest and weed control, and machinery advances), yields were detrended before modelling following Benso et al. (2023) and Bucheli et al. (2021) approach.

Detrending was implemented as a single robust trend model fitted at the state level across all municipality-year yield observations, rather than separately by municipality. Both linear and quadratic specifications of the year trend were estimated using robust regression (M-estimation via MASS package in R), to limit the influence of extreme yield years, and the preferred specification was selected by comparing Akaike Information Criterion (AIC) values between the two. Detrended yield was then obtained by an anchor-to-reference-year adjustment: each observation’s yield was shifted by the difference between the fitted trend value at a fixed reference year (2022) and the fitted trend value at that observation’s own year,

$$\text{yield}_{\text{detrended}} = \text{yield} + (\hat{y}_{2022} - \hat{y}_{\text{year}}) \quad (1)$$

where $\hat{y}_{\text{year}}$ is the fitted value of the selected trend model ($\hat{y}_i = \hat{\alpha} + \hat{\beta}\text{year}_i$) at the observation’s year and $\hat{y}_{2022}$ is the fitted value at the 2022 reference year. This re-expresses each observation as its yield would have been under the 2022 trend level, preserving each municipality-year’s deviation from the overall technological OR managerial trend while removing the state-level secular growth component. The resulting detrended series, common to both the early and late maturity datasets, forms the dependent variable, Y , in Equation 2.

3.3.2 Climate data and index construction

Climate data comprised monthly climate extreme indices constructed from daily gridded weather observations at $0.1^\circ \times 0.1^\circ$ spatial resolution, covering 1960–2024, and spanning minimum and maximum temperature, precipitation, solar radiation, evapotranspiration, relative humidity, and wind speed. From an initial pool of 48 monthly indices, variables were aggregated and screened in four stages to arrive at the pruned index set:

1. Seasonal aggregation. Monthly indices falling within the relevant agronomic window (October–December for the early maturity specification; October–January for late maturity) were averaged at the municipality level to produce a single seasonal value per index.
2. Variance and missingness screening. Seasonal indices exhibiting near-zero variance were dropped, as were indices with more than 20% missing values across the panel.

3. Redundancy screening. Pairwise correlations among the remaining indices were computed, and one variable from each pair correlated above $r = 0.7$ was removed following the threshold recommended by Dancey & Reidy (2007), reducing multicollinearity among candidate predictors.
4. Lasso-based selection. The surviving indices were entered into a Lasso regression of detrended yield on the full candidate set. Indices with non-zero coefficients were retained as the final selected variable set used in all subsequent yield–weather models.

This four stage procedure was applied separately for the early and late maturity windows.

3.3.3 Agroclimatic clusters

Geographic location data for all 399 municipalities, together with an associated agroclimatic cluster classification (five clusters), were supplied as part of the IRB(Re) dataset. Cluster membership is treated as an exogenous grouping variable in this study and is used to aggregate and compare basis risk outcomes spatially; no clustering algorithm was estimated as part of this analysis.

3.4 Yield–weather model specification

Following Bucheli et al. (2021), Sun (2025) and Tsiboe et al. (2023), the general crop yield–weather model is depicted as:

$$Y = h(Z) + \epsilon \quad (2)$$

where Y is detrended municipal soybean yield, Z is the vector of selected climate extreme indices from Section 3.3.2, and ϵ is an error term capturing omitted influences on yield.

The data are structured as an unbalanced municipality–year panel. Three yield–weather specifications are estimated on this panel, differing in how they use the panel structure and in how they weight prediction errors across the yield distribution:

1. Panel fixed-effects regression (PFER) exploits the panel structure directly, including a municipality fixed effect to absorb time-invariant heterogeneity such as soil type, topography (Eyre et al., 2021; Hamaker & Muthén, 2020). The PFER is modelled as:

$$Y_{it} = \mathbf{X}_{it}^\top \beta + \alpha_i + \epsilon_{it}, \quad \epsilon_{it} \sim \text{i.i.d.}(0, \sigma^2) \quad (3)$$

where Y_{it} is the crop yield for municipality i at time t . $\mathbf{X}_{it}^\top$ is the vector of variables for weather extremes observed for municipality i at time t . α_i is the unobserved

heterogeneity associated with municipality i . β are coefficients that measure the impact of $\mathbf{X}_{it}$ on Y_{it} . Equation 3 is estimated via the standard within transformation as follows:

$$\min_{\beta} \sum_{i=1}^N \sum_{t=1}^T [(Y_{it} - \bar{Y}_i) - (\mathbf{X}_{it} - \bar{\mathbf{X}}_i)^{\top} \beta]^2 \quad (4)$$

where $\bar{Y}_i = \frac{1}{T} \sum_{t=1}^T Y_{it}$ and $\bar{\mathbf{X}}_i = \frac{1}{T} \sum_{t=1}^T \mathbf{X}_{it}$.

2. Quantile regression (QR) and Lasso quantile regression (LQR) models are used to characterise how the yield–weather relationship varies across the conditional yield distribution, with particular attention to the lower tail (adverse seasons) relevant for insurance design (Conradt, Finger & Bokusheva, 2015; Sun, 2025). The QR specification is given by:

$$Q_{\tau}(Y_{it}) = \mathbf{X}_{it}^{\top} \beta(\tau) + \beta_{i0}, \quad \tau \in (0, 1) \quad (5)$$

where $Q_{\tau}(Y_{it})$ is the τ th quantile of Y_{it} that is modeled by variables for weather extremes $\mathbf{X}_{it}^{\top}$ observed for municipality i at time t . $\beta(\tau)$ is the quantile-specific coefficient vector and β_{i0} is an intercept term. The estimates for $\beta(\tau)$ are obtained by minimising the sum of weighted absolute deviations using a quantile loss function:

$$\min_{\beta(\tau), \beta_{i0}} \sum_{i=1}^N \sum_{t=1}^T \rho_{\tau}(Y_{it} - \beta_{i0} - \mathbf{X}_{it}^{\top} \beta(\tau)) \quad (6)$$

where the quantile loss or check function, $\rho_{\tau}(u_{it})$ is defined as:

$$\rho_{\tau}(u_{it}) = \begin{cases} \tau \cdot |u_{it}| & \text{if } u_{it} \geq 0 \quad (\text{underprediction}) \\ (1 - \tau) \cdot |u_{it}| & \text{if } u_{it} < 0 \quad (\text{overprediction}) \end{cases} \quad (7)$$

The prediction error or residual $u_{it} = Y_{it} - \hat{Y}_{it}$ is the difference between the observed and the predicted value. If the observed value is underpredicted, then u_{it} is penalised by τ ; otherwise, it is penalised by $1 - \tau$.

The LQR differs from the QR because it has an additional penalty term, $L_1 = \zeta \sum_{j=1}^p |\beta_j(\tau)|$ and hence the minimisation is as follows:

$$\min_{\beta(\tau), \beta_{i0}} \left\{ \sum_{i=1}^N \sum_{t=1}^T \rho_{\tau}(Y_{it} - \beta_{i0} - \mathbf{X}_{it}^{\top} \beta(\tau)) + \zeta \sum_{j=1}^p |\beta_j(\tau)| \right\} \quad (8)$$

where $\zeta > 0$ is a tuning parameter which controls the strength of the L_1 penalty (Liu et al., 2024). It is important for balancing model fit and complexity. A larger tuning parameter leads to simpler models by shrinking some coefficients to zero,

which prevents overfitting (L. Wang & He, 2024). The optimal tuning parameter is determined through cross-validation. j is the identifier for the penalised quantile coefficient. Because LQR is applied to the variable set already selected via the Lasso screening in Section 3.3.2, LQR’s own penalty functions as a second-stage shrinkage step rather than an independent variable selection exercise. Both QR and LQR use $\tau = 0.3$ as the baseline quantile, targeting the lower (adverse-yield) tail of the distribution. For sensitivity analysis, $\tau \in \{0.2, 0.4\}$ is examined in Section 4.4.

3. Weighted model aggregation (WMA) combines the three individual models’ predictions into a single ensemble forecast, with weights derived from each model’s relative out-of-sample accuracy (Section 3.6).

Together, this constitutes a two-stage modelling procedure: an initial Lasso-based variable selection stage common to all models, followed by model-specific estimation on the selected variable set.

3.5 Index insurance contract design

We design an index insurance product that pays out whenever the estimated crop yield derived from Equation 2 is below the pre-agreed yield threshold. The crop yield model utilises Brazilian extreme climate indices data. To formalise the payout, we let the compensation, R_{it} , made to farmers in municipality i at the end of the growing season in year t be defined by:

$$R_{it} = C \times \max(G_{it} - \hat{Y}_{it}, 0) = C \times (G_{it} - \hat{Y}_{it})^+ \quad (9)$$

where G_{it} the pre-defined yield threshold for municipality i , in year t . C is the market price of soybean in year t . The predicted crop yield is $\hat{Y}_{it}$ is determined from a crop yield-weather model, while the threshold G_{it} is specified in advance using equation 10 which takes into account the historical average crop yields $\bar{Y}_i$ and the level of coverage κ .

$$G_{it} = \bar{Y}_i \kappa \quad (10)$$

κ is valid for the interval $[0, 1]$. We set $\kappa = 1$ to reflect that a farmer has full coverage. Replacing $\hat{Y}_{it}$ in equation 9 with observed crop yield Y_{it} , we obtain an actual loss function:

$$A_{it} = C \times (G_{it} - Y_{it})^+ \quad (11)$$

The market price C is set to 1 throughout the analysis, so that payouts, losses, and the resulting basis risk measures (Section 3.6) are expressed in yield units rather than monetary terms. This isolates the contribution of model prediction error to basis risk from price-related variation and allows the framework to be applied independently of a specific market price series or pricing convention; a monetary translation can be obtained by multiplying the reported yield-unit basis risk measures by a chosen price series in

downstream applications. The difference between R_{it} and A_{it} is basis risk, which can be viewed as either a negative or positive basis risk (Palwishah et al., 2023). The extent to which basis risk can be reduced depends on the regression model used to derive $\hat{Y}_{it}$.

3.6 Out-of-sample evaluation design

Model performance is evaluated out-of-sample using an expanding window forecasting scheme, following H. Li et al. (2021) and Sun (2022). For each test year t from 2017 to 2022, all observations with year $\leq t - 1$ form the training set, and observations in year t form the test set; all models (PFER, QR, LQR) are re-estimated on the training set and used to predict yields in the held-out test year. This is repeated sequentially for each test year in 2017–2022, so that the training window expands by one year at each step while the model is always evaluated on data unseen during estimation. Predictions from all six test years are pooled into a single out-of-sample prediction set for each model, which forms the basis for the RMSE calculations and the basis risk decomposition.

Ensemble weights for WMA are derived from each model’s overall out-of-sample accuracy across the pooled expanding-window prediction set (2017–2022) rather than from a separate cross-validation procedure. For each model $m \in \{\text{PFER}, \text{QR}, \text{LQR}\}$, RMSE is computed over all pooled out-of-sample predictions:

$$\text{RMSE}^{(m)} = \sqrt{\frac{1}{\sum_{k=1}^K n_k} \sum_{k=1}^K \sum_{(i,t) \in \text{Test}_k} \left(Y_{it}^{(k)} - \hat{Y}_{it}^{(m,k)} \right)^2} \quad (12)$$

where n_k is the number of observations in fold k . The unnormalised weight for each model is given by:

$$w_m^* = \frac{1}{\text{RMSE}^{(m)}} \quad (13)$$

To normalise the weights for use in the ensemble prediction we compute:

$$w_m = \frac{w_m^*}{\sum_{m=1}^3 w_m^*} = \frac{1/\text{RMSE}^{(m)}}{\sum_{m=1}^3 \left(1/\text{RMSE}^{(m)} \right)} \quad (14)$$

The WMA values are predicted as:

$$\hat{Y}_{it}^{\text{WMA}} = w_{\text{PFER}} \hat{Y}_{it}^{(\text{PFER})} + w_{\text{QR}} \hat{Y}_{it}^{(\text{QR})} + w_{\text{LQR}} \hat{Y}_{it}^{(\text{LQR})} \quad (15)$$

3.7 Basis risk decomposition and stakeholder-weighted loss function

Following Sun (2025), we compute the total basis risk for i -th municipality relevant to model m as:

$$B_i^{(m)} = \sum_{t=1}^T \left| R_{it}^{(m)} - A_{it} \right| \quad (16)$$

where T depicts the total number of years.

The total basis risk is further split into false negative (FN) basis risk (uncompensated losses) which is assessed as:

$$B_i^{(m,FN)} = \sum_{t=1}^T (A_{it} - R_{it}^{(m)})^+ \quad (17)$$

and false positive (FP) (unnecessary payouts) basis risk calculated as:

$$B_i^{(m,FP)} = \sum_{t=1}^T (R_{it}^{(m)} - A_{it})^+ \quad (18)$$

To facilitate comparison across municipalities, we normalise each basis risk component by the mean yield as follows:

$$\tilde{B}_i^{(m)} = \frac{B_i^{(m)}}{\bar{Y}_i} \quad (19)$$

$$\tilde{B}_i^{(m,FN)} = \frac{B_i^{(m,FN)}}{\bar{Y}_i} \quad (20)$$

$$\tilde{B}_i^{(m,FP)} = \frac{B_i^{(m,FP)}}{\bar{Y}_i} \quad (21)$$

Given the geographical and agroclimatic differences within the state of Paraná, municipalities are organised into five clusters. Let $\mathcal{I}_c$ denote the set of municipalities in cluster c . We calculate the average normalised basis risk for each model m in cluster c :

$$\bar{B}_c^{(m)} = \frac{1}{|\mathcal{I}_c|} \sum_{i \in \mathcal{I}_c} \tilde{B}_i^{(m)} \quad (22)$$

$$\bar{B}_c^{(m,FN)} = \frac{1}{|\mathcal{I}_c|} \sum_{i \in \mathcal{I}_c} \tilde{B}_i^{(m,FN)} \quad (23)$$

$$\bar{B}_c^{(m,FP)} = \frac{1}{|\mathcal{I}_c|} \sum_{i \in \mathcal{I}_c} \tilde{B}_i^{(m,FP)} \quad (24)$$

where $|\mathcal{I}_c|$ is the cardinality of the set $\mathcal{I}_c$, representing the number of municipalities in cluster c . This aggregation enables cluster-level comparisons and supports spatially informed index crop insurance design and mitigation of basis risk (Rigo et al., 2022).

Finally, to account for varying risk priorities, we introduce a stakeholder-weighted loss function that allows decision makers to adjust the emphasis placed on uncompensated losses and unnecessary payouts. This provides them with control over the risk trade-off they care about. Let $\lambda \in [0, 1]$ be the policy weight placed on FN basis risk. The weighted

total basis risk for cluster c under model m is defined as:

$$\bar{B}_c^{(m,\text{total})} = \lambda \cdot \bar{B}_c^{(m,FN)} + (1 - \lambda) \cdot \bar{B}_c^{(m,FP)} \quad (25)$$

The weight λ is a scenario-based decision parameter rather than an empirically estimated stakeholder preference. A value of $\lambda = 1$ assigns all relative policy importance to negative basis risk, whereas $\lambda = 0$ assigns all importance to positive basis risk, with $\lambda = 0.5$ giving equal weight to both. The analysis evaluates model selection at three policy scenarios, $\lambda \in \{0, 0.5, 1\}$, corresponding to insurer-oriented, equally-weighted, and farmer-oriented policy scenarios, allowing the preferred model to be compared across these priorities for each cluster and maturity window.

The scenarios reflect the different consequences of the two basis risk components. Farmers may place greater emphasis on protecting themselves from financial losses due to unpredictable events such as crop failure or adverse weather (Fu et al., 2018). They may prioritise receiving payouts in the event of losses, and this preference strongly influences their decisions to purchase insurance or participate in risk-mitigation contracts (Carter et al., 2017). On the other hand, insurers may be concerned about designing a product that avoids making unnecessary payments when no losses occur because it increases claim costs. For each policy scenario, the preferred model m_c^* for cluster c is selected as the one that minimises this weighted total basis risk:

$$m_c^* = \arg \min_m \bar{B}_c^{(m,\text{total})} \quad (26)$$

Equations 25 and 26 provide a transparent mechanism for identifying the model that minimises stakeholder-weighted basis risk under each of the three policy scenarios and clusters.

4. Results

4.1 Climate indices and yield relationship

Table 1 presents the pruned subset of climate indices and their estimated effects on detrended soybean yields for each window. The coefficients reported in Table 1 correspond to an ordinary least squares refit of detrended yield on this Lasso-selected variable set, rather than the (shrunk) Lasso coefficients themselves. It uses a standard "Lasso then OLS" post-selection approach that improves interpretability of coefficient magnitudes while retaining Lasso's role in variable screening.

The highly significant F-tests results indicate that the selected climate features help to economically explain the production outcomes in Paran, while still leaving room for idiosyncratic and management-related factors. Among the extreme characteristics of the climate, the intensity and persistence of heat are strongly and consistently suppressing the

yield. Specifically, the number of days exceeding 35°C (tx35) and heat-wave days (wsdi) are strongly associated with reduced yields, with more pronounced effects in the Late Maturity window (tx35: -0.1473 Late versus (vs). -0.0383 Early; wsdi: -0.0634 Late vs. -0.0209 Early). Additionally, the frequency of very hot days (Tmax_above_p90) negatively impacts yields (-0.0060 Early), while cooler than average daytime conditions Tmax_below_p10 are conducive to yield gains in both windows.

Nighttime temperatures and diurnal thermal range also influence yields. Warm nights (Tmin_above_p90) show slight positive effects across both windows, while very cold nights (Tmin_below_p10) are positively associated with yields—likely reflecting clear-sky conditions early in the season. The lowest monthly minimum temperature (tnn) exhibits asymmetric effects: negative in Early and positive in Late. A larger mean diurnal temperature range (drt) is beneficial in both windows, consistent with clearer skies and higher solar radiation.

Indicators of evaporative demand suggest that low-energy conditions strain yields. Early and Late agronomic windows dominated by days with low reference evapotranspiration (ETo_below_p10) show substantial negative effects, reinforcing the notion that stagnant, cloudy conditions suppress crop productivity.

Relative humidity extremes pose risks at both ends, with very high humidity (RH_above_p90) and very low humidity (RH_below_p10) linked to lower yields. Additionally, frequent days with relative humidity above 70% (u70) impose further penalties in the Early window. Interestingly, the single highest humidity day (max_rh) is positively associated with yields, suggesting that persistent high humidity rather than isolated spikes is the damaging condition.

Solar radiation scarcity is another critical factor. The lowest monthly solar radiation (min_radiation) carries large negative coefficients in both windows, whereas maximum radiation levels are not significant. This highlights that prolonged periods of low light drive yield losses.

Regarding rainfall dynamics, a dual effect is reflected. Longer dry spells (Consecutive Dry Days, CDD) are consistently harmful (Early: -0.0505 ; Late: -0.0563), while more Consecutive Wet Days (cww) contribute positively to yield outcomes (Early: 0.0378 ; Late: 0.0365), suggesting that well-distributed rainfall supports crop development. Heavy rainfall events (≥ 50 mm; precip_days_50) reduce yields, whereas other events (≥ 80 mm; precip_days_80) support positive yields (Early: 0.1124 , not robust in Late). Wet-day frequency at 10 mm (precip_days_10) is helpful where included (Early), while mean event intensity (sdii) is mildly harmful in Early and negligible in Late. Extremely heavy rainfall (≥ 100 mm; precip_days_100) are insignificant.

Wind extremes also contribute to yield losses. Very windy days (u2_above_p90) are detrimental across both windows, while calm wind conditions (u2_below_p10) are not significant. A higher minimum wind speed (min_wind) shows a positive association in the Early window, possibly reflecting favorable microclimatic conditions, although this

benefit fades in the Late window.

Table 1: Climate indices drivers of soybean yield

Variable	Early Maturity ¹		Late Maturity ²	
	Coefficient	SE	Coefficient	SE
ETo_below_p10	-0.0997***	0.0037	-0.1101***	0.0043
RH_above_p90	-0.0144***	0.0020	-0.0233***	0.0019
RH_below_p10	-0.0153***	0.0008	-0.0156***	0.0009
Tmax_above_p90	-0.0060***	0.0011		
Tmax_below_p10	0.0697***	0.0048	0.0613***	0.0062
Tmin_above_p90	0.0172***	0.0009	0.0102***	0.0007
Tmin_below_p10	0.0481***	0.0083	0.0878***	0.0106
cwd	0.0378***	0.0052	0.0365***	0.0042
drt	0.1548***	0.0123	0.1285***	0.0115
max_radiation	-0.0095	0.0061	0.0034	0.0060
max_rh	0.0287***	0.0038	0.0241***	0.0042
min_radiation	-0.1207***	0.0043	-0.1318***	0.0043
min_wind	0.1505***	0.0405	0.0617	0.0425
pr	-0.0505***	0.0038	-0.0563***	0.0042
precip_days_100			0.0638	0.1006
precip_days_10	0.0195***	0.0059		
precip_days_50	-0.0869***	0.0192	-0.0646**	0.0214
precip_days_80	0.1124*	0.0454	0.0275	0.0589
sdii	-0.0070*	0.0032	0.0030	0.0029
tnn	-0.0261***	0.0041	0.0330***	0.0041
tx35	-0.0383***	0.0079	-0.1473***	0.0088
u2_above_p90	-0.0020**	0.0007	-0.0029***	0.0008
u2_below_p10	0.0019	0.0018	0.0029	0.0016
u70	-0.0125***	0.0017		
wsdi	-0.0209***	0.0046	-0.0634***	0.0044
R^2	0.3306		0.3583	
F -statistic	201.9***		249***	

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

¹ Soybean season from October to December.

² Soybean season from October to January.

4.2 Model selection and basis risk results: Early maturity

Table 2 reports, for each cluster and each of the three policy scenarios: the insurer-oriented ($\lambda = 0$), equally-weighted ($\lambda = 0.5$), and farmer-oriented ($\lambda = 1$). We evaluate model performance using the weighted basis risk metric $\bar{B}_c^{(m, \text{total})}$, negative basis risk $B_c^{(m, \text{FN})}$, and positive basis risk $B_c^{(m, \text{FP})}$.

For an insurer-oriented scenario, the results show that in all clusters, the PFER minimises weighted basis risk. Positive basis risk is low and tightly bounded: Cluster 3 is the standout at 0.0087, with the other clusters ranging 0.0205–0.0315. This scenario

delivers the smallest false payout footprint but leaves sizeable uncompensated losses in several clusters, for example, negative basis risk of 0.0939 and 0.0863 in clusters 0 and 1, respectively. This foreshadows a demand challenge for farmer protection.

PFER remains the preferred model in all clusters under equally-weighted scenario. The lowest weighted basis risk is observed in Cluster 2 (0.0195), followed by Cluster 4 (0.0254), indicating zones where a balanced-inclined product can be both simple and effective. Clusters 0–1 are in the 0.053–0.060 range, and Cluster 3 is highest at 0.0686, reflecting its combination of very low positive basis risk but elevated negative basis risk.

When the policy scenario is farmer-oriented, the objective will be to minimise negative basis risk. In that regard, quantile-based models dominate: QR at $\tau = 0.3$ is the preferred model in Clusters 0–3, and LQR at $\tau = 0.3$ is selected for Cluster 4. Relative to PFER, these choices cut negative basis risk by approximately 13% (Cluster 0: from 0.0939 to 0.0821), 15% (Cluster 1: from 0.0863 to 0.0731), 47% (Cluster 2: from 0.0075 to 0.0040), 19% (Cluster 3: from 0.1290 to 0.1040), and 21% (Cluster 4: from 0.0221 to 0.0175). The trade-off is a marked increase in positive basis risk: for instance, Cluster 3’s positive basis risk rises from 0.0087 (PFER) to 0.0559 (QR), and Cluster 2’s from 0.0315 (PFER) to 0.0885 (QR). These patterns reveal that a farmer-oriented index insurance product reduces missed-loss events.

Cluster 2 is consistently low risk, whichever priority is chosen (0.0195 at $\lambda = 0.5$; 0.0040 FN at $\lambda = 1$), suggesting better tracking of yield losses from climate extremes and high readiness for a streamlined index crop insurance. By contrast, Cluster 3 is excellent at avoiding unnecessary payouts (positive basis risk = 0.0087 when priorities are insurer-inclined), but misses the most real losses (negative basis risk = 0.129 with PFER). To better protect farmers in this cluster, tail-sensitive models (QR and LQR) are needed to reduce uncompensated losses.

4.3 Model selection and basis risk results: Late maturity

Late maturity basis risk performance (Table 3) shows clear model preferences that depend on the policy weight (λ) placed on uncompensated losses. With an equally-weighted policy scenario, the PFER minimises weighted basis risk in all five clusters: cluster-level weighted basis risk ranges from 0.0161 in Cluster 2 (best) to 0.0631 in Cluster 3 (worst), indicating substantial spatial heterogeneity that may warrant a cluster-centred index product.

When the objective is to curb unnecessary payouts (insurer-oriented policy scenario, $\lambda = 0$), PFER again dominates, yielding the lowest positive basis risk in Cluster 3 (0.0085) and the highest in Cluster 4 (0.0275). These results indicate that the PFER excels at avoiding overpaying farmers but increases farmers’ protection gap because of negative basis risk.

Shifting scenario to the farmer ($\lambda = 1$), changes the preferred model selection: QR at $\tau = 0.3$ becomes the choice in Clusters 0–3, cutting negative basis risk relative to PFER by 18.7% (Cluster 0: from 0.0873 to 0.0710), 24.5% (Cluster 1: from 0.0804 to

Table 2: Preferred models under three policy scenarios: Early maturity

Cluster	Model	$\bar{B}_c^{(m)}$	$\bar{B}_c^{(m, FN)}$	$\bar{B}_c^{(m, FP)}$	$\bar{B}_c^{(m, total)}$	λ
0	PFER	0.1200	0.0939	0.0257	0.0257	0
1	PFER	0.1070	0.0863	0.0205	0.0205	0
2	PFER	0.0390	0.0075	0.0315	0.0315	0
3	PFER	0.1370	0.1290	0.0087	0.0087	0
4	PFER	0.0508	0.0221	0.0287	0.0287	0
0	PFER	0.1200	0.0939	0.0257	0.0598	0.5
1	PFER	0.1070	0.0863	0.0205	0.0534	0.5
2	PFER	0.0390	0.0075	0.0315	0.0195	0.5
3	PFER	0.1370	0.1290	0.0087	0.0686	0.5
4	PFER	0.0508	0.0221	0.0287	0.0254	0.5
0	QR ³	0.1320	0.0821	0.0501	0.0821	1
1	QR	0.1320	0.0731	0.0593	0.0731	1
2	QR	0.0925	0.0040	0.0885	0.0040	1
3	QR	0.1600	0.1040	0.0559	0.1040	1
4	LQR ⁴	0.0640	0.0175	0.0465	0.0175	1

^{3,4} QR and LQR results are based on $\tau = 0.3$.

0.0607), 42.0% (Cluster 2: from 0.0069 to 0.0040), and 26.6% (Cluster 3: from 0.1180 to 0.0866). In Cluster 4, LQR is preferred, trimming negative basis risk from 0.0192 to 0.0177 (−7.8%). This negative basis risk reduction comes with higher positive basis risk exposure. For example, positive basis risk rises by approximately 0.03 to 0.053 in Clusters 0–3 (QR vs. PFER) and by 0.0097 in Cluster 4 (LQR vs. PFER), a trade-off consistent with the λ weighted objective.

4.4 Sensitivity analysis

We stress tested the baseline model rankings from Table 2 (Early maturity) and Table 3 (Late maturity) which use QR and LQR at $\tau = 0.3$ against alternative quantiles $\tau \in \{0.2, 0.4\}$. Across scenarios (tables 4–7) we report changes in model selection by cluster and stakeholder priority, together with movements in negative and positive basis risk.

4.4.1 Early maturity window

For the insurer and equally-weighted scenarios, the PFER model that minimises weighted basis risk in the base case is selected in all clusters (Table 4) at $\tau = 0.2$. At $\tau = 0.4$, a light improvement from ensembling appears: WMA displaces PFER in cluster 0 and 4. The positive basis risk for clusters 0–3 remains stable and for Cluster 4, it drops from 0.0287 to 0.0281. Although these changes are small, they indicate that modest aggregation across (PFER, QR, and LQR) can reduce positive basis risk without materially increasing negative basis risk in select clusters.

A policy scenario that prioritises farmer protection ($\lambda = 1$) and by lowering quantile

Table 3: Preferred models under three policy scenarios: Late maturity

Cluster	Model	$\bar{B}_c^{(m)}$	$\bar{B}_c^{(m,FN)}$	$\bar{B}_c^{(m,FP)}$	$\bar{B}_c^{(m,total)}$	λ
0	PFER	0.1130	0.0873	0.0252	0.0252	0
1	PFER	0.1000	0.0804	0.0199	0.0199	0
2	PFER	0.0323	0.0069	0.0254	0.0254	0
3	PFER	0.1260	0.1180	0.0085	0.0085	0
4	PFER	0.0467	0.0192	0.0275	0.0275	0
0	PFER	0.1130	0.0873	0.0252	0.0563	0.5
1	PFER	0.1000	0.0804	0.0199	0.0502	0.5
2	PFER	0.0323	0.0069	0.0254	0.0161	0.5
3	PFER	0.1260	0.1180	0.0085	0.0631	0.5
4	PFER	0.0467	0.0192	0.0275	0.0233	0.5
0	QR ⁵	0.1260	0.0710	0.0551	0.0710	1
1	QR	0.1310	0.0607	0.0703	0.0607	1
2	QR	0.0746	0.0040	0.0707	0.0040	1
3	QR	0.1480	0.0866	0.0615	0.0866	1
4	LQR ⁶	0.0550	0.0177	0.0372	0.0177	1

^{5,6} QR and LQR results are based on $\tau = 0.3$.

from $\tau = 0.3$ base (Table 2) to $\tau = 0.2$ (Table 4) shifts the model selection toward LQR in several clusters. The LQR model choice leads to a reduction in negative basis risk but this comes at a higher cost of an increased positive basis risk. For example, Cluster 2 negative basis risk falls from 0.0040 to 0.0028 while positive basis risk rises from 0.0885 to 0.1250. Similarly, in clusters 3 and 4 negative basis risk by approximately 14.2%-34.8% and positive basis risk by 45.8%-60.4%. Conversely, raising the quantile to $\tau = 0.4$ (Table 5) pulls the solution back toward QR in all clusters, generally increasing negative basis risk relative to the base while lowering positive basis risk. In practical terms, $\tau = 0.2$ offers stronger protection for farmers by reducing events with payout shortfalls, but requires accepting more unnecessary payouts; $\tau = 0.4$ does the opposite.

4.4.2 Late maturity window

The base-case dominance of PFER largely persists for insurer-oriented and equally-weighted scenarios at $\tau = 0.2$. However, exceptions appear at $\tau = 0.4$, where WMA is selected and reduces the weighted basis risk (Cluster 4: from 0.0275 to 0.0226 (insurer); Cluster 0: from 0.0563 to 0.0562 (balanced)). This mirrors the Early window finding that mild ensembling model benefits clusters 0 and 4.

With the farmer-oriented scenario, we observe that at $\tau = 0.2$, QR remains preferred for clusters 0–3 (Table 6) and delivers lower negative basis risk but notably higher positive basis risk. For example, Cluster 2’s negative basis risk improves from 0.0040 to 0.0026 while positive basis risk rises from 0.0707 to 0.1030. At $\tau = 0.4$ (Table 7), LQR becomes optimal in Cluster 2 with a balanced improvement in positive basis risk from 0.0707 to

Table 4: Sensitivity of preferred models: Early maturity ($\tau = 0.2$)

Cluster	Model	$\bar{B}_c^{(m)}$	$\bar{B}_c^{(m,FN)}$	$\bar{B}_c^{(m,FP)}$	$\bar{B}_c^{(m,total)}$	λ
0	PFER	0.1200	0.0939	0.0257	0.0257	0
1	PFER	0.1070	0.0863	0.0205	0.0205	0
2	PFER	0.0390	0.0075	0.0315	0.0315	0
3	PFER	0.1370	0.1290	0.0087	0.0087	0
4	PFER	0.0508	0.0221	0.0287	0.0287	0
0	PFER	0.1200	0.0939	0.0257	0.0598	0.5
1	PFER	0.1070	0.0863	0.0205	0.0534	0.5
2	PFER	0.0390	0.0075	0.0315	0.0195	0.5
3	PFER	0.1370	0.1290	0.0087	0.0686	0.5
4	PFER	0.0508	0.0221	0.0287	0.0254	0.5
0	QR	0.1500	0.0708	0.0795	0.0708	1
1	LQR	0.1600	0.0623	0.0979	0.0623	1
2	LQR	0.1270	0.0028	0.1250	0.0028	1
3	QR	0.1790	0.0892	0.0897	0.0892	1
4	LQR	0.0792	0.0114	0.0678	0.0114	1

Table 5: Sensitivity of preferred models: Early maturity ($\tau = 0.4$)

Cluster	Model	$\bar{B}_c^{(m)}$	$\bar{B}_c^{(m,FN)}$	$\bar{B}_c^{(m,FP)}$	$\bar{B}_c^{(m,total)}$	λ
0	WMA	0.1180	0.0926	0.0257	0.0257	0
1	PFER	0.1070	0.0863	0.0205	0.0205	0
2	PFER	0.0390	0.0075	0.0315	0.0315	0
3	PFER	0.1370	0.1290	0.0087	0.0087	0
4	WMA	0.0494	0.0213	0.0281	0.0281	0
0	WMA	0.1180	0.0926	0.0257	0.0591	0.5
1	PFER	0.1070	0.0863	0.0205	0.0534	0.5
2	PFER	0.0390	0.0075	0.0315	0.0195	0.5
3	PFER	0.1370	0.1290	0.0087	0.0686	0.5
4	WMA	0.0494	0.0213	0.0281	0.0247	0.5
0	QR	0.1180	0.0905	0.0279	0.0905	1
1	QR	0.1140	0.0810	0.0331	0.0810	1
2	QR	0.0676	0.0051	0.0625	0.0051	1
3	QR	0.1480	0.1150	0.0329	0.1150	1
4	QR	0.0530	0.0211	0.0319	0.0211	1

0.0468 for only a slight negative basis risk trade-off (from 0.0040 to 0.0055), while Cluster 4 reverts from LQR (Table 3) to PFER (Table 7) resulting in a negative basis risk of 0.0192. This suggests that higher quantiles can favour simpler models in certain clusters.

From the sensitivity analysis of Early and Late maturity windows, retaining $\tau = 0.3$ as the baseline for the QR and LQR models appears ideal. This threshold effectively targets bad seasons (lower tail) while minimizing excessive false payouts. Across the sensitivity range $\tau \in \{0.2, 0.4\}$, $\tau = 0.3$ consistently offers a stable basis risk profile and preserves

model rankings for both insurer-oriented and equally-weighted scenarios (PFER remains dominant, with only marginal gains from WMA in a few clusters). Under farmer-oriented scenario, $\tau = 0.3$ already achieves substantial reductions in missed-loss events compared to PFER. Lowering τ to 0.2 further lowers negative basis risk but increases positive basis risk, whereas $\tau = 0.4$ moderates false positives at the cost of higher false negatives. Thus, $\tau = 0.3$ is the most favourable balance among the three values examined.

Table 6: Sensitivity of preferred models: Late maturity ($\tau = 0.2$)

Cluster	Model	$\bar{B}_c^{(m)}$	$\bar{B}_c^{(m,FN)}$	$\bar{B}_c^{(m,FP)}$	$\bar{B}_c^{(m,total)}$	λ
0	PFER	0.1130	0.0873	0.0252	0.0252	0
1	PFER	0.1000	0.0804	0.0199	0.0199	0
2	PFER	0.0323	0.0069	0.0254	0.0254	0
3	PFER	0.1260	0.1180	0.0085	0.0085	0
4	PFER	0.0467	0.0192	0.0275	0.0275	0
0	PFER	0.1130	0.0873	0.0252	0.0563	0.5
1	PFER	0.1000	0.0804	0.0199	0.0502	0.5
2	PFER	0.0323	0.0069	0.0254	0.0161	0.5
3	PFER	0.1260	0.1180	0.0085	0.0631	0.5
4	PFER	0.0467	0.0192	0.0275	0.0233	0.5
0	QR	0.1480	0.0570	0.0907	0.0570	1
1	QR	0.1640	0.0479	0.1160	0.0479	1
2	QR	0.1060	0.0026	0.1030	0.0026	1
3	QR	0.1650	0.0677	0.0970	0.0677	1
4	LQR	0.0724	0.0149	0.0575	0.0149	1

Table 7: Sensitivity of preferred models: Late maturity ($\tau = 0.4$)

Cluster	Model	$\bar{B}_c^{(m)}$	$\bar{B}_c^{(m,FN)}$	$\bar{B}_c^{(m,FP)}$	$\bar{B}_c^{(m,total)}$	λ
0	PFER	0.1130	0.0873	0.0252	0.0252	0
1	PFER	0.1000	0.0804	0.0199	0.0199	0
2	PFER	0.0323	0.0069	0.0254	0.0254	0
3	PFER	0.1260	0.1180	0.0085	0.0085	0
4	WMA	0.0422	0.0196	0.0226	0.0226	0
0	WMA	0.1120	0.0837	0.0287	0.0562	0.5
1	PFER	0.1000	0.0804	0.0199	0.0502	0.5
2	PFER	0.0323	0.0069	0.0254	0.0161	0.5
3	PFER	0.1260	0.1180	0.0085	0.0631	0.5
4	WMA	0.0422	0.0196	0.0226	0.0211	0.5
0	QR	0.1130	0.0806	0.0321	0.0806	1
1	QR	0.1110	0.0728	0.0383	0.0728	1
2	LQR	0.0522	0.0055	0.0468	0.0055	1
3	QR	0.1400	0.1020	0.0374	0.1020	1
4	PFER	0.0467	0.0192	0.0275	0.0192	1

5. Discussion

The results speak to the three questions posed in the Introduction section. First, a consistent set of extreme climate indices explains soybean yield variation across both maturity windows (Section 5.1). Second, alternative yield models produce materially different negative and positive basis risk outcomes, and this difference is not uniform across agro-climatic clusters (Section 5.2). Third, the preferred model changes systematically with the relative importance assigned to uncompensated losses versus unnecessary payouts, and this policy sensitivity is itself robust to how the quantile-based models are calibrated (Sections 5.3). We discuss each in turn, followed by the role of model ensembling (Section 5.4) and the scope for extending the framework beyond Paraná (Section 5.5).

5.1 Climate drivers of soybean yield loss in Paraná

Across Paraná’s rain-fed soybean systems, losses are most consistently driven by (i) heat intensity and persistence (very hot days and multi-day heat waves), (ii) poor rainfall distribution (long dry spells vs. runs of wet days), (iii) low energy and cloudy regimes (very low evapotranspiration and solar radiation), (iv) humidity persistence, and (v) very windy days. By contrast, a wider diurnal temperature range and cooler than usual days tend to support yield outcomes. Extreme heat magnitudes are larger in the Late window, highlighting phenology-specific vulnerability.

These patterns are consistent with known physiological mechanisms rather than purely statistical association. Intense and persistent heat during reproductive stages impairs pollination, stresses plants, and causes premature senescence, with effects that can extend beyond the heatwave itself (Siebers et al., 2015; Thomey et al., 2019). The duration of dry spells governs root zone water stress, while prolonged cloudiness and low evaporative demand limit the energy available for photosynthesis in humid and sub-humid climates. Frequent rainfall, meanwhile, creates longer periods of high humidity and leaf wetness that promote fungal disease pressure (Del Ponte et al., 2006; Zagui et al., 2022).

The stronger Late window heat results are consistent with work showing the largest losses under compound hot–dry extremes during reproductive stages (Hamed et al., 2021; He et al., 2022; Poudel et al., 2024). The prominence of rainfall deficit and excess is coherent with Brazilian hydro-climate studies documenting shifting climate indices from the Expert Team on Climate Change Detection and Indices (ETCCDI) and distribution effects across the Paraná River basin (de Medeiros et al., 2022; Rafee et al., 2020; Zandonadi et al., 2016). The low energy signals match Brazilian analyses tying reduced solar radiation to lower flower retention, pod set, and yields (Caron et al., 2018; Müller et al., 2017), and the humidity persistence result dovetails with soybean rust epidemiology in Brazil (Del Ponte et al., 2006; Zagui et al., 2022). The wind-related loss signal agrees with agronomy showing lodging under strong winds and rain can cut yields by roughly 10–30% depending on timing and cultivar (Woods & Swearingin, 1977).

Two findings merit closer comparison with the literature rather than straightforward confirmation. First, rainfall effects appear more complex than the common assumption that excess rainfall uniformly reduces yields (Iizumi et al., 2024; Kim et al., 2024; Y. Li et al., 2019). Exceedances of the 50 mm threshold are associated with lower yields, whereas exceedances of the 80 mm threshold are positively associated with yield in the Early window, and the 100 mm threshold is statistically insignificant. This suggests the yield response to heavy rainfall in Paraná’s soybean systems is threshold-dependent rather than uniformly negative, and that intensity alone is an incomplete predictor without accounting for event frequency and within-season timing. Second, very cold nights ($T_{min_below_p10}$) are positively associated with yield in both windows, which at first reading sits in tension with a substantial literature on frost damage to crops (W. Guo et al., 2024; Nuttall et al., 2019; Y. Zhao et al., 2024). We interpret this as a measurement distinction rather than a genuine contradiction: $T_{min_below_p10}$ is a percentile-relative measure of unusually cool nights within the observed seasonal distribution, not an absolute threshold near or below freezing, and is more plausibly picking up a clear sky, high radiation daytime regime (consistent with the positive coefficient on diurnal temperature range, drt) than capturing frost events per se. This distinction is important to avoid misinterpreting our results as evidence against the established literature on frost-related crop damage.

5.2 Spatial heterogeneity in basis risk across agroclimatic clusters

The cluster-level results show substantial spatial heterogeneity. Cluster 2 generally records the lowest negative basis risk and the lowest equal-weighted loss. Cluster 3 presents a different pattern: it has the lowest positive basis risk under PFER but the highest negative basis risk under that model. Cluster 3 therefore illustrates most clearly why low excess payment error should not be interpreted as uniformly good insurance performance.

These differences indicate that a model selected using state-wide average performance may conceal substantial variation in municipal or cluster-level outcomes. This finding is consistent with previous research showing that spatial differences in weather exposure, production environments and index–loss relationships contribute to agricultural basis risk (Dalhaus & Finger, 2016; Eltazarov et al., 2023; Stigler & Lobell, 2024). The results support spatially differentiated evaluation, although they do not by themselves establish that separate commercial contracts or premiums should be implemented for every cluster.

The similarity of the selected models across the early and late maturity windows should also not be interpreted as evidence that maturity timing is irrelevant. Although the preferred model classes are largely unchanged, the magnitudes of negative, positive and equally-weighted basis risks differ between the windows. Maturity-window specification therefore affects the size of the payment discrepancies even when it does not change the identity of the preferred model.

5.3 Model selection under stakeholder priorities

The preferred model depends on whether the decision criterion prioritises avoiding undercompensation or limiting payments beyond those implied by realised losses. The stakeholder-weighted loss function makes this trade-off explicit without claiming to estimate actual stakeholder preferences. This follows directly from how each model’s loss function treats prediction errors. Quantile regression at $\tau = 0.3$ asymmetrically penalises underprediction more heavily than overprediction, directing estimation toward the lower tail of the conditional yield distribution. Since payouts trigger whenever predicted yield falls below the threshold, this systematically increases the frequency with which the model predicts a shortfall, reducing missed-loss events at the cost of more frequent payouts unmatched by an equivalent realised loss. PFER, by contrast, minimises squared error under a symmetric loss and absorbs municipality-level heterogeneity through fixed effects, producing forecasts that track the conditional mean rather than the lower tail. This explains both its advantage in limiting positive basis risk and its comparatively weaker performance on negative basis risk in clusters where yield shocks are frequent. As λ shifts toward the farmer, QR and LQR become preferred; when λ favours the insurer or an equally weighted policy scenario, PFER is preferred (Conradt, Finger & Spörri, 2015).

Because the market price is fixed at $C=1$ (Section 3.5), the reported basis risk reductions describe relative improvements in a normalised yield-unit metric rather than a monetary or welfare magnitude. Translating these reductions into an amount of money saved or additional protection delivered would require a specific price series and premium structure, which lies beyond the scope of the present framework. The sensitivity analysis also shows that quantile calibration can affect basis risk and model selection. The reduction of τ from 0.3 to 0.2 in the farmer-oriented scenario reduces the negative basis risk but amplifies positive basis risk, while increasing τ to 0.4 produces the opposite effect. Quantile-based models are preferred, although they occasionally shift between QR and LQR, and Cluster 4 in the Late window reverts from LQR to PFER when $\tau = 0.4$. Under insurer-oriented and equally-weighted scenarios, PFER remains the preferred model in the Early window, with WMA becoming preferred only in the Late window when $\tau = 0.4$. These changes affect the preferred specification in particular cluster-scenario combinations, but they do not alter the broader conclusion that model selection is driven by the trade-off between negative and positive basis risk.

5.4 Limited value of model ensembling

Contrary to common expectations, the ensembling model, WMA, delivered only marginal and inconsistent gains, becoming the preferred model in a small number of clusters and quantile settings but not systematically across the full analysis. This is broadly consistent with the wider forecast-combination literature, where gains from combining correlated models are often situation-dependent and modest (Blackmore et al., 2025; X. Wang et

al., 2023). PFER, QR, and LQR are estimated on the same underlying variable set; hence, their forecast errors are likely correlated, so the limited scope for ensembling gains observed here is largely what the literature would predict rather than a surprising result specific to this application.

5.5 Generalisability and scope of the framework

The specific climate indices and cluster-level basis-risk patterns identified above are particular to Paraná and should not be extrapolated to other soybean producing regions without re-estimation on local data. The model selection pattern discussed in Section 5.3 rests on a more portable property. However, it follows from the asymmetric loss underlying quantile regression versus the symmetric, mean-tracking loss underlying panel fixed-effects regression, a characteristic of the estimators themselves rather than of Paraná’s climate. This suggests that the qualitative finding that tail-sensitive models tend to align more closely with farmer-protective objectives, whereas mean-fitting models tend to align more closely with insurer-oriented objectives, is more likely to generalise than the specific magnitudes reported here.

Applying the full framework elsewhere would require similar data conditions, including a sufficiently long yield panel, adequately resolved gridded climate data, and an exogenous or estimable spatial grouping. Where these conditions are not met, the basis risk decomposition and stakeholder-weighted selection procedure could still be applied, but the underlying yield-weather model, and therefore the basis risk estimates themselves, would require separate validation. The framework should therefore be viewed as a transferable approach to model evaluation and basis risk assessment rather than a Paraná-specific prescription for model choice.

6. Conclusions

Basis risk remains a fundamental challenge limiting the success of index insurance in agriculture. This study examined which climate indices are associated with soybean yield and how model selection for index insurance design changes across policy scenarios, agroclimatic clusters and maturity windows in Paraná, Brazil. Municipal soybean yields and gridded extreme climate indices were used to estimate PFER, QR, LQR, and WMA specifications across early and late maturity windows. Their out-of-sample performance was evaluated by (i) decomposing basis risk into negative and positive basis risk and (ii) applying a stakeholder-weighted loss function that reflects three policy scenarios: insurer-oriented, equal-weighting and farmer-oriented.

The study highlights several notable empirical findings. Among the most influential drivers of soybean yield variability were climate indices related to heat intensity and persistence, rainfall distribution, low energy and cloudy conditions, humidity and wind extremes. The effects of extreme weather are generally more pronounced in the late ma-

turity window (October–January). We also find that no model is universally preferred, and model selection for basis risk reduction depends on policy scenario and spatial heterogeneity. Under the farmer-oriented scenario, QR and LQR models offer better protection against uncompensated losses, while PFER models more effectively limit positive basis risk and perform well under insurer and equal-weighted scenarios. WMA provides only marginal and inconsistent gains over the individual models, limited to a subset of clusters and quantile settings. Additionally, our sensitivity analysis confirms $\tau = 0.3$ in quantile-based models as a stable compromise for targeting adverse yield events without excessive payouts.

On the theoretical front, our study contributes to advancements in the literature on index insurance and agricultural risk modelling. We reframe basis risk analysis by moving away from a singular design problem to a dual-component trade-off between negative and positive basis risk. This highlights the trade-offs inherent in index insurance design, where reducing one basis risk component may increase the other. In addition, we formalise stakeholder basis risk priorities through the introduction of a policy weight (λ) in the model selection procedure. This demonstrates that the model that minimises weighted basis risk is not fixed but varies according to the relative importance assigned to farmer protection and insurer cost exposure. The results support a context-dependent and objective-oriented view of model selection and reinforce that climate risk is not uniform across space or time.

The findings have practical relevance for soybean yield model selection and basis risk management in index insurance design and evaluation. For insurers, the cluster- and window-specific basis risk decomposition could serve as an input into product design discussions by distinguishing model choices that limit uncompensated losses from those that limit excess payouts. However, translating this into priced products, subsidy design, or re-insurance arrangements would require dedicated pricing and demand analysis beyond the present framework. For farmers, the basis risk decomposition clarifies how different modelling approaches distribute insurance protection across early and late windows, though this study does not assess farmer preferences, willingness to pay, or actual protection outcomes. For policymakers and agencies such as the Ministry of Agriculture, Livestock and Food Supply (MAPA) and EMBRAPA, the identified climate drivers could complement existing tools like ZARC when refining risk-zoning. The methodology provides a structured and transferable approach that can be adapted to other rain-fed production systems, subject to the data and institutional constraints of each setting.

While this study provides a data-driven basis for index insurance model selection for soybeans, it comes with some limitations. The reliability of the yield-weather models is constrained by the availability of quality long-term and high-resolution data. As such, we use spatial clustering to ensure that the design is tailored to local municipal conditions in Paraná. In addition, the assumption of climate stationarity, where historical relationships are presumed to hold in the future, may not be valid under changing climate regimes, potentially undermining the long-term effectiveness of the index insurance. To address this

limitation, we applied an expanding window forecasting approach to improve temporal validation, but it does not eliminate uncertainty arising from climate nonstationarity. Also, our findings are limited to rain-fed soybean within specified agronomic windows and hence sensitivity may differ for other crops, irrigated systems, or alternate phenology calendars. Looking forward, future research should expand the framework to compound risk scenarios, leverage emerging satellite data sources, and critically extend the analysis to premium pricing, demand, and welfare outcomes, none of which are assessed here. More evidence is also needed to establish whether the marginal WMA gains observed in a subset of clusters generalise to other regions or datasets. Lastly, since our study was based on monthly climate indices, there is a research opportunity in using daily weather extreme data to model the yield-climate relationship.

Despite these limitations and avenues for future research, the central conclusion remains unchanged. Index insurance model selection is not merely a question of identifying the model with the lowest average prediction error. It is a policy-dependent decision shaped by the relative importance assigned to different payment discrepancies, the agro-climatic setting and the maturity window. Making these conditions explicit provides a more transparent foundation for evaluating candidate soybean index insurance models.

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Author Contribution

Batsirai Mazviona: Conceptualization, Writing – original draft, Writing—review & editing, Methodology, Data Curation, Formal analysis, Software. **Simon Sølvesten:** Conceptualization, Writing—review & editing, Funding acquisition, Supervision. **Reinaldo Marques:** Writing—review & editing, Funding acquisition. **Carolina Piazzarolo:** Data curation.

Data Availability

The data that support the findings of this study are available from IRB(Re) but restrictions apply to the availability of these data, which were used under licence for the current

study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of IRB(Re).

Declarations

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