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Leveraging process-based models to improve index crop insurance design

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1 Introduction

Crop production is constrained by uncertainty in climate conditions and extreme weather events globally (Afshar et al., 2021). These barriers not only reduce crop yields but also compromise the livelihoods of smallholder farmers, emphasizing the urgent necessity to implement effective risk management strategies (Adelesi et al., 2024). Traditional indemnity-based crop insurance offers compensation based on actual losses, but only after a formal loss assessment has been completed. While this approach provides tailored protection, it often involves delays that can be challenging for those farmers who need timely financial support the most. A potential—though not perfect—alternative is index-based crop insurance (IBCI), which determines payouts differently. Instead of relying on post-loss evaluations, IBCI triggers payments based on predefined indices, such as rainfall levels or temperature thresholds. This allows for faster disbursement of funds, though it may not always perfectly match individual losses, if the index used does not correlate one-to-one with the loss. However, index insurance can mitigate many of the drawbacks of traditional indemnity insurance, offering more transparent, cost-effective risk transfer mechanisms and a rapid loss settlement process (Kapphan et al., 2012). However, a significant challenge in designing IBCI lies in ensuring that the selected index accurately reflects the actual losses experienced by farmers. When there is a mismatch between the index-triggered payout and the farmer's real loss, a problem known as basis risk arises (Afshar et al., 2021). An often-overlooked fact about basis risk is that it can be negative, where farmers suffer losses but receive no compensation, or positive, where payouts are made despite no actual loss. Both forms undermine the credibility, efficiency of IBCI, potentially discouraging farmer participation and limiting the insurance's protective value.

A potential way to reduce basis risk can be found in process-based crop models, also referred to as crop simulation models. These models offer a powerful avenue for enhancing the design and performance of index crop insurance (Will et al., 2022). While a large body of research exists on index-based insurance design using statistical, econometric, and remote-sensing approaches (Singh and Agrawal, 2019; Abdi et al., 2022; Ghahari et al., 2019), the direct application of process-based crop models in this context remains relatively scarce (Abdi et al., 2022). This gap highlights the novelty and importance of exploring how mechanistic models can contribute to more robust index design and reduced basis risk. These models utilize quantitative descriptions of the physiological and biophysical processes governing crop growth and development, simulating yield responses to various environmental factors and management practices (Will et al., 2022). By providing a mechanistic understanding of crop-environment interactions, process-based models can contribute to the development of more robust and relevant insurance indices, potentially reducing basis risk and improving the overall effectiveness of IBCI schemes (Will et al., 2022). Despite their potential, process-based crop models remain underutilized in developing IBCI. We explore their application in designing IBCI, addressing critical issues such as (1) data requirements, (2) calibration and validation approaches, and (3) spatial and temporal scales. By examining these factors, we identify key challenges and offer guidance to support future research that integrates process-based crop models into index insurance development. Our analysis is restricted to studies that solely applied process-based models to index crop insurance; hybrid models are excluded, although relevant regional examples are referenced to illustrate context.

2 Key data inputs and their influence on model accuracy

The utility of process-based crop models in agricultural risk assessment and insurance design is fundamentally dependent on the availability and quality of a range of key data inputs (Will et al., 2022). These inputs drive the model simulations and directly influence the accuracy and reliability of their outputs, which subsequently inform the design and pricing of index insurance contracts (Nguyen-Huy et al., 2024). Key data inputs can be primarily grouped into weather data, soil characteristics, crop management practices, and crop phenology.

2.1 Weather data

Simulating crop growth responses to atmospheric conditions requires high-resolution, temporally continuous weather data that include daily or sub-daily measurements of temperature (minimum and maximum), precipitation, and solar radiation (Will et al., 2022). Decades of historical weather datasets are necessary for model calibration, validation, and for simulating the range of yield variability under different climatic scenarios, which is important for actuarial assessments in insurance (Kapphan et al., 2012). Yet, spatially dense networks of weather stations may not be available, especially in remote or developing areas, creating a large source of uncertainty in model inputs and outputs (Li et al., 2021a), while the quality and completeness of historical records also affect the strength of the yield data produced by simulation (Nieto et al., 2012); for example, missing rainfall measurements or temperature errors can inaccurately characterize key stages of crop development and stress, resulting in erroneous yields with potentially higher basis risk in derived insurance products (Li et al., 2021a). Recent studies in developing and data-scarce regions demonstrate that supplementing sparse ground observations with satellite or model-based data can significantly enhance process-based model performance and yield simulation reliability (Feleke et al., 2021; Kumara et al., 2023).

2.2 Soil characteristics

The availability of water and nutrients for plant growth is one of the main determinants of crop yield and production, which is governed by soil properties such as type, texture, depth, water-holding capacity, organic matter content, and nutrient profiles (Will et al., 2022; Kapphan et al., 2012). In particular, detailed and spatially explicit data on soil properties are necessary inputs to simulate soil water balance and nutrient dynamics, both key drivers of crop performance under water-limited or nutrient-deficient conditions (Adelesi et al., 2024). Therefore, using coarse-resolution or inaccurate soil maps can introduce significant errors into model simulations (Li et al., 2021a), which may increase basis risk in insurance contracts if the models are used as a basis for such contracts (Kost et al., 2012). Evidence from regional applications in Africa and South Asia confirms that improving local soil data and digital mapping substantially increases simulation accuracy, reduces uncertainty, and enhances agricultural resilience (Banerjee et al., 2025; Carcedo et al., 2023; Benaly et al., 2025).

2.3 Crop management practices

The management decisions made by a farmer, such as sowing dates, planting density, crop varieties, fertilizer application rates and timing, irrigation schedules, other agronomic interventions including foliar sprays or use of herbicides to control weeds, and the representation of these practices in a crop model can impact the accuracy of yield simulations under different management scenarios (Kapphan et al., 2012; Will et al., 2022). We further note that the cropping history of a given land, reflected by previous crops grown, rotation systems, and historical management intensity, plays a key role in determining soil fertility status, pest pressures, and yield potential. Therefore, cropping history can be incorporated as a subcomponent of crop management data or as an initialization factor influencing soil and nutrient parameters in process-based models (Adelesi et al., 2023; Liu and Basso, 2020; Adelesi et al., 2024; Brogi et al., 2020).

This heterogeneity in management practices across farms, particularly in smallholder systems, presents one of the most significant challenges for applying models on farms because a lack of accurate data for such practices can result in differences between simulated and actual farm-level yields that contribute to basis risk for insurance contracts (Afshar et al., 2021; Adelesi et al., 2024). Recent research in tropical smallholder settings highlights that capturing field-level variability in management, especially planting date, cultivar selection, and fertilizer timing, improves prediction and the reliability of model-informed insurance products (Adelesi et al., 2023; Liu and Basso, 2020; Singh, 2023).

2.4 Crop phenology

The timing of crop development stages, such as emergence, flowering, and maturity, is essential for matching model simulations of crop sensitivity to weather events with actual plant physiology (Kapphan et al., 2012). Phenological information on when crops reach certain stages, along with the length of each stage, can be found in historical records, farmer knowledge, or more recently from remote sensing data such as Leaf Area Index (LAI) trajectories (Afshar et al., 2021). In addition, accurate representation of crop phenology remains crucial in process-based model applications, where seasonal variability and management interactions affect model calibration (Severini et al., 2024; Diao et al., 2021). Inaccuracies or a lack of phenological data that are temporally specific can cause mismatches between simulated crop responses to stresses (such as drought during flowering) and the actual impact on yield (Afshar et al., 2021), which will result in insurance payouts not matching critical periods for crop vulnerability and undermine the product (Li et al., 2021a). Once the necessary data inputs are secured, the next aspect is ensuring the model's accuracy through rigorous calibration, validation, and performance assessment.

To aid researchers and practitioners, particularly in data-scarce regions, Table 1 summarizes feasible sources of the critical data inputs discussed in this section.

3 Calibration, validation, and performance assessment

To ensure that process-based crop models are suitable for index crop insurance applications, they must be calibrated and validated rigorously (Afshar et al., 2021). These processes determine the capacity of the model to accurately simulate historical and potential future conditions necessary for risk assessment and insurance design (Kapphan et al., 2012).

3.1 Calibration

The calibration process involves adjusting parameters in a process-based crop model so that simulated outputs align closely with observed data under historical conditions, using historical yield data from official statistics or crop cutting experiments (Afshar et al., 2021). Three calibration approaches are commonly used. The first approach optimizes parameters through algorithms that systematically modify model parameters until simulated yields match historical observations as closely as possible, often measured with metrics such as the root mean square error (RMSE) (Li et al., 2021b). The second approach uses data assimilation techniques that incorporate multiple data streams, such as remotely sensed vegetation indices like LAI and phenological observations directly into the model during simulation to refine parameter estimates and enhance the representation of real-time crop development, for example, multi-step assimilation crop model with multi-source data (MSAcmMD) (Li et al., 2021b). The third approach constrains parameter ranges using expert knowledge and literature reviews based on scientific understanding of crop physiology and local agronomic practices to guide the calibration process and prevent unrealistic parameter values (Nguyen-Huy et al., 2024).

3.2 Validation

A crop model's predictive capability is validated by utilizing independent datasets that were not used during calibration (Afshar et al., 2021). This provides a more objective evaluation of the model's ability to generalize and accurately simulate crop performance under novel conditions (Kapphan et al., 2012). The first commonly used validation approach involves evaluating the model's performance against yield data from different years or locations than those used for calibration (Afshar et al., 2021). The second assesses the model's ability to simulate key biophysical variables, such as LAI, against independent satellite-derived observations (Afshar et al., 2021). The third is based on a historical burn analysis, where long-term historical weather data is used to simulate yield time series and then evaluate the performance of a hypothetical insurance contract based on these simulated yields against historical loss data or expectations (Kapphan et al., 2012). This helps to assess the contract's payout characteristics and potential basis risk over time (Kapphan et al., 2012).

3.3 Model performance assessment

Several quantitative metrics are used to evaluate the performance of a model when applied in the IBCI context: coefficient of determination (R^2), RMSE, normalized RMSE (NRMSE), hedging effectiveness metric, and correlation (Afshar et al., 2021). R^2 indicates how much variability a model explains; therefore, it is a key metric to evaluate the fit of a model. The RMSE and NRMSE metrics are used to measure the extent of alignment of simulated values with observed values; a lower RMSE depicts better performance (Setiyono et al., 2018). Hedging effectiveness metric quantifies how effective an insurance contract based on the model is by measuring the reduction in variance in income or yield of farmers, where a higher hedging effectiveness indicates a more effective insurance product (Kapphan et al., 2012). Finally, the correlation measures the relationship between the index used in the model and the yield loss to understand basis risk (Kapphan et al., 2012).

Robust calibration and validation are indispensable for building confidence in the reliability of process-based crop models for informing agricultural insurance design and risk assessment (Afshar et al., 2021). Demonstrating strong model performance across relevant metrics provides stakeholders, including farmers, insurers, and reinsurers, with the assurance that the insurance product is based on a sound and scientifically defensible foundation (Giannini et al., 2009). Beyond model performance, the practical application of process-based models in insurance also depends on their spatial and temporal scalability.

4 Spatial and temporal applications in insurance

Process-based crop models have been applied at a range of spatial and temporal scales for agricultural insurance design, each with its advantages and limitations (Kapphan et al., 2012). The choice of scale employed is dictated by the characteristics of the

TABLE 1 Feasible data sources for key model inputs in data-scarce regions.

Model input category	Examples of required variables	Feasible data sources
Weather data	Daily temperature, rainfall, solar radiation	CHIRPS, ERA5-Land, national meteorological stations
Soil characteristics	Soil texture, organic matter, depth, water-holding capacity	Harmonized World Soil Database, ISRIC SoilGrids
Crop management practices	Sowing date, crop type, rotation history, fertilization, irrigation	Local extension services, national statistics, participatory surveys, multi-year satellite imagery (Landsat, Sentinel)
Crop phenology	Growth stages, flowering, maturity timing, LAI	MODIS, Sentinel-2, Landsat, ground observations

insurance product and the availability of relevant data (Setiyono et al., 2018).

4.1 Spatial scales

Deploying a model at finer spatial resolution may capture within-field variability in yields that could benefit individual farm-level insurance contracts, but this requires input data such as soil maps and management practices at similar resolutions, which are often sparse in smallholder farming (Li et al., 2021a). Consequently, validation of models at field scale is challenging, so modelers usually select aggregated scales such as village clusters or districts to apply crop models in the design of area-yield index insurance, where payments are made when yields fall below a threshold average yield for a defined geographic region (Afshar et al., 2021). The use of aggregated spatial scale may have the advantage of local yield variability being averaged out and a less stringent data requirement than plot-level applications (Setiyono et al., 2018). However, one study shows that crop models can explain more variance in yields at the village level than field level (Afshar et al., 2021), which is consistent with the practicalities of implementation and management of area-based insurance schemes as they eliminate farm-level loss assessments and potentially reduce administrative costs (Kapphan et al., 2012). Crop models can also be used at a national level for assessing agricultural losses over large areas (Kapphan et al., 2012).

4.2 Temporal scales

Process-based models simulate crop growth and development at finer temporal resolutions, using daily or sub-daily scaling, to capture dynamic responses of plants to changing environmental conditions during the growing season (Kapphan et al., 2012), which is important for understanding timing and duration of critical stress periods, such as drought occurring during flowering, that can impact final yield (Afshar et al., 2021). Further, long-term historical weather data are used to drive models in simulations of historical periods, generating simulated time series of crop yields that characterize yield variability, estimate the frequency and severity of potential losses, and actuarially price index insurance contracts (Li et al., 2021b). In addition to daily or sub-daily and historical scaling, future scaling provides long-term evaluation using climate change scenarios to drive crop models that can be used to project future yield risks, thereby assisting in gauging the long-run viability of designed and existing IBCI products (Will et al., 2022; Kapphan et al., 2012).

Scaling model applications, both spatially and temporally, presents several challenges. Scaling down (to finer spatial scales) requires access to high-resolution and accurate input data, including weather, soil, and management, which is often a major limitation (Li et al., 2021a). Representing the inherent heterogeneity of smallholder farming systems at the plot level within a model can be complex (Adelesi et al., 2024). Validation of field-level model outputs against limited observed data can also be difficult (Afshar et al., 2021). Scaling up (to coarser spatial scales) can lead to a loss of information about local variations in risk, potentially increasing basis risk for individual farmers within the insured area (Afshar et al., 2021). Aggregating diverse farming systems and environmental conditions within a larger area can mask important differences in crop responses to weather events (Li et al., 2021a).

In the context of temporal scaling, historical simulations are well-established. However, projecting future yields under climate change involves uncertainties due to climate model projections and assumptions about future adaptations (Kapphan et al., 2012). Furthermore, ensuring the relevance of historical data for future risk assessment in a changing climate is a problem. Another problem arises when deciding on the most suitable spatial and temporal scale to apply process-based crop models in IBCI design, where several factors must be considered, including specific objectives of the insurance product, availability and quality of relevant data, as well as the trade-offs between model complexity, accuracy, and basis risk (Li et al., 2021a). To counter these limitations, advancements in remote sensing technologies, data assimilation techniques, and the integration of crop models with statistical and machine learning approaches expand the possibilities of applying these hybrid models across different scales (Setiyono et al., 2018).

5 Synthesis and future directions

Integrating process-based crop models into IBCI has great potential to strengthen the robustness, relevance, and effectiveness of risk transfer mechanisms for farmers worldwide (Will et al., 2022). Process-based crop models provide a mechanistic understanding of crop yield formation and its response to environmental and management factors, allowing improved design of more precise insurance indices with reduced basis risk, one of the main challenges hindering IBCI uptake on a larger scale (Afshar et al., 2021). Addressing basis risk when applying process-based models requires robust input data, including improving weather monitoring networks, soil information systems, and developing methods to capture spatiotemporal variability of crop management practices. Data-scarce regions can utilize process-based models by taking advantage of the availability of remote sensing data to complement ground-based observations with high-resolution and model inputs such as LAI and phenology (Setiyono et al., 2018).

The application of process-based models in designing IBCI for smallholder farming systems, while challenging, is increasingly feasible. Key strategies include (1) leveraging freely available remote sensing data for weather, soil, and phenology to overcome ground-data scarcity, (2) calibrating models with localized management data, even if representative rather than plot-specific, and (3) operating at aggregated spatial scales (e.g., village or district level) that align with area-yield insurance schemes, which are more practical and cost-effective for implementation in these data-scarce environments.

Additionally, research into new calibration methods, such as data assimilation and comprehensive validation with independent datasets, must continue to build confidence in the predictive ability of crop models. Standardizing performance metrics and benchmarks specific to IBCI applications will also ensure a more uniform and transparent assessment of model suitability and comparison across regions (Afshar et al., 2021). Another important area requiring further research and development is how to navigate the challenges associated with spatial and temporal scaling, which involves determining the optimal scales for different IBCI products and agricultural systems, taking into account data availability, computational resources, as well as the trade-offs between local risk capture and the practicality of insurance contract design and implementation (Afshar et al., 2021).

Finally, linking process-based models with socioeconomic and financial modules will help assess product affordability and policy relevance, ensuring that scientific innovations translate into scalable solutions that improve smallholder resilience to climate variability.

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