



© Author (s)

E-ISSN 2611-6634

ISSN 2385-0825



4.0 INTERNATIONAL



SAPIENZA
UNIVERSITÀ EDITRICE

Critical review

First published online: July 23, 2026

Davide Feleppa*

CLIMATE CHANGE AND PARAMETRIC INSURANCE: RETHINKING INDICES AND DEPENDENCE

Abstract

Parametric insurance is an increasingly important risk transfer instrument for managing weather related risks, particularly in agriculture, where traditional insurance is constrained by information asymmetries and high verification costs. Parametric insurance mitigates moral hazard and adverse selection but introduces basis risk due to imperfect alignment between index realizations and actual losses. This paper reviews the literature along three interconnected dimensions: the theoretical foundations of basis risk, the construction of indices for agricultural insurance, and the modeling of the dependence structure between them and agricultural yields or revenues. By synthesizing these strands, the review highlights that reducing basis risk requires not only improved index design but also an accurate representation of the joint distribution of climatic variables and agricultural outcomes, particularly in the lower tail where catastrophic losses concentrate. This challenge is further amplified by climate change, which increases the frequency and severity of extreme events and threatens the stability of historically estimated climate–yield relationships.

Keywords: parametric insurance, index insurance, basis risk, climate change

*(Corresponding author). Department of Methods and Models for Territory, Economics and Finance, Sapienza Università di Roma, Rome, Italy

1 Introduction

Parametric insurance, also referred to as index based insurance, is a class of risk transfer instruments in which indemnity payments are contingent upon the realization of a predefined and objectively observable index, rather than on the direct assessment of the policyholder's realized losses. Let I denote the index and $g : \mathbb{R} \rightarrow \mathbb{R}^+$ the contractual payoff schedule; the indemnity is given by $P = g(I) \geq 0$, where g is specified ex ante and triggered when I crosses a contractual threshold. Applications span diverse sectors, including apparel (Štulec et al., 2019), energy (Foster et al., 2015; Boyle et al., 2021), and agriculture, where rainfall based index insurance has been widely studied due to the simplicity of precipitation indices and the broad availability of historical weather data (Yoshida et al., 2019). Despite this growth, the literature remains methodologically heterogeneous with respect to index construction and dependence modeling, motivating a structured synthesis.

The present review focuses explicitly on parametric insurance in agriculture, where the interaction between climatic risk, biological production processes, and data limitations makes index design and dependence modeling particularly critical. The remainder is organized as follows. Section 2 formalizes parametric insurance and its main trade offs. Section 3 reviews the construction of indices used in practice. Section 4 surveys econometric, statistical, and machine learning approaches for modeling the dependence between indices and agricultural outcomes. Section 5 concludes and discusses open research directions under climate change.

2 Index insurance and basis risk

Under indemnity based insurance, payouts depend on the assessment of realized damages, requiring costly and dispute prone verification and loss adjustment procedures. By contrast, parametric contracts trigger indemnity payments automatically once an observable index crosses a predefined threshold, without individual loss verification (Shirsath et al., 2019), reducing administrative costs and accelerating claim settlement.

In classical insurance models, payouts depend on individual loss realizations that are privately observed and costly to verify, giving rise to adverse selection and moral hazard. Because indemnities are decoupled from individual loss realizations, index insurance mitigates these information asymmetries. However, this advantage comes at the cost of imperfect risk matching whenever the index serves only as an imperfect proxy for individual losses. These properties make index insurance particularly attractive where loss verification is expensive and shocks are systemic, especially in sectors exposed to climatic risks (Re, 2013). Climate change further amplifies this relevance by altering the frequency, intensity, and spatial heterogeneity of extreme events, potentially weakening historically estimated index–loss relationships.

In practice, parametric contracts rely on externally observable indices, including meteorological variables, remotely sensed indicators, or other verifiable physical measurements (Assa et al., 2025). However, the reliance on an external index introduces a fundamental trade off. While parametric insurance mitigates moral hazard and adverse

selection, it exposes policyholders to basis risk, defined as the discrepancy between the index based payout and the actual loss experienced by the insured. In probabilistic terms, basis risk is governed by the joint distribution of the index and realized losses, and is particularly sensitive to lower tail dependence, since the value of insurance concentrates in states associated with extreme losses. Basis risk arises when the index imperfectly correlates with individual losses, potentially leading to situations in which substantial damages occur without triggering a payout, or conversely, payouts are made in the absence of significant losses. This misalignment is widely recognized as a central limitation of index insurance and a primary factor underlying its low adoption rates, particularly among smallholder farmers (Cole et al., 2013; Chantarat et al., 2013; Cummins et al., 2004; Deng et al., 2007; Jensen et al., 2016).

Let L denote the policyholder's true loss. Basis risk reflects the degree to which the joint distribution of L and index realizations I departs from perfect comovement (Skees et al., 1997; Ghosh et al., 2021). It can be interpreted as the stochastic discrepancy between L and the conditional expectation $\mathbb{E}[L|I]$, highlighting that index insurance insures the predictable component of losses conditional on public information. More precisely, if $L \in L^2$, the conditional expectation $\mathbb{E}[L | I]$ coincides with the orthogonal projection of L onto the closed subspace of square integrable random variables that are measurable with respect to the σ -algebra generated by I . Index insurance can thus cover at most this projection, while the residual $L - \mathbb{E}[L | I]$, which is orthogonal to that subspace, remains uninsurable. This mismatch can be expressed probabilistically through two types of classification errors relative to the correspondence between index realizations and actual losses (Li et al., 2021). The incidence of these errors depends on both the statistical relationship between I and L and the design of the indemnity function $g(\cdot)$. It is useful to distinguish the index I , the observable variable whose realization activates the contract, from the payoff schedule g , which maps that realization into the indemnity actually disbursed: a payment occurs only when I breaches the contractual trigger, and its magnitude is governed by the slope of g beyond the trigger, i.e. the payout slope. Specifically, basis risk can be decomposed into:

1. Type I Error: The policyholder experiences a loss, but the realized index does not breach the contractual trigger, so that the payoff $g(I)$ is null or insufficient relative to the loss. In hypothesis testing terms, this corresponds to the failure to reject a false null hypothesis. Type I errors are detrimental as they undermine the primary objective of insurance by leaving the policyholder exposed despite having paid a premium.
2. Type II Error: The index breaches the trigger and the schedule disburses a positive indemnity $g(I) > 0$, in the absence of a corresponding loss for the policyholder. While such events may benefit the insured ex post, they increase the expected cost of the contract and pose challenges for actuarial fairness, pricing accuracy, and long-term financial sustainability from the insurer's standpoint.

Beyond this probabilistic decomposition, basis risk can also be classified according to the structural sources of the breakdown in correlation between the index and realized losses. The literature commonly distinguishes three main sources (Zhu, 2015), summarized in Table 1.

Table 1. Basis risk classification in index insurance and mitigants

Type	Description	Mitigation Strategies
Spatial	Arises when the index is measured at a location that is geographically distant from the insured asset. Weather conditions recorded at a reference station or grid cell may differ substantially from those prevailing at the production site, and this divergence generally increases with spatial distance.	Increasing the number of measurement observations can improve insurance demand (Mobarak and Rosenzweig, 2013). Proper modeling of weather variables and their dependence structure is also critical to reduce spatial basis risk (Zhu et al., 2018).
Temporal	Emerges from a misalignment between the timing of index measurement and the periods during which the insured asset is most sensitive to the underlying risk factor. In agriculture, for instance, crops are vulnerable to weather shocks only during specific phenological stages, whereas indices are often defined over fixed calendar windows (Abdi et al., 2022; Schmidt et al., 2022).	The use of phenological information has been shown to drastically reduce temporal basis risk (Dalhaus et al., 2018). Considering different growing stages and crop-specific weather sensitivity through time-dependent indices can further mitigate this risk.
Design	Reflects limitations inherent in the index specification itself, arising when the chosen index fails to adequately explain variations in losses. This may be due to nonlinear weather–yield relationships, omitted risk factors, or losses driven by idiosyncratic shocks such as pests, diseases, or management practices that are not captured by the index (Chantarat et al., 2013).	High-dimensional weather index systems and improved modeling of nonlinear relationships can help reduce design basis risk (Chantarat et al., 2013; Li et al., 2021; Zhu et al., 2019).

Source: author's elaboration.

Parametric insurance is primarily designed to hedge covariate risk, that is, aggregate losses driven by common shocks affecting many policyholders simultaneously. By construction, it cannot fully insure idiosyncratic risk, which is uncorrelated with the index and varies across individuals (Clement et al., 2018). Basis risk can thus be viewed as the sum of a design-related error reflecting the imperfect capture of covariate risk, and an irreducible idiosyncratic variance component (Kodama et al., 2022), corresponding to the share of $\text{Var}(L)$ not explained by the index.

The next section reviews the construction of these indices and how design choices affect their ability to proxy yields.

3 Construction of indices for agricultural insurance

Index construction for agricultural insurance ranges from simple agronomic formulas to multivariate and machine learning approaches, with the primary objective of minimizing basis risk. Two families of underlyings are reviewed: indices built from climatic variables, which act as physical proxies for the determinants of yield losses, and the area-yield benchmark, which instead rests on realized aggregate outcomes. For each class we indicate which source of basis risk, whether spatial, temporal, or design, it is primarily intended to attenuate, thereby reading the construction choices against the taxonomy introduced in Section 2.

The most fundamental class of indices relies on the direct aggregation of meteorological variables reflecting basic biological requirements of crops. Among these, cumulative indices are the most widely used due to their simplicity and data availability, though they abstract from interactions, timing, and nonlinear responses. Two canonical examples are cumulative rainfall (CR) and growing degree days (GDD). The latter measures heat accumulation by summing daily temperatures above a predefined base threshold and is commonly employed to model crop development stages (Shibabaw et al., 2023). These indices capture first order climatic effects but abstract from interactions, timing, and nonlinear responses, which can generate substantial design related basis risk. Early applications include a pilot rainfall-based program in Morocco (Stoppa and Hess, 2003) and a GDD-based pricing framework showing that standard approaches overvalue at-the-money contracts (Turvey, 2001). Similar pilots were promoted with the World Bank in India, Mexico, Mongolia, and Nicaragua (Skees et al., 1999; Skees and Enkh-Amgalan, 2002).

Subsequent studies propose multivariate linear combinations. Karuaihe et al. (2006) model insurance contracts as options on indices composed of cumulative rainfall, average temperature, and GDD, demonstrating improved hedging within an expected utility framework. However, these remain low dimensional linear summaries that may fail to capture nonlinear or stage specific crop responses.

In viticulture, the Winkler index (Winkler, 1974) and the Huglin index (Huglin, 1978) characterize growing season thermal conditions. However, when used as sole insurance underlyings, substantial basis risk may arise from omitting other factors, particularly precipitation (Zara, 2010). More sophisticated bioclimatic indices integrate multiple weather variables. One of the earliest is the Branas, Bernon and Levadoux (BBL) index (Branas et al., 1946). It is a seasonal indicator given by the sum of the products of monthly

cumulative rainfalls R_j and monthly average temperature T_j , $BBL = \sum_{j=1}^J T_j R_j$, where j denotes the month of each growing season and J is the last month of the season. Another established index in literature is the Ribereau-Gayon and Peynaud hydrothermal scale (RGP) (Ribereau-Gayon and Peynaud, 1957), computed as $RGP = \sum_{i=1}^I (T_i - 10)^+ - R_i$, where T_i is the average daily temperature, R_i stands for the cumulative daily rainfalls, i is the day of the growing season and $(\cdot)^+ := \max\{\cdot, 0\}$.

Empirical evidence suggests that combined bioclimatic indices improve the representation of the climate–yield relationship, reducing design basis risk by incorporating additional climatic drivers and their interactions. Salgueiro (2019) models the dependence between wine yields and bioclimatic indices using copulas and demonstrates the effectiveness of index-based insurance contracts in hedging both extreme and non-extreme events.

A distinct class of indices focuses on drought conditions and water balance dynamics, which are central drivers of yield losses in rainfed agriculture where water scarcity is the primary risk. By capturing water availability more faithfully, these measures address the design basis risk left open when rainfall sums alone omit evapotranspiration. Commonly used measures include water storage (WS), water deficit (WD), consecutive dry days (CDD), the standardized precipitation index (SPI) (Svoboda et al., 2012), and the standardized precipitation evapotranspiration index (SPEI) (Beguería et al., 2014). While nearly half of the empirical studies rely solely on rainfall-based drought indices due to data availability (Benso et al., 2023), such approaches are limited when water balance dynamics play a central role. This limitation translates into higher basis risk when temperature driven evapotranspiration plays a significant role.

Integrated indices such as SPEI incorporate both precipitation and temperature but require additional inputs, posing challenges where meteorological networks are sparse.

An alternative combined indicator is the Ped Drought Index (PDI) (Ped, 1977), useful to measure drought severity in selected regions. It standardizes the deviations of monthly cumulative precipitations and temperatures from the average value by their standard deviation,

$$PDI = \sum_{j=1}^J \left(\frac{R_j - \mathbb{E}[R]}{\sigma_R} - \frac{T_j - \mathbb{E}[T]}{\sigma_T} \right),$$

where $\mathbb{E}[\cdot]$ is the expectation and $\sigma_R, \sigma_T > 0$ are the standard deviation of each weather variable. Standardization allows the index to capture relative anomalies rather than absolute levels, improving comparability across seasons and locations. This is particularly useful for cross-regional insurance design. Variants of PDI have been proposed in literature to improve yield correlation, see e.g. (Bokusheva, 2018), where the authors create a modified version restricting the computation to critical summer months.

More advanced approaches account for crop response heterogeneity across phenological stages, since ignoring this temporal structure increases basis risk. Such growth sensitive indices therefore target temporal basis risk directly. A prominent growth sensitive index is the water requirement satisfaction index (WRSI) (Allen et al., 1998), defined as the ratio between actual crop evapotranspiration and potential crop water demand.

An early WRSI-based contract was implemented in Malawi in 2005 for maize and

groundnut producers, relying on locally calibrated parameters rather than historical yield data.

A fundamental challenge is the scarcity of ground-based weather stations, particularly in developing countries. Remote sensing offers an alternative: it denotes the acquisition of information about the Earth’s surface from satellite or aircraft mounted sensors that measure the electromagnetic radiation reflected or emitted by vegetation and soil across several spectral bands, without physical contact with the site. Vegetation indices exploit the fact that healthy canopies absorb visible light for photosynthesis while strongly reflecting near-infrared radiation, so that combinations of these bands track vegetation vigor and biomass. The normalized difference vegetation index (NDVI) (Mulla, 2013; Piñeiro et al., 2006) is computed as

$$NDVI = \frac{NIR - VIS}{NIR + VIS},$$

where $NIR, VIS \geq 0$ are the near infrared and visible light reflected by vegetation, so that $NDVI \in [-1, 1]$. NDVI provides high spatial resolution and mitigates data scarcity issues, attenuating spatial basis risk through dense and continuous areal coverage, but suffers from sensitivity to soil background effects. To address these limitations, improved variants have been developed, including the green normalized difference vegetation index (GNDVI), enhanced vegetation index (EVI), modified soil adjusted vegetation index (MSAVI2), and optimized soil adjusted vegetation index (OSAVI). Several operational commercial grassland insurance programs have adopted vegetation indices approach, including in Spain, Mexico, Canada and the U.S. (Zhu et al., 2025).

Biophysical indices, notably the Leaf Area Index (LAI) (Price, 1993), often outperform vegetation indices in yield prediction (Aschbacher and Milagro-Pérez, 2012; Brock Porth et al., 2020).

The last class departs from the climatic paradigm, since its underlying is a realized outcome rather than a physical proxy. An alternative is area-yield index insurance, where indemnity payments are determined by the average yield of a specific geographic area, such as a county or district, rather than the actual yield of an individual farm (Bourgeon and Chambers, 2003). Unlike climatic indices, area-yield indices rely on realized outcomes rather than physical proxies, shifting basis risk from weather–yield mismatch to spatial aggregation error, so that the dominant residual exposure is of the spatial type. Because the payout is based on an aggregate index, an individual producer cannot influence the outcome, eliminating moral hazard and adverse selection. Miranda (1991) formalizes the relationship between individual and area yields through the linear model

$$y_k = \mu_k + \beta_k (\bar{y}_i - \mu_i) + \varepsilon_k,$$

where y_k is the actual yield of farm k located in region i , $\bar{y}_i$ is the area (regional) yield, $\mu_k = \mathbb{E}[y_k]$ and $\mu_i = \mathbb{E}[\bar{y}_i]$ denote the expected individual and regional yields, $\beta_k = \text{Cov}(y_k, \bar{y}_i) / \sigma_{\bar{y}_i}^2$ is the sensitivity of the farm’s yield to the systemic factors affecting the region, and ε_k is the idiosyncratic component, uncorrelated with $\bar{y}_i$ ($\text{Cov}(\bar{y}_i, \varepsilon_k) = 0$). The main limitation is reference area size: too small a size reduces basis risk but increases moral hazard; too large a size aggregates heterogeneous producers (Skees et al., 1997).

Elabed et al. (2013) propose a multilevel structure with payouts at different aggregation levels, limiting both risks.

The effectiveness of these indices depends on how well the dependence between index realizations and yields is modeled.

4 Index-yields dependence structure

The effectiveness of parametric insurance critically depends on the dependence structure between the climatic index I and agricultural yield Y . A weak or misspecified dependence structure translates into elevated basis risk, particularly in the tails where extreme losses occur. The joint distribution $F_{I,Y}$ determines the expected indemnity, hedging effectiveness, and welfare implications. Modeling this joint behavior requires explicitly characterizing dependence, including nonlinearities, asymmetries, and tail dependence.

The literature proposes four broad categories. Parametric models impose fully specified functional forms, often assuming linear relationships and joint normality, offering analytical tractability. Semiparametric approaches relax some of these assumptions by combining parametric components with flexible nonparametric elements. Nonparametric and data-driven methods, most notably copula-based models, explicitly separate marginal behavior from dependence and capture nonlinear and tail dependence without restrictive distributional assumptions. Finally, machine learning and high dimensional methods, including neural networks and ensemble algorithms, model complex nonlinear interactions, particularly in settings with rich datasets. These approaches differ in their trade-offs between interpretability, statistical efficiency, data requirements, and ability to capture tail dependence relevant for insurance design.

These categories can be cut along a second and more fundamental axis, which organizes the discussion that follows. Most regression, time series, factor, and machine learning specifications are predictive models: they target the conditional mean $\mathbb{E}[Y \mid I]$, or a point forecast of the yield given the index, and are assessed by goodness of fit or out of sample accuracy. Such models describe the systematic component of the relationship but remain largely silent on the dependence in the tails, which is what determines the value of insurance. A separate strand, instead, models the full joint law $F_{I,Y}$, of which copulas are the leading instance, and so characterizes asymmetry and tail dependence explicitly. An accurate conditional mean does not guarantee an accurate joint distribution, and it is the latter that governs pricing and downside risk.

The earliest and most widely adopted approach relies on parametric regression frameworks, in which crop yield or revenue is expressed as an explicit function of one or more weather-derived indices. These models provide a transparent and analytically tractable representation of the index–loss relationship and have been extensively used both for yield estimation and for the design and pricing of parametric insurance contracts.

The most basic specification assumes a linear relationship between agricultural outcomes and climatic indices. Linear models provide a first order approximation, capturing average marginal effects of climatic conditions on yields, and are often used as a benchmark for more complex models. Despite their widespread use, they are limited

in their ability to capture asymmetric responses, nonlinearities, and threshold effects characteristic of biological processes, a limitation especially relevant under climate change.

To address heteroskedasticity and proportional effects, log-linear models have been introduced. These models are particularly useful when the impact of climate variables is multiplicative rather than additive (Li et al., 2021). Empirical evidence from viticulture and agriculture (Puga et al., 2022; Mérel and Gammans, 2021; Schlenker, 2006) shows that log-linear specifications provide improved fit and more stable elasticities when modeling the impact of growing season temperature or rainfall on output prices. Ashenfelter (2008) formalizes the predictive content of log-linear regressions, emphasizing their usefulness for both ex post explanation and ex ante forecasting of agricultural quality and economic value. These specifications, often referred to as the “Bordeaux equation”, consistently explain a large fraction of interannual price variations. Extensions to multiple viticultural regions (Ashenfelter, 2017) confirm robustness while highlighting region and varietal specific sensitivities to climatic drivers. However, strong predictive performance does not automatically translate into optimal insurance payouts if downside risk and tail dependence are not adequately captured.

Subsequent contributions extend linear models by introducing quadratic and higher order polynomial terms. Quadratic specifications are particularly common in the climate–yield literature, as they allow for the identification of optimal climatic conditions beyond which additional warming or precipitation becomes detrimental. Such models capture concave or convex response functions essential for assessing downside risk and tail losses, which are central to insurance design. Despite capturing curvature, these specifications remain global approximations and may perform poorly in localized regions where losses concentrate. Jones et al. (2005) show that the addition of a quadratic term to account for optimum growing season temperatures refines linear specifications and indicates that many wine regions may be at or near their ideal climates.

Polynomial regressions have also been employed to compare the hedging effectiveness of linear versus nonlinear index-based contracts, showing that allowing for curvature in the payoff–index relationship can significantly reduce basis risk (Chen et al., 2024).

When cross-sectional or regional data are used, error variance often depends on farm size, production scale, or regional characteristics. Weighted least squares (WLS) estimators address this by assigning greater weight to observations with more reliable information. This approach has been applied in cross sectional studies of climate impacts on agricultural prices, where yields or prices are aggregated at the regional level and weighted by cultivated area or production volume (Puga et al., 2022). WLS improves the estimation of the systematic component of yield risk, enhancing calibration of index-based contracts.

To control for unobserved heterogeneity across regions or farms, panel data models with fixed effects have become increasingly prominent. By relying only on the variation observed within each unit over time, these models absorb time invariant unobserved characteristics and thereby reduce omitted variable bias, which makes them well suited to measuring the short run response of yields to year-to-year climatic fluctuations. However, they may underestimate adaptive responses and long run structural changes, a limitation especially relevant for assessing climate change impact.

Puga et al. (2022) address unobserved regional and production system heterogeneity by

incorporating fixed effects controls through a dimensionality reduction strategy based on principal component analysis within a WLS framework, and demonstrate that neglecting such controls induces significant omitted variable bias, systematically overstating the adverse effect of growing season temperature on grape prices.

Beyond static regressions, stochastic process models have been introduced to describe the temporal dynamics of climatic variables and their relationship with agricultural losses. Temperature indices are often modeled as mean-reverting processes, with the Ornstein–Uhlenbeck (OU) process being a natural choice (Benth and Šaltytė-Benth, 2005):

$$dI_t = \kappa(\theta - I_t) dt + \sigma dW_t,$$

where $\kappa > 0$ is the speed of reversion, $\theta \in \mathbb{R}$ is the long run mean, $\sigma > 0$ is the volatility, and $(W_t)_{t \geq 0}$ is a standard Wiener process. OU-based models provide closed-form solutions for pricing weather derivatives (Swishchuk and Cui, 2013) and enable consistent joint modeling of index evolution and payouts (Shibabaw et al., 2023).

Time series econometric models are also frequently employed. ARIMA and SARIMA models capture autocorrelation and seasonality in weather variables (Masala et al., 2022), while ARFIMA models allow for long-memory behavior, particularly relevant for temperature and precipitation exhibiting persistent deviations (Wang and Ni, 2025). These are primarily used for forecasting and simulation in insurance pricing rather than direct yield–index dependence modeling, and their ability to capture nonlinear dependence remains limited.

Parametric regression models offer transparency and ease of implementation, but their reliance on global functional forms limits their ability to capture nonlinearities, asymmetries, and tail behavior central to insurance performance. Semiparametric and nonparametric methods address this limitation by allowing the data to determine the shape of the conditional expectation without imposing a rigid global structure.

A natural first step beyond global parametric regression is local regression, where the relationship is approximated by a simple model locally through kernel weights. Roucher et al. (2022) implement local least squares (LLS) kernel regression to model the effect of weather features on Bordeaux vintage prices, motivated by the idea that the climate–quality linkage is time varying over long historical periods. Empirically, LLS outperforms standard OLS and several ML benchmarks, consistent with the view that time variation in the dependence structure improves predictive performance.

A central semiparametric workhorse is the generalized additive model (GAM), which represents the conditional mean as an additive combination of smooth functions of indices

$$\mathbb{E}[Y|I] = \mu + \sum_k f(I_k),$$

where f is a smooth function of the index and μ is the baseline yield.

Tan and Zhang (2024) propose a flexible design framework for weather index insurance based on penalized spline methods, explicitly motivated by the fact that linear payout schedules cannot capture the complex and often nonmonotone dependence between weather indices and losses. Authors represent the indemnity function over multiple weather indices

using a B-spline basis and introduce a roughness penalty to prevent overfitting, thereby formalizing an explicit bias–variance trade off in contract design. This approach is particularly relevant when the dependence is nonlinear and the joint model is hard to specify.

Zou et al. (2023) integrate GAM estimation with penalized B-splines to estimate a nonparametric weather–yield loss relation, and embed the estimated conditional functionals into an optimal insurance design framework. A key feature is the explicit recognition that dependence between yield losses and weather variables is stage-dependent over the plant’s growth cycle. They partition the vegetation cycle into multiple growth phases and fit phase-specific smooth components. Their results show that phase-division models outperform whole cycle specifications in fit and hedging metrics, confirming that semiparametric flexibility combined with biologically meaningful temporal structure reduces both design and temporal basis risk. Nonparametric approaches are not limited to regression of conditional means; they also appear in the estimation of loss distributions required for pricing and risk evaluation. Shi and Jiang (2016) discuss the choice between parametric and nonparametric distributional assumptions and adopt kernel density estimation (KDE), specifically Gaussian kernel smoothing, to estimate the yield distribution when sample sizes are limited and selecting a correct parametric family may be difficult. Authors compute actuarially fair premiums as integrals of indemnity times estimated density, highlighting the practical role of KDE when closed forms are unavailable.

A major conceptual advance in the literature is the explicit modeling of dependence through copulas, which marks the passage from the predictive models reviewed so far to the direct modeling of the joint distribution. Copula models provide a natural and flexible framework for overcoming limitations of classical models by explicitly separating the modeling of marginal distributions from the specification of the dependence structure. A seminal contribution is provided by Bokusheva (2018), who develops a copula based methodology for rating weather index insurance and explicitly compares it to standard regression approaches. The study demonstrates that farm yields exhibit asymmetric dependence with weather indices, with stronger dependence in the lower tail. Using Archimedean copulas, specifically survival Gumbel and survival Joe copulas, copula-based contracts achieve substantially higher downside risk reduction than regression-based schemes, as measured by expected shortfall and other tail risk metrics. These results provide strong evidence that linear correlation systematically understates dependence in catastrophic states, contributing to basis risk.

Copula methods have also been extended to multivariate settings, reflecting the fact that agricultural losses are jointly driven by multiple climatic variables. Chidzalo et al. (2023) propose a trivariate stochastic framework in which rainfall, temperature, and reference evapotranspiration are jointly modeled through copulas and embedded into a weather derivative pricing scheme. Their results show that accounting for the full dependence structure among climatic drivers leads to more realistic pricing and a clearer mapping between joint climatic stress and yield loss, compared to contracts based on single indices or linear combinations thereof.

As the set of relevant climatic and environmental predictors expands (e.g., gridded reanalysis, remote sensing, soil databases, and high-frequency weather panels), modeling dependence increasingly becomes a high-dimensional statistical learning problem.

Classical low dimensional specifications are constrained by (i) limited yield histories, (ii) strong multicollinearity among weather covariates, and (iii) nonlinear and interaction effects. The recent literature addresses these issues via dimension reduction, regularization, and flexible nonlinear learners.

A leading econometric approach to high dimensional climate–yield dependence is to compress a large predictor set into a few latent common factors and then model yields as functions of these factors. Li et al. (2021) propose a dynamic factor forecasting framework for crop yield prediction and subsequently use it to design an enhanced weather index insurance contract, estimating factors via PCA. The log yield is modeled as

$$\log(Y_t) = a + bt + \beta F_t + \varepsilon_t,$$

where b captures technological trends and F_t is a subset of estimated factors. Authors report that the dynamic factor approach improves both in-sample and out-of-sample forecasting relative to classical models and that the resulting index insurance design exhibits smaller basis risk and higher hedge effectiveness.

An alternative to factor compression is sparse modeling through regularization. In high-dimensional climate applications, LASSO type estimators address variable selection by penalizing model complexity. The key benefit is simultaneous estimation and variable selection, yielding interpretable climatic drivers. However, important limitations in high dimensional settings motivate factor methods as complementary tools.

Tree based learners provide a flexible way to capture nonlinearities and interaction effects among many weather variables while retaining some degree of interpretability. In the index insurance context, they are naturally used to learn the mapping from a high dimensional weather vector to yields. Chen et al. (2024) compare their neural network contract to multiple tree based benchmarks, including regression trees, bagging, random forests, and tree boosting. Their evidence indicates that neural networks outperform these alternatives in contract performance and basis risk reduction, but highlights tree based methods as a relevant benchmark class.

Neural networks represent the most flexible class, suited to learning high dimensional, nonlinear, and nonmonotonic dependence structures. Chen et al. (2024) argue that low dimensional indices and piecewise linear payout rules are a major source of basis risk, and propose a neural network optimization scheme embedded in expected utility maximization to design index insurance. This places the contribution in a third, decision oriented category: rather than estimating a conditional mean or a dependence structure as an intermediate step, it optimizes the payout function against the welfare objective. A distinctive contribution is that the framework determines pricing and demand endogenously in equilibrium, rather than imposing an exogenous premium rule, achieving reductions in basis risk and improvements in farmers' utility along with lower premiums. While highly flexible, these approaches raise important questions regarding transparency, data requirements, and robustness under structural change, which are central concerns in insurance applications.

A limitation common to all the approaches surveyed in this section, regardless of their flexibility, is that they are estimated on historical records and, with few exceptions, treat the index–yield relationship as stationary. Climate change makes this assumption increasingly difficult to maintain, since it alters the mean, the variability, and the dependence structure

of the underlying variables. Mazviona and Sølvyen (2025) argue that reliance on historical data alone is becoming untenable and call for climate-adjusted pricing and forward looking risk models, while Kapphan et al. (2012) show that contracts calibrated on past data lose hedging effectiveness in a changing climate, whereas contracts adjusted to the projected distributions of weather and yields preserve and even enhance it.

A first response is to relax stationarity within the model itself, by letting the parameters evolve over time or switch between regimes. This connects to the stochastic process models introduced earlier in this section: the Ornstein–Uhlenbeck specification can be extended with a time varying mean and volatility, while Evarest et al. (2018) model temperature through a regime switching process that alternates between a mean reverting base state and a shifted state, capturing discrete transitions that a single stationary regime cannot represent. The same logic extends to the tails, where allowing the parameters that govern the distribution of extreme losses to drift over time keeps tail dependence, the quantity that determines insurance value, aligned with a moving climate.

A complementary and more operational response acts on the data and on recalibration. Wang et al. (2013) provide statistical tests, based on local, change point, and Mann–Kendall procedures together with quantile regression on the tails, to detect whether and how weather risk is genuinely increasing, and find that the pattern varies markedly with the type of risk and the location. Before such series enter a rating model, the technological trend in yields is usually removed by detrending, and Ye et al. (2015) document that the choice of detrending model materially affects the resulting risk assessment, with deviations in the estimated premium of an order of magnitude comparable to the premium itself. This makes periodic recalibration on recent data, rather than a once and for all calibration, a prerequisite for credibility under non-stationarity.

5 Conclusion

Parametric insurance replaces ex post loss verification with rule-based payouts triggered by observable climatic indices, thereby reducing administrative costs and mitigating moral hazard and adverse selection. Its effectiveness as a risk transfer instrument, however, is fundamentally constrained by basis risk, which can be formally interpreted as the component of loss variability not captured by the index. As discussed in this review, basis risk manifests through probabilistic mismatch events (Type I and Type II errors) as well as through structural sources related to spatial aggregation, temporal misalignment, and index design.

Existing literature can be organized along two tightly interconnected dimensions. The first concerns index construction, spanning simple cumulative weather variables, multivariate and phenology aware indices, water balance measures, satellite derived indicators, and area-yield benchmarks. The second focuses on the modeling of dependence between indices and agricultural outcomes, ranging from parametric regressions and stochastic time series models to semiparametric smoothing techniques, nonparametric distributional methods, copula based joint modeling, and high dimensional, data driven approaches. A consistent conclusion emerging from this body of work is that improvements in index construction alone are insufficient: effective insurance performance critically

depends on an accurate representation of the joint distribution of climatic variables and yields, particularly in the lower tail where welfare relevant catastrophic losses occur.

Several directions follow. First, index insurance should be treated as a joint design problem optimizing the index, payout function, and pricing rule simultaneously under actuarial and welfare constraints. Second, further comparative work should assess copula-based and machine learning approaches using insurance-aligned criteria such as expected shortfall reduction and utility based measures. Third, high dimensional data call for frameworks balancing flexibility with interpretability, including factor augmented nonlinear models and hybrid approaches integrating crop knowledge with statistical learning.

Finally, climate change poses a fundamental challenge to parametric insurance by undermining the stationarity of the historical relationship between climatic indices and agricultural outcomes. Shifts in means, variances, and dependence structures, together with an increased frequency of extreme events, call for contract designs and estimation procedures that explicitly account for structural change. Time varying parameters, regime switching dependence models, adaptive learning schemes, and stress testing under climate projections emerge as key tools in this context. In a warming world, improving parametric insurance is therefore not merely a matter of designing better indices, but of developing dynamic and transparent statistical architectures capable of tracking evolving climate–yield linkages while preserving credibility, trust, and long run sustainability of index-based risk transfer.

References

- Abdi, M. J., Raffar, N., Zulkafli, Z., Nurulhuda, K., Rehan, B. M., Muharam, F. M., Khosim, N. A., and Tangang, F. (2022). Index-based insurance and hydroclimatic risk management in agriculture: A systematic review of index selection and yield-index modelling methods. *International Journal of Disaster Risk Reduction*, 67:102653.
- Allen, R. G., Pereira, L. S., Raes, D., Smith, M., et al. (1998). Crop evapotranspiration-guidelines for computing crop water requirements-fao irrigation and drainage paper 56. *Fao, Rome*, 300(9):D05109.
- Aschbacher, J. and Milagro-Pérez, M. P. (2012). The European Earth monitoring (GMES) programme: Status and perspectives. *Remote Sensing of Environment*, 120:3–8.
- Ashenfelter, O. (2008). Predicting the prices and quality of Bordeaux wines. *The Economic Journal*, 118(529):F174–F184.
- Ashenfelter, O. (2017). The hedonic approach to vineyard site selection, adaptation to climate change and grape growing in emerging markets. *Journal of Wine Economics*, 12(1):3–22.
- Assa, H., Liu, P., and Wang, S. (2025). *Quantitative Risk Management in Agricultural Business*. Springer Nature.
- Beguiría, S., Vicente-Serrano, S. M., Reig, F., and Latorre, B. (2014). Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *International journal of climatology*, 34(10):3001–3023.
- Benso, M. R., Gesualdo, G. C., Silva, R. F., Silva, G. J., Castillo Rápalo, L. M., Navarro, F. A. R., Marques, P. A. A., Marengo, J. A., and MENDIONDO, E. M. (2023). Design and evaluation of weather index insurance for multi-hazard resilience and food insecurity. *Natural Hazards and Earth System Sciences*, 23(4):1335–1354.
- Benth, F. E. and Šaltytė-Benth, J. (2005). Stochastic modelling of temperature variations with a view towards weather derivatives. *Applied mathematical finance*, 12(1):53–85.
- Bokusheva, R. (2018). Using copulas for rating weather index insurance contracts. *Journal of Applied Statistics*, 45(13):2328–2356.
- Bourgeon, J.-M. and Chambers, R. G. (2003). Optimal area-yield crop insurance reconsidered. *American Journal of Agricultural Economics*, 85(3):590–604.
- Boyle, C. F., Haas, J., and Kern, J. D. (2021). Development of an irradiance-based weather derivative to hedge cloud risk for solar energy systems. *Renewable Energy*, 164:1230–1243.
- Branas, J., Bernon, G., and Levadoux, L. (1946). *Éléments de viticulture générale*. École National d’Agriculture de Montpellier.
- Brock Porth, C., Porth, L., Zhu, W., Boyd, M., Tan, K. S., and Liu, K. (2020). Remote sensing applications for insurance: A predictive model for pasture yield in the presence of systemic weather. *North American Actuarial Journal*, 24(2):333–354.
- Chantararat, S., Mude, A. G., Barrett, C. B., and Carter, M. R. (2013). Designing index-based livestock insurance for managing asset risk in northern Kenya. *Journal of Risk and Insurance*, 80(1):205–237.
- Chen, Z., Lu, Y., Zhang, J., and Zhu, W. (2024). Managing weather risk with a neural

- network-based index insurance. *Management Science*, 70(7):4306–4327.
- Chidzalo, P., Ngare, P. O., and Mung'atu, J. K. (2023). Pricing weather derivatives under a tri-variate stochastic model. *Scientific African*, 21:e01768.
- Clement, K. Y., Botzen, W. W., Brouwer, R., and Aerts, J. C. (2018). A global review of the impact of basis risk on the functioning of and demand for index insurance. *International Journal of Disaster Risk Reduction*, 28:845–853.
- Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., and Vickery, J. (2013). Barriers to household risk management: Evidence from India. *American Economic Journal: Applied Economics*, 5(1):104–135.
- Cummins, J. D., Lalonde, D., and Phillips, R. D. (2004). The basis risk of catastrophic-loss index securities. *Journal of Financial Economics*, 71(1):77–111.
- Dalhaus, T., Musshoff, O., and Finger, R. (2018). Phenology information contributes to reduce temporal basis risk in agricultural weather index insurance. *Scientific reports*, 8(1):46.
- Deng, X., Barnett, B. J., and Vedenov, D. V. (2007). Is there a viable market for area-based crop insurance? *American Journal of Agricultural Economics*, 89(2):508–519.
- Elabed, G., Bellemare, M. F., Carter, M. R., and Guirking, C. (2013). Managing basis risk with multiscale index insurance. *Agricultural Economics*, 44(4-5):419–431.
- Evarest, E., Berntsson, F., Singull, M., and Yang, X. (2018). Weather derivatives pricing using regime switching model. *Monte Carlo Methods and Applications*, 24(1):13–27.
- Foster, B. T., Kern, J. D., and Characklis, G. W. (2015). Mitigating hydrologic financial risk in hydropower generation using index-based financial instruments. *Water Resources and Economics*, 10:45–67.
- Ghosh, R. K., Gupta, S., Singh, V., and Ward, P. S. (2021). Demand for crop insurance in developing countries: New evidence from India. *Journal of agricultural economics*, 72(1):293–320.
- Huglin, P. (1978). Nouveau mode d'évaluation des possibilités héliothermiques d'un milieu viticole. *Comptes Rendus de l'Académie d'Agriculture de France*, 64:1117–1126.
- Jensen, N. D., Barrett, C. B., and Mude, A. G. (2016). Index insurance quality and basis risk: Evidence from northern Kenya. *American Journal of Agricultural Economics*, 98(5):1450–1469.
- Jones, G. V., White, M. A., Cooper, O. R., and Storchmann, K. (2005). Climate change and global wine quality. *Climatic change*, 73(3):319–343.
- Kapphan, I., Calanca, P., and Holzkaemper, A. (2012). Climate change, weather insurance design and hedging effectiveness. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 37(2):286–317.
- Karuaihe, R. N., Wang, H. H., and Young, D. L. (2006). Weather-based crop insurance contracts for African countries. 2006 Annual Meeting, August 12-18, 2006, Queensland, Australia 25378, International Association of Agricultural Economists.
- Kodama, W., Miura, K., and Sakurai, T. (2022). Basis risk and low demand for weather index insurance. *NRE Discussion Papers*, (2021-02).
- Li, H., Porth, L., Tan, K. S., and Zhu, W. (2021). Improved index insurance design and yield estimation using a dynamic factor forecasting approach. *Insurance: Mathematics and Economics*, 96:208–221.

- Masala, G., Micocci, M., and Rizk, A. (2022). Hedging wind power risk exposure through weather derivatives. *Energies*, 15(4):1343.
- Mazviona, B. and Sølvssten, S. (2025). Can index insurance keep up with climate change? rethinking historical data models. *Frontiers in Climate*, 7:1649540.
- Mérel, P. and Gammans, M. (2021). Climate econometrics: Can the panel approach account for long-run adaptation? *American Journal of Agricultural Economics*, 103(4):1207–1238.
- Miranda, M. J. (1991). Area-yield crop insurance reconsidered. *American Journal of Agricultural Economics*, 73(2):233–242.
- Mobarak, A. M. and Rosenzweig, M. R. (2013). Informal risk sharing, index insurance, and risk taking in developing countries. *American Economic Review*, 103(3):375–380.
- Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems engineering*, 114(4):358–371.
- Ped, D. A. (1977). The analysis of two summer seasons with different weather conditions. *Trudy GNIC*, 171:3–19.
- Piñeiro, G., Oosterheld, M., and Paruelo, J. M. (2006). Seasonal variation in aboveground production and radiation-use efficiency of temperate rangelands estimated through remote sensing. *Ecosystems*, 9(3):357–373.
- Price, J. C. (1993). Estimating leaf area index from satellite data. *IEEE Transactions on Geoscience and Remote Sensing*, 31(3):727–734.
- Puga, G. et al. (2022). Impact of growing season temperature on grape prices in Australia. *Australian Journal of Grape and Wine Research*, 28(4):651–657.
- Re, S. (2013). Partnering for food security in emerging markets. *Sigma*, 1:1–44.
- Ribéreau-Gayon, J. and Peynaud, E. (1957). *Trattato di enologia*. Edagricole Bologna, Italy:.
- Roucher, A., Aristodemou, L., and Tietze, F. (2022). Predicting wine prices based on the weather: Bordeaux vineyards in a changing climate. *Frontiers in Environmental Science*, 10:1020867.
- Salgueiro, A. M. (2019). Weather index-based insurance as a meteorological risk management alternative in viticulture. *Wine Economics and Policy*, 8(2):114–126.
- Schlenker, W. (2006). Inter-annual weather variation and crop yields. *New York NY: Unpublished Working Paper, Dept. of Economics and School of International and Public Affairs, Columbia University*.
- Schmidt, L., Odening, M., Schlanstein, J., and Ritter, M. (2022). Exploring the weather-yield nexus with artificial neural networks. *Agricultural Systems*, 196:103345.
- Shi, H. and Jiang, Z. (2016). The efficiency of composite weather index insurance in hedging rice yield risk: evidence from China. *Agricultural Economics*, 47(3):319–328.
- Shibabaw, A., Berhane, T., Awgichew, G., Walelgn, A., and Muhamed, A. A. (2023). Hedging the effect of climate change on crop yields by pricing weather index insurance based on temperature. *Earth Systems and Environment*, 7(1):211–221.
- Shirsath, P., Vyas, S., Aggarwal, P., and Rao, K. N. (2019). Designing weather index insurance of crops for the increased satisfaction of farmers, industry and the government. *Climate Risk Management*, 25:100189.
- Skees, J. R., Black, J. R., and Barnett, B. J. (1997). Designing and rating an area yield crop

- insurance contract. *American journal of agricultural economics*, 79(2):430–438.
- Skees, J. R. and Enkh-Amgalan, A. (2002). *Examining the feasibility of livestock insurance in Mongolia*, volume 2886. World Bank Publications.
- Skees, J. R., Hazell, P. B., and Miranda, M. (1999). New approaches to crop yield insurance in developing countries.
- Stoppa, A. and Hess, U. (2003). Design and use of weather derivatives in agricultural policies: the case of rainfall index insurance in Morocco. In *International Conference “Agricultural Policy Reform and the WTO: Where are we heading”, Capri (Italy)*.
- Štulec, I., Petljak, K., and Naletina, D. (2019). Weather impact on retail sales: How can weather derivatives help with adverse weather deviations? *Journal of Retailing and Consumer Services*, 49:1–10.
- Svoboda, M., Hayes, M., and Wood, D. (2012). Standardized precipitation index: user guide.
- Swishchuk, A. and Cui, K. (2013). Weather derivatives with applications to canadian data. *Journal of Mathematical Finance*, 3(1):81–95.
- Tan, K. S. and Zhang, J. (2024). Flexible weather index insurance design with penalized splines. *North American Actuarial Journal*, 28(1):1–26.
- Turvey, C. G. (2001). The pricing of degree-day weather options.
- Wang, S. and Ni, N. (2025). A recursive method on estimating arfima in agricultural time series. In *Quantitative Risk Management in Agricultural Business*, pages 217–248. Springer Nature Switzerland Cham.
- Wang, W., Bobojonov, I., Härdle, W., and Odening, M. (2013). Testing for increasing weather risk. *Stochastic environmental research and risk assessment*, 27(7):1565–1574.
- Winkler, A. J. (1974). *General viticulture*. Univ of California Press.
- Ye, T., Nie, J., Wang, J., Shi, P., and Wang, Z. (2015). Performance of detrending models of crop yield risk assessment: evaluation on real and hypothetical yield data. *Stochastic environmental research and risk assessment*, 29(1):109–117.
- Yoshida, K., Srisutham, M., Sritumboon, S., Suanburi, D., Janjiraattikul, N., and Suanpaga, W. (2019). Evaluation of economic damages on rice production under extreme climate and agricultural insurance for adaptation measures in Northeast Thailand. *Engineering Journal*, 23(6):451–460.
- Zara, C. (2010). Weather derivatives in the wine industry. *International Journal of Wine Business Research*, 22(3):222–237.
- Zhu, W. (2015). *Actuarial Ratemaking in Agricultural Insurance*. PhD thesis, University of Waterloo.
- Zhu, W., Porth, L., and Tan, K. S. (2019). A credibility-based yield forecasting model for crop reinsurance pricing and weather risk management. *Agricultural Finance Review*, 79(1):2–26.
- Zhu, W., Tan, K. S., Porth, L., and Wang, C.-W. (2018). Spatial dependence and aggregation in weather risk hedging: A Lévy subordinated hierarchical Archimedean copulas (LSHAC) approach. *ASTIN Bulletin: The Journal of the IAA*, 48(2):779–815.
- Zhu, W., Zhang, J., Porth, L., and Tan, K. S. (2025). Index-based insurance design for climate and weather risk management: A review. *Quantitative Risk Management in Agricultural Business*, pages 5–39.

Zou, J., Odening, M., and Okhrin, O. (2023). Plant growth stages and weather index insurance design. *Annals of Actuarial Science*, 17(3):438–458.