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ORIGINAL ARTICLE

Advancements in Weather Index Insurance: A Review of Data-Driven Approaches to Design, Pricing and Risk Management

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Abstract

Weather index insurance is a financial tool that enhances climate resilience in agriculture by providing timely compensation linked to objective weather parameters. While payouts in traditional crop insurance are based on actual losses experienced by the farmer, WII payouts are triggered when a predetermined index (e.g. temperature or rainfall) exceeds a specified threshold. This review paper underscores that the primary challenge associated with WII is its susceptibility to basis risk, wherein triggered payouts may not align with actual crop yield losses. This thesis comprehensively reviews 71 quantitative studies on WII design and pricing. The review findings highlight the potential for machine learning models in optimising WII parameters, such as contract dates, strike and exit thresholds, and in developing customised multi-indexes, while also exploring the utility of phenological and remote sensing data. The main contribution of this review is a novel focus on quantitative and data driven methodologies for WII product design, pricing and evaluating hedging efficiency. Additionally, recommendations are suggested to tailor WII design and pricing to different agricultural systems and regions with spatial and temporal climate variation, enabling optimisation of risk mitigation to the agricultural communities. This review also proposes research gaps to address the multi-faceted nature of basis risk including spatial, design and temporal basis risk. With the global demand for WII on the rise, these efforts are pivotal in ensuring that WII evolves into a dependable risk management tool capable of safeguarding against extreme crop yield losses effectively.

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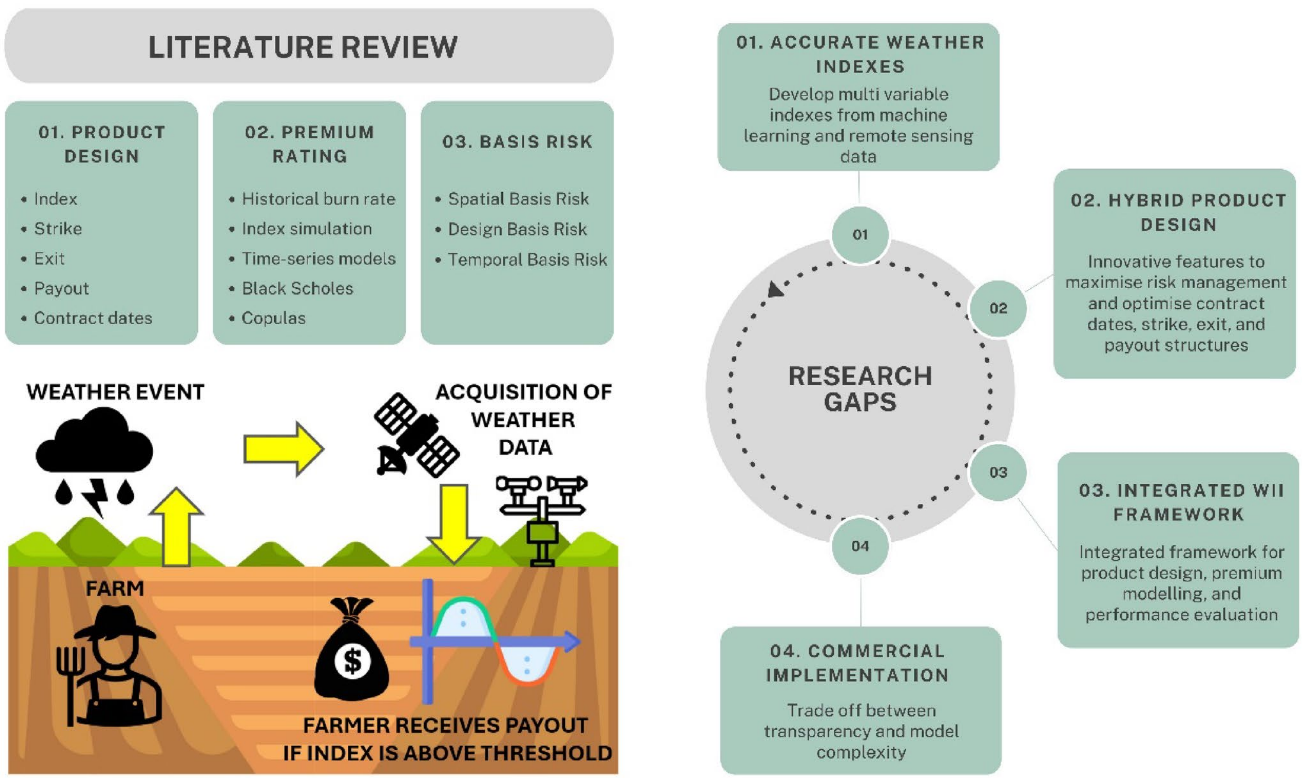
Graphical Abstract

This graphical abstract provides a visual representation of the literature review conducted on Weather Index Insurance (WII) product design, pricing and hedging efficiency. Climate change is expected to increase the frequency of extreme weather conditions. WII is an innovative financial tool to protect farmers adverse weather events on crop yield. However the primary challenge of WII is basis risk when the weather index measured by weather stations or satellite data does not correspond to the actual crop yield loss, causing a misalignment in triggered WII payouts to the farmer. This study reviews 71 research papers, with a novel focus on studies which utilised quantitative and data-driven methodologies for WII parameter optimisation in product design and pricing models. The review identifies the need to explore remote sensing data and machine learning to create multi-variable weather indexes with improved accuracy. Further research is required to optimise contract parameters, incorporate phenological crop data to reduce basis risk, and develop sophisticated premium-setting models. Future research should focus on balancing model complexity with transparency and developing an integrated WII framework to optimise risk mitigation for the farmer. As the demand for WII grows, these advancements are critical for transforming WII into a reliable risk management tool, and we encourage readers to explore the full article for further insights.



Keywords Basis risk · Crop yield prediction · Machine learning · Pricing · Remote sensing · Weather index insurance

1 Introduction

Extreme weather events such as droughts, floods, hail and storms have a devastating impact on agricultural crop production. These adverse weather conditions can disrupt planting cycles, critical growth phases, creating stunted growth and destroying crops entirely (Verma et al. 2025; Toromade et al. 2024; Yuan et al. 2024; Grigorieva et al. 2023). Climate change is projected to increase the frequency and severity of such events, catalysing adverse conditions for crop growth, productivity, and sustainability of agricultural systems (Belissa 2024; Wang et al. 2015). IPCC (2023) anticipates a rise in crop yield losses, particularly in low and mid-latitude regions, and projects a reduction in the effectiveness of standard agronomic adaptation strategies to mitigate climate risks from 2 °C to higher levels of warming. Smallholder farmers with limited financial reserves, adaptive capacity and access to rainfed agriculture may be exposed to long term setbacks from a single extreme weather event (Ojo et

Table 1 WII benefits compared to traditional insurance

Category	Benefits compared to traditional insurance
Adverse selection/moral hazard	A farmer is unable to manipulate the actual loss amount since payouts are based on an independent index rather than actual crop yield losses
Policy underwriting	Since policyholder loss experience does not need to be modelled, the policy origination process and underwriting costs are significantly reduced
Claims assessment	Operating expenditure is minimised since an independent weather index determines the payout, eliminating the need for onsite inspections to estimate crop yield loss
Prompt access to funds	Prompt access to funds is especially needed in developing countries where low-income farmers are vulnerable to short-term liquidity gaps
Affordable premiums	Reduced policy underwriting and claims assessment expenses, enable more affordable WII premiums, facilitating greater accessibility and diminishing the need for government subsidies

Table 2 WII contract parameters

Contract parameters	Description
Index	WII will provide a payout based on weather index value measured at closest weather station or from remote sensing data
Tick	Monetary payout per unit from WII contract
Strike and exit	Payout will be initiated when index exceeds strike threshold, with maximum payout at exit threshold
Payout function	Defines the structure of the payout e.g. linear payout between strike and exit thresholds
Premium	Price paid by policyholder to insurer to purchase a WII contract
Contract period	Start and end date of contract which usually coincides with crop growing season

al. 2024; Zenda 2024; Batungwanayo et al. 2023; Gwambene et al. 2023; Mutengwa et al. 2023). Due to heightened exposure to financial vulnerability, the role of crop insurance becomes increasingly critical. Regrettably, traditional indemnity crop insurance has often proven to be impractical, a phenomenon frequently attributed in numerous studies to information asymmetry, underwriting costs, and the expensive claims assessment process (Adelesi et al. 2024; Adeyinka 2015; Hatt et al. 2012).

Traditional indemnity crop insurance is susceptible to moral hazard as payouts are based on actual losses experienced by the policyholder. It has been estimated that moral hazard and adverse selection inflate costs by 30–50%, leading to premium unaffordability (Powell and Goldman 2016). Another new and promising risk management tool to protect farmers from climate risks is Weather Index Insurance (WII). In WII payouts are triggered when a predetermined index (e.g. rainfall or temperature) exceeds a specified threshold. This subtle distinction enables numerous advantages compared to traditional indemnity crop insurance, particularly a reduction in moral hazard risk. The World Bank (2011) estimates that WII enables administrative costs to be reduced by 60% relative to traditional indemnity crop insurance. WII utilises indexes such as rainfall or temperature as proxies for crop yield. If an index has been appropriately selected, it should be highly correlated with the farmer's crop yields. The benefits of WII in comparison to traditional indemnity products have been discussed in many studies (Abrego-Perez et al. 2023; Amarnath et al. 2023; Barnett and Mahul 2007; Singh 2024). The benefits discussed in these studies are broadly categorised and summarised in Table 1.

The design of WII products should consider the following contract parameters, as summarised in Table 2 (Chen et al. 2017).

WII is still relatively a new financial product in many regions worldwide however has been successful in many developing countries (Lavorato and Braga 2023; Wang et al. 2023). India is often cited as having the first WII program in the world. This WII program was a rainfall insurance program underwritten by ICICI-Lombard General Insurance Company in 2003 for groundnut and castor farmers in Andhra Pradesh (Clarke et al. 2012a, b). WII programs in India have transitioned from small scale pilot programs scattered across the country to large scale programs, which is one of the largest in the world (Clarke et al. 2012a, b). India's primary WII scheme is the Restructured Weather Based Crop Insurance Scheme (RWBCIS) which has been recently redesigned to include recent technological advancements to improve protection for farmers (Vishnoi et al. 2020). Similarly the Catastrophic Attention to Natural Disasters (CADENA) program in Mexico was launched in 2003 by the Mexican Ministry of Agriculture. This program offers WII to maize farmers, and by 2013 the scheme had expanded nationwide coverage of over 6 million hectares of farms (De Janvry et al. 2016). Furthermore, Kenya's Kilimo Salama ("Safe Farming") program, launched in 2009, integrated mobile technology to reduce administrative costs

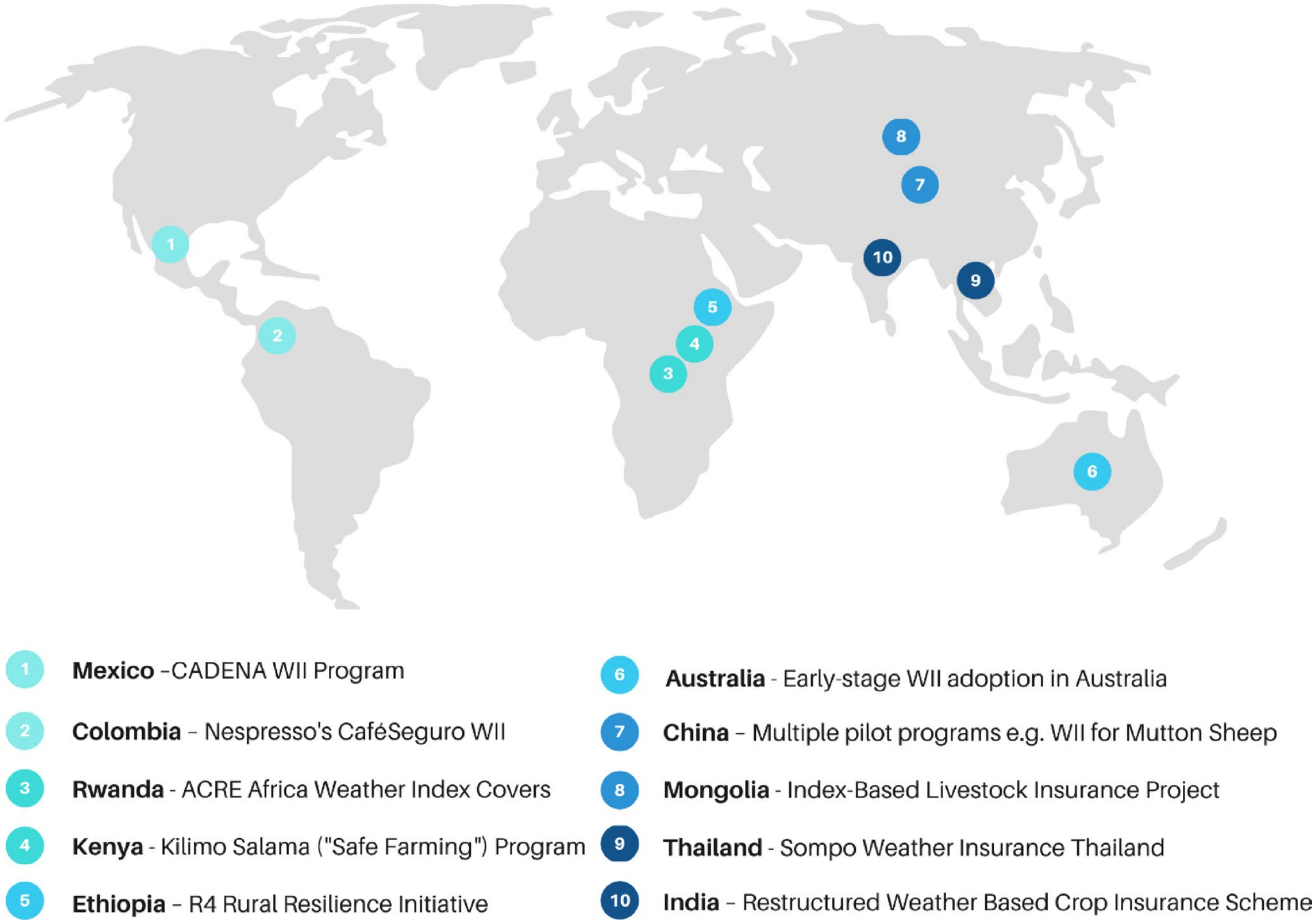


Fig. 1 Geographic Distribution of Global WII Programs

and is widely regarded as a model for WII in Sub-Saharan Africa (Muleke et al. 2025). Figure 1 presents a geographic distribution of global WII programs.

The challenges that have been cited in these commercial implementations are low uptake, distrust in insurers, sparse weather station data and basis risk (Barnett and Mahul 2007; Cesarini et al. 2021). Basis risk arises when there is a mismatch between triggered payouts and actual crop yield loss (Skees 2008). Further, research is required to optimise WII parameters and pricing methodologies, aiming to mitigate basis risk in WII (Tan and Zhang 2024; Wang and Abdullah 2024; Zou et al. 2023). Ultimately, reducing basis risk will enable WII's appeal as a risk transfer product, thereby increasing demand and take up of this product for both farmers and the insurance industry.

Several reviews have explored different dimensions of WII, reflecting the growing academic interest in its design, implementation, and impact. A review by Singh and Agrawal (2019) provided a broad overview of farmer's willingness to pay for WII, demand for WII, adoption of WII, climate change impact on WII, subsidy for WII, and social protection and welfare impact of WII. Alternatively, other reviews have focused on specific aspects of WII. A review by Singh (2024) focused on WII and climate change, including climate risks in agriculture, changing perception of WII and climate finance policy. In addition, a review by Gairola and Dey (2023) focused on factors that impact the willingness to pay for WII. There have been no reviews that specifically focus on only WII product development from end-to-end parameter selection, premium rating and performance evaluation which is the main contribution of this review. Although Benso et al. (2023) covered some aspects of WII design and pricing, this study was limited to the 26 most cited papers published in the past 5 years.

The objective of this paper is to conduct a systematic review of the literature to identify key future directions for WII design and pricing. This review offers a novel in-depth focus on quantitative methodologies utilised to derive WII parameters (index, strike thresholds, payout), premium rating and evaluate hedging efficiency in each stage of WII product development. In contrast to previous reviews, this review is the first to systematically compare the modelling techniques, including machine learning and statistical approaches. This review captures a broad set of studies

Table 3 Eligibility criteria

Inclusion criteria	Description
Publication period	Published after 2000
Language	English language
Document type	Peer reviewed journal articles (exclude conference papers)
Insurance type	WII only (exclude area yield insurance and traditional indemnity crop insurance)
Product	Focused on crops (exclude livestock)

across multiple regions and crop types to provide input for a global framework for WII design and pricing. By focusing on technical and methodological advancements, this review provides clarity for future research areas and actionable insights for both researchers and practitioners.

This review was guided by the following questions:

1. How has the literature evolved in designing and pricing WII to reduce basis risk?
2. What methods are available to assess the hedging efficiency of proposed WII products?
3. What are the promising future research directions?

The findings of this review aim to guide the development of more reliable and scalable WII products, ensuring effective protection for farmers against extreme weather-induced crop yield losses. Improving the profitability and risk management capability of WII will be crucial for the agricultural sector to be resilient to extreme weather events and fulfil increasing global demand (Amarnath et al. 2023; Osgood et al. 2024).

2 Literature Search

PRISMA broad search criteria was used, as initial narrow searches missed key articles in the literature. The following search criteria was applied to the title, abstract and keyword fields.

("weather index insurance" OR "rainfall index insurance" OR "index insurance" OR "weather index") AND ("pricing" OR "viable" OR "viability" OR premium OR "rating" OR model* OR "design" OR "basis risk").*

This broad search retrieved 508 articles. The criteria listed in Table 3 were applied to further refine the search results, resulting in 227 articles. Articles were screened for relevance to research objectives by reviewing the title and abstract. As this research is focused on developing a comprehensive framework, only articles that proposed a holistic framework for WII design and pricing were selected. For example, articles that proposed a premium for WII without explaining the pricing methodology were excluded. Furthermore, articles focusing on only one component, such as index development or hedging efficiency performance, were also excluded. These criteria filtered the search to 64 articles. A further 7 articles were obtained by reference searching, resulting in a total of 71 papers for our literature review.

This process of literature identification and filtering is illustrated in Fig. 2.

2.1 Overview of Studies

WII has gained popularity in recent years, as shown in Fig. 3, which reveals a rise in quantitative WII studies since 2014. This increase may be attributed to the increased frequency and severity of extreme weather events, wherein traditional crop insurance products have failed to provide sufficient protection to farmers (Adeyinka 2015).

Drought emerged as the dominant type of weather risk targeted in WII studies in the reviewed literature. Other studies analysed risks such as excessive rainfall, low temperature, and rainfall deficit. Multi-risks such as high and low temperature, were analysed by only five studies. The illustration in Fig. 4 presents the most frequently studied crops. Wheat, corn and rice were commonly studied crops in WII studies worldwide. Multi-crops were analysed by only 20% of studies, with the majority focusing on a single crop.

The studies were based on 41 different countries, with 70% of them conducted in developing countries, as shown in Fig. 5. Only a few studies were at a macro country level (Hohl et al. 2021; Kath et al. 2019; Kusuma et al. 2018). Most studies were conducted in specific regions, underscoring the necessity for localised WII contracts with premium rates tailored to the variability in weather patterns, terrain, and agricultural practices of each region (Poudel et al. 2016; Vedenov and Barnett 2004). A few studies segmented the study region into homogeneous regions with similar rainfall, temperature, and soil quality using clustering models (Schmidt et al. 2021; Roberto Valverde-Arias et al. 2020).

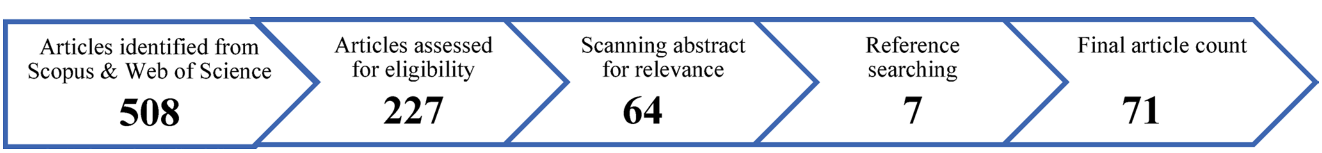


Fig. 2 Eligibility criteria used for the literature identification

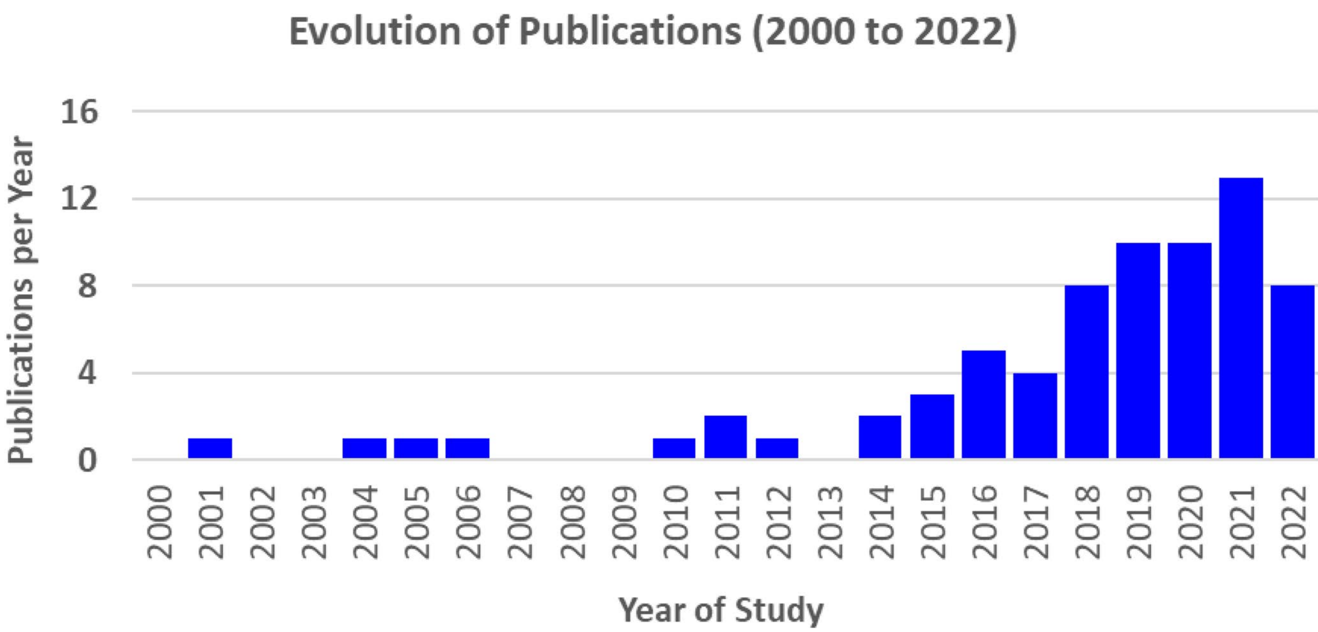


Fig. 3 Evolution of WII publications from 2000 to 2022

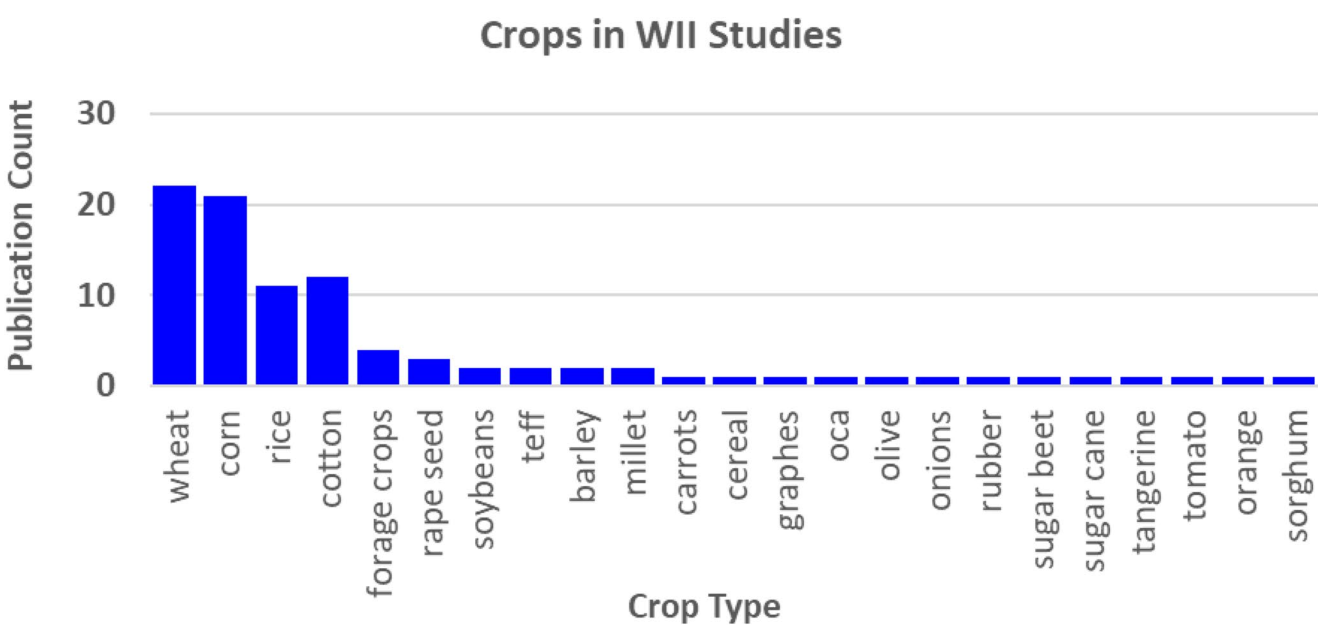


Fig. 4 Distribution of Crop Types in WII studies

3 Weather Index

3.1 Indexes Used in WII Studies

Obtaining an optimised weather index, serving as a proxy for crop yields, is a significant step in the development of a viable WII product (Hughes et al. 2022). Lu (2021) proposed that an optimal index should not fluctuate, have minimal human interference, directly influence crop growth, and be simple to understand. Table 4 categorises weather indexes from reviewed articles, revealing that rainfall indexes were most widely used in the literature. In comparison, degree day indexes and temperature indexes were adopted in fewer studies. While meteorological drought indexes are widely used in drought monitoring, fewer WII studies have considered these indexes (Bokusheva 2018). Limited studies have investigated the potential of customised multi-indexes.

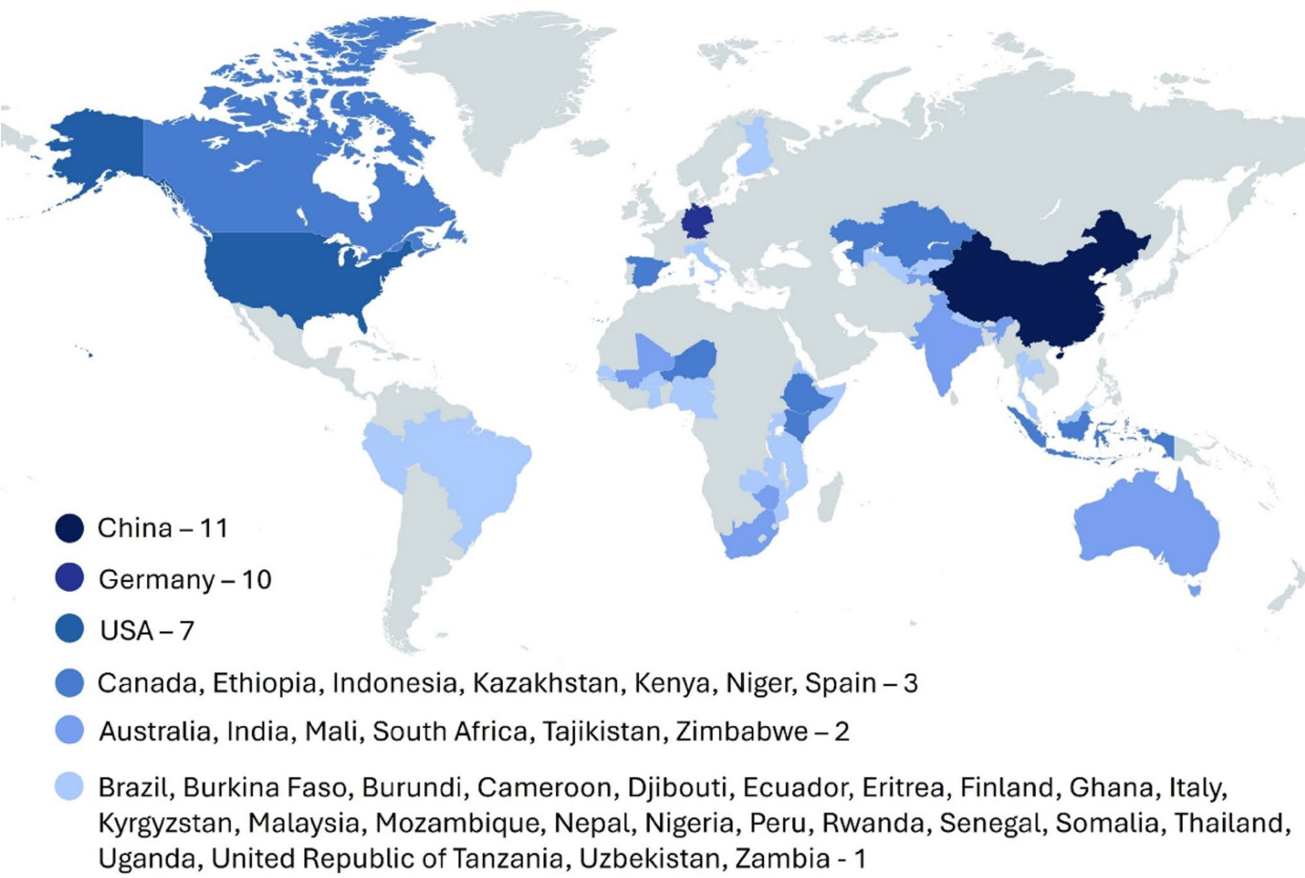


Fig. 5 Geographical distribution of WII studies

3.1.1 Drought Indexes

The Standardised Precipitation Index (SPI) is widely used to predict meteorological drought, yet has been applied in only a few WII studies (Miquelluti et al. 2022). SPI uses standardised values, enabling comparison across locations with different climates, unlike absolute metrics such as precipitation (Bucheli et al. 2021). Crop growth depends on diverse factors including soil water storage capacity and evapotranspiration (Miquelluti et al. 2022). Consequently, Standardised Precipitation Evapotranspiration Index (SPEI) was developed as an extension of the SPI, considering the impact of insufficient precipitation and extreme temperatures, thus rendering it an ideal index for WII (Hohl et al. 2021).

Soil moisture has proven to be an effective predictor of drought, yet only considered as an index in a few WII studies (Bucheli et al. 2021; Doms et al. 2018; Okpara et al. 2017; Vroege et al. 2021). Soil moisture reflects location-specific details such as water retention capacity, while also indicating if there is insufficient water to nourish roots even prior to the WII contract start date (Bucheli et al. 2021). Furthermore, only a few studies, such as Mortensen and Block (2018) have investigated climate indexes. Mortensen and Block (2018) tested several El Nino Southern Oscillation indexes based on products in Peru, where El Nino had a significant impact on precipitation.

3.1.2 Satellite-Based Indexes

Indexes based on satellite offer the advantage of being freely available, continuous, and high spatial resolution (Vroege et al. 2021). These indexes are generated by reputable third-party agencies, hence they cannot be manipulated by insurers or farmers and are particularly useful in regions with sparse weather station infrastructure (Makaudze and Miranda 2010). Platforms such as Sentinel, Landsat and MODIS provide diverse spatial and temporal resolutions. MODIS provides high frequency data (daily to 8 day) at moderate spatial resolution of 250 m to 1000 m. Alternatively Landsat offers higher spatial resolution data of 30 m but lower temporal frequency of 16 days. A comparison of the spatial and temporal resolution of these platforms are presented in Table 5. According to the agroecological characteristics of the study region, typical farm size, and timing of critical phenological stages of the selected crop,

Table 4 Common indices in WII studies in the literature

Index	Count of Studies
Rainfall indexes	**29**
Cumulative rainfall	23
Flooding	1
Rainfall deficit	2
Rainfall excess	3
Remote sensing indexes	**21**
Enhanced vegetation index (EVI)	1
Evaporative stress index (ESI)	2
Land surface temperature (LST)	1
Normalized difference vegetation index (NDVI)	6
Soil moisture index (SMI)	4
Temperature condition index (TCI)	2
Temperature vegetation index (TVI)	1
Vegetation condition index (VCI)	2
Vegetation health index (VHI)	2
Drought indexes	**15**
El nino–southern oscillation index (ENSO)	1
Palmer drought severity index (PDSI)	2
Ped drought index (PDI)	1
Standardised precipitation evapotranspiration index (SPEI)	5
Standardised precipitation index (SPI)	6
Degree day indexes	**11**
Cooling degree days (CDD)	7
Growing degree days (GDD)	3
Heating degree days (HDD)	1
Temperature indexes	**6**
Cumulative daily average temperature anomaly	1
Temperature	5
Multi indexes	**5**
Other	**8**
Total	**95**

appropriate satellite platforms should be selected according to spatial and temporal resolution requirements.

Remote sensing indexes have been recently explored in a few WII studies. A study by Eltazarov et al. (2021) investigated the accuracy of remote sensing data compared to weather station data for potential use in implementing WII in Uzbekistan. Another study by Mollmann et al. (2019) explored the potential of three indexes derived from remote satellite data: the Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI). Various studies have demonstrated that the Normalised Difference Vegetation Index (NDVI), which reflects the density and vitality of vegetation, was able to accurately predict crop yield (Eze et al. 2020; Makaudze and Miranda 2010; Masiza et al. 2022; Roberto Valverde-Arias et al. 2020).

3.1.3 Customised Indexes

Some studies have considered more innovative and customised indexes, which are valuable given the significant regional, topographical, and climatic variations in crop yield (Sun 2022a, b). A study by Leblois et al. (2014b) utilised a weighted average of cumulative precipitation, where the weights corresponded to the water requirements during different crop growth periods. Several studies have explored multi-indexes derived from combinations of various indexes. For instance, Li et al. (2021) argued that a multi-index derived from meteorological, remote sensing, and phenological data was more effective than a single index in modelling the multi-dimensional aspects of chilling risk. Shi and Jiang (2016) also developed a multi-index for rice yield in China, noting that this approach enabled farmers to be protected against multi-weather perils. Boyd et al. (2020) developed two multi-indexes based on partial least squares regression (PLSR) and on principal component regression (PCR), utilising 31 weather variables as inputs. These multi-indexes reduced basis risk more effectively than the cumulative precipitation index. Other studies have observed that while multi-indexes decrease basis risk and enhance accuracy in WII, there is a trade-off between simplicity and ease of implementation (Skees 2008; Vedenov and Barnett 2004).

Table 5 Comparison of satellite platforms

Satellite Platform	Operator	Spatial resolution	Temporal resolution	Key data products
Sentinel-1	ESA	10 m (SAR)	6–12 days	Soil moisture proxy, SMI, VSM
Sentinel-2	ESA	10–20 m	5 days	NDVI, red edge indices
Landsat 7/8/9	NASA/USGS	30 m (multispectral)	16 days	NDVI, surface reflectance
MODIS	NASA	250–1000 m	Daily / 8-day	LST, FPAR, ET, PET, GPP
SMAP	NASA	~9–36 km	2–3 days	Soil moisture (surface)
VIIRS	NOAA/NASA	375–1000 m	Daily	NDVI, VCT, TCI, VHI
CHIRPS	UCSB/FEWS NET	~5 km	Daily	Rainfall estimates

3.1.4 Machine Learning Derived Indexes

Cesarini et al. (2021) explored the potential of machine learning techniques for improving index design, enhanced with satellite data. This study demonstrated that utilising neural network and support vector machine models, as opposed to logistic regression models, resulted in significant improvements in classifying floods and droughts. Hence, machine learning models have the potential to determine which factors are predictive and ideal for use as an index. Biffis and Chavez (2017) leveraged classification and regression trees (CART) models to construct optimal weather indexes for maize cultivation in Mozambique, incorporating both rainfall and excess temperature data. Machine learning techniques allowed for index customisation at the pixel level, effectively modelling local climatic variability through the identification of non-linear patterns and higher-order variable interactions. Blakeley et al. (2020) utilised classification tree models to predict low yields below the 20th percentile using precipitation, evapotranspiration, and SPEI variables. Afshar et al. (2021a, b) employed crop simulation models to generate synthetic yield data for training a random forest model that utilised both meteorological and phenological data. The results highlight the significance of crop simulation models and satellite data in creating phenology based indexes for WII. Overall, there are limited studies investigating the potential of machine learning in WII design, possibly due to the large amounts of historical data required to train machine learning models.

Various weather perils from excessive rainfall to drought conditions have a substantial impact on crop yield. These multifaceted weather perils cannot be adequately represented by a single weather index. A potential area of future research is to utilise machine learning algorithms to create a multi-index that combines meteorological variables. Machine learning algorithms are particularly effective in optimal feature selection and dimensionality reduction, allowing for the identification of variables which closely predict the multi-index. Methods such as principal component analysis (PCA) can also be employed to reduce dimensionality (Chaparro et al. 2024). Machine learning models can also facilitate the development of weather indexes tailored to localised weather patterns of different regions (Wijesena and Pradhan 2024).

Table 6 Yield index models for WII studies

Crop yield - index model	Count of studies
Regression model	16
Correlation	14
Quantile regression	8
Generalised additive model	3
Geographically weighted regression	2
Copulas	2
Total	45

3.2 Yield– Index Modelling

In designing a WII product, it is critical to quantitatively assess the relationship between the crop yield and the weather index to ensure that triggered payouts align with crop yield losses (Poudel et al. 2016). A quarter of the studies analysed in the review developed a WII product without explicitly considering this relationship. Regression models were commonly used for yield index modelling, as shown in Table 6 (Baskot and Stanic 2020; Mazviona 2022; Sun et al. 2018; Turvey et al. 2006; Wu et al. 2021;). Linear regression models often provide a simplified explanation of the crop-yield relationship (Lu 2021). Some studies, such as Li et al. (2021), tested a variety of models including linear, logarithmic, inverse, quadratic, cubic, power, and exponential, selecting the model with the highest coefficient of determination. Geographically weighted regression models have also been used in WII studies, where coefficients vary by location (Kusuma et al. 2018; Miquelluti et al. 2022). Other studies in the literature have acknowledged that this relationship may be non-linear (Biffis and Chavez 2017). Kath et al. (2019) employed a generalised additive model (GAM) to demonstrate the non-linear relationship between rainfall index and wheat yield in Australia. Alternatively, a few studies such as Lu (2021), involved local agricultural experts in determining an appropriate index for rice yield.

Farmers are typically more concerned with downside risk, which would potentially impact the continuation of the farm (Conradt et al. 2015). Quantile regression has been identified as superior to linear regression in crop yield-index modelling as it can be tailored to lower quantiles and is robust to outliers (Conradt et al. 2015; Dalhaus and Finger 2016). Quantile regression has become increasingly prevalent in contemporary studies (Conradt et al. 2015; Dalhaus and Finger 2016; Dalhaus et al. 2018; Leppert et al. 2021; Mollmann et al. 2019; Vroege et al. 2021). Copulas are another sophisticated method employed to quantify tail dependence for extreme events. Xiao and Yao (2019) used copulas to model the tail dependence between corn yield and cumulative precipitation. Their study tested three copulas (Frank, Clayton and Gumbel copula) and selected the copula with the highest p-value. Schmidt et al. (2022) investigated the potential of machine learning to estimate the complex and nonlinear relationship between crop yield and weather variables by applying artificial neural networks to wheat and rapeseed yield data in Germany. Significant improvement in accuracy was achieved compared to the benchmark nonlinear regression model, which utilised soil moisture, precipitation, and temperature.

Although complex yield-index models may provide superior goodness of fit, they require significant historical data. Historical crop yield data may not be reliable due to changes in farming practices, fertilisers and irrigation (Chen et al. 2017), as well as technological advancements (Kusuma et al. 2018). As a result, about 50% of studies specifically mentioned applying yield detrending to the data. However, even with appropriate detrending, reliable crop data would still be limited to 30 to 40 annual observations per region (Vedenov and Barnett 2004).

4 Basis Risk

WII is susceptible to basis risk, which occurs when there is a mismatch between WII payouts and actual crop yield losses (Chen et al. 2017). Various studies have attempted to quantify basis risk in the literature. Ultimately, reducing basis risk will ensure that WII is an effective risk management tool enabling greater demand for both farmers and the insurance industry. The three components of basis risk are summarised in Table 7.

The following sections discuss current developments in basis risk analysis in the literature.

4.1 Spatial Basis Risk

Spatial basis risk arises due to the differences in index values and the actual location of crops. Studies have observed that weather data should be measured within 20 km to 30 km from a farm to reduce basis risk (Chen et al. 2017). Furthermore, spatial basis risk can be reduced if WII is targeted against catastrophic events, which typically exhibit a stronger spatial correlation (Bokusheva 2018). Interpolating indexes is a common methodology in the literature to reduce spatial basis risk. A few studies in this literature review investigated the potential of interpolated indexes, primarily in developing countries where there is likely to be a low density of weather stations.

Leblois et al. (2014b) utilised the inverse distance weighting interpolation technique for weather station data in Cameroon, while Taib and Darus (2019) investigated the universal kriging method to interpolate the CDD index from five weather stations in Malaysia. Chen et al. (2017) utilised interpolation to derive indices in China, but only for regions beyond a 25 km radius. A study by Leppert et al. (2021) compared interpolated CDD indexes using three interpolation methods: inverse-distance weighting, regression kriging and ordinary kriging. The regression kriging method was most effective at reducing spatial basis risk with a risk reduction of 2–3% compared to the closest weather station index. As expected, spatial basis risk was reduced as the distance between the county and the nearest weather station increased. A study by Boyd et al. (2019) assessed the performance of seven interpolation techniques (regression, nearest neighbour, inverse distance weighting, regression based inverse distance weighting, regression kriging, ordinary kriging, and spatiotemporal regression kriging) for forage crop yield in Ontario, Canada. Boyd et al. (2019) recommended that while governments or insurance companies may invest in additional weather stations to improve spatial basis risk, an alternative may be to enhance existing data with satellite-based data.

Additionally, remote sensing data, which offers granular, high-resolution data that is closer to the actual site of crops than weather station data, can be used to address spatial basis risk. The potential of remote sensing data to enhance WII design has been discussed in multiple studies (Blakeley et al. 2020; Cesarini et al. 2021) Furthermore as described in Sect. 3.1.4, machine learning models offer the ability to integrate a vast volume of remote sensing data, facilitating the development of predictive multi-weather indexes. These indexes can capture localised weather patterns and climate variability at a granular regional level, thereby mitigating spatial basis risk. A study by Wijesena and Pradhan (2024) utilised a neural network model to develop a multi-weather index using a combination of remote sensing index, including NDVI, EVI, EVI, LST and VHI. This composite index captured the interrelated nature of weather perils impacting crop yield including water storage capacity, sunlight, photosynthesis, drought and temperature variation, which would not have been possible with a single index. In addition due

Table 7 Categories of basis risk type

Basis Risk Type	Definition	Studies
Spatial basis risk	Basis risk due to discrepancies in the index value measured at the weather station compared to the policyholder's actual location	(Chen et al. 2017) (Leppert et al. 2021) (Taib and Darus 2019)
Design basis risk	Basis risk due to design of the WII product e.g. choice of index selected	(Bokusheva 2018) (Conradt et al. 2015) (Poudel et al. 2016)
Temporal basis risk	Basis risk due to misalignment in the timeframe of WII contract dates and crop growing season	(Conradt et al. 2015) (Dalhaus and Finger 2016) (Kapphan et al. 2012)

to the granular nature of remote sensing data the weather index captured nuanced localised weather patterns, hence reducing spatial basis risk.

4.2 Design Basis Risk

Design basis risk can result from selecting an index that inadequately predicts crop yield losses. Examining the relationship between crop yield and weather variables has been identified as a critical step in WII design. If the correlation between the weather index and crop yield is weak, then WII may not accurately reflect the farmer's risk profile (Poudel et al. 2016). A study by Leblois et al. (2014a) quantified basis risk as the difference in percentage of utility gain from WII contract compared to an area yield index insurance (AYII) contract. In AYII, the indemnity is based on the yield in a specified area (e.g. district), and the payout is triggered if the actual yield is below the insured yield in the area, regardless of the actual farmer's yield (Xiao and Yao 2019). Xiao and Yao (2019) proposed three variations of "double trigger" insurance products to reduce basis risk. These hybrid products combine indemnity payouts from both a WII contract and an AYII contract. Overall, there have been few WII studies that have considered innovative modifications to WII product design, to reduce design basis risk.

Some studies in the literature have reported a weak correlation between crop yield and the selected weather index (Masiza et al. 2022). Masiza et al. (2021) used partial dependence plots from a random forest model to determine that, in addition to surface moisture, precipitation, and GDDs, non-weather variables such as seed variety, fertiliser, and machinery ownership also significantly impacted crop yield. Hence, this study recommended exploring methods to incorporate non-weather factors into index insurance design.

4.3 Temporal Basis Risk

Generally, WII contracts have fixed calendar periods during which the index is measured. Temporal basis risk occurs because the insurance contract period does not align with the actual growing season when crops are most sensitive to extreme weather (Dalhaus et al. 2018). Temporal basis risk refers to the misalignment between WII payout and actual crop yield losses, arising from discrepancies between the timing of actual weather events and the coverage period specified in WII contract. For instance, if a weather event that significantly damages crops occurs after the contract end dates then a corresponding payout will not be triggered, hence undermining the fairness of insurance coverage and exposing policyholders to unmitigated risk. Since actual crop sowing dates may be difficult for the insurer to verify, the literature has often discussed that incorporating crop phenology data would be a cost-effective and comprehensive tool to reduce temporal basis risk (Kath et al. 2019). However, only a few studies have explicitly incorporated crop phenology information into WII design to determine optimal contract dates (Bucheli et al. 2021; Conradt et al. 2015; Dalhaus and Finger 2016; Kapphan et al. 2012; Tappi et al. 2022).

A study by Kapphan et al. (2012) used growing degree days (GDD) to model the occurrence dates of four phenology phases for maize crop production: emergence, vegetative period, grain filling, and maturity. Conradt et al. (2015) leveraged GDD to determine annual variable insurance contract dates for wheat in Kazakhstan. The study concluded that flexible contract dates led to a reduction in farmers' downside risk exposure. Similarly, Dalhaus and Finger (2016) utilised GDD to predict occurrence dates of stem elongation and anthesis phases for wheat, which is particularly sensitive to drought. This study demonstrated that phenological data significantly increased the expected utility. However, phenological patterns can vary widely across regions, requiring detailed regional data and potentially leading to more localised models with limited coverage.

The current literature has mainly considered these basis risks in isolation, failing to adopt a more integrated and holistic approach to basis risk management which considers their interdependencies. There is potential to combine the aforementioned methodologies into a WII product that addresses the multi-faceted nature of basis risk including spatial, design and temporal basis risk. For instance, remote sensing data and phenological data can be combined to develop a multi index which addresses both spatial and temporal risk, while also considering hybrid design features. Synthesising the above methodologies will create a more robust framework and enable a comprehensive WII product.

5 WII Product Design

Ideally, a quantitative approach is required to derive WII parameters (strike, exit and payout function) that optimise the hedging efficiency (Chen et al. 2017). Hohl et al. (2021) recommended several iterations from initial setting of the WII parameters to the final parameter selection to optimise affordability and risk reduction for end beneficiaries.

5.1 WII Strike and Exit Thresholds

The setting of strike and exit thresholds is a critical consideration in WII design. Table 8 summarises the methodologies used to set strike and exit thresholds in the literature.

Table 8 Methodologies for strike threshold setting in the literature

Strike setting methodology	Count of Studies
Index percentile	12
Yield-index regression	8
Historical average index value	7
Predefined definition (e.g. critical temperature that impacts crops)	5
Algorithmic optimisation	4
Cluster analysis	3
Index standard deviation	2
Set to offset production costs	1
Other	3
Total	45

The simplest method of setting the strike threshold is to equate it to the historical average index (Erec and Musshoff 2011; Erec et al. 2012). A more refined method is to set the strike level as the average of the crop yield (Chen et al. 2017; Dalhaus et al. 2018; Leppert et al. 2021; Miquelluti et al. 2022). This is calculated by inputting the average yield into a yield-index regression function, which predicts the corresponding index. This methodology is widely used in the literature and is superior to using historical index data, since strike threshold is derived from the insured variable (Mollmann et al. 2019).

Ideally, a WII product should be targeted against catastrophic events rather than average losses, to improve both demand and affordability and decrease spatial basis risk (Bokusheva 2018). Consequently, many studies have set the strike level to be one to two standard deviations below the average index (Hohl et al. 2021; Shibabaw et al. 2023). An alternative method is to set the strike value to a percentile, such as the 70th percentile of crop yield, to tailor WII to extreme weather events (Conradt et al. 2015). This was the most common methodology adopted in the literature (Azka et al. 2021; Doms et al. 2018; Lu 2021; Weber et al. 2015).

Algorithmic optimisation is a sophisticated method for parameter setting in WII that is designed to maximise efficiency. This methodology selects the optimal strike, exit, and payout value that optimises hedging efficiency, and has been utilised in multiple WII studies (Leblois et al. 2014a; Poudel et al. 2016; Xiao and Yao 2019). While this method optimises the WII contract, it can be argued that it is less transparent than previously discussed methods. Furthermore, algorithmic optimisation can lead to overfitting. Weather data is inherently unpredictable and often suffers from the presence of outliers. Overfitting occurs when the optimisation algorithm captures random noise in the training data, rather than the underlying weather patterns. Overfitting is especially pronounced when the optimisation algorithm is too complex and becomes too closely fitted to the training data. Cross-validation ensures that the parameters are not influenced by outliers and can robustly adapt to diverse regions with different climate conditions (Leblois et al. 2014a).

A study by Choudhury et al. (2016) applied an innovative technique of determining optimal strike and exit values through cluster modelling of index and crop yield, a method also used in other studies such as Eze et al. (2020) and Kusuma et al. (2018). Cluster analysis aims to maximise the similarity of observations within each cluster while maximising the differences between clusters. Ideally, weather variables reflecting drought conditions should be grouped with low crop yield, and conversely, the same for high crop yield. The average values in the cluster reflect the strike and exit thresholds.

Interestingly, a study by Roberto Valverde-Arias et al. (2020) developed two intuitive thresholds based on NDVI index: an economic threshold relating to the minimum yield to break even and cover production costs, as well as a physiological threshold related to extreme weather events where total investment cannot be recovered. Additionally, two economic thresholds were further determined for rainfed and irrigated crops separately, as they have different production costs.

5.2 WII Payout Structure

A proportion of studies did not justify the selection of the payout value or payout structure, although it is a fundamental component of WII design. Alternatively, most studies employed a simplifying assumption to only consider a unit payout and calculated a single pure premium rate (Mazviona 2022; Miquelluti et al. 2022; Poudel et al. 2016). Azka et al. (2021) selected an appropriate payout for their proposed WII product for rubber plantations by interviewing rubber farmers. A study by Hohl et al. (2021) defined the payout as the total estimated yield multiplied by production costs. However, the authors proposed that payout can also be calculated by multiplying the average projected yield and commodity prices. A study by Lu (2021) for rice yield WII in China also utilised the market price of rice to propose a suitable payout. Another common technique is setting the payout as the value that maximises the hedging effectiveness of the WII contract (Doms et al. 2018; Mollmann et al. 2019; Xiao and Yao 2019).

Various payout structures are discussed in the literature, however most commonly, a linear payout structure was adopted where payout is linearly proportional to the intensity of the index between strike and exit thresholds (Chen et al. 2017; Hohl et al. 2021; Leppert et al. 2021). Alternatively, Azka et al. (2021) proposed a payout of 50% when the index was between the strike and exit threshold, and 100% when the index exceeded the exit threshold. A less common payout structure is a lump sum payment triggered when the index reaches the strike value (Darus and Taib 2019). Overall, the payout structure of WII products have not been widely studied in the literature.

6 WII Premium Rating

Table 9 provides a summary of various pricing methodologies for WII in the literature. Among the limited studies investigating premium rating, historical burn rate analysis or index simulation was often implemented. Only a few studies have explored time series models that incorporate seasonal dynamics.

6.1 Historical Burn Analysis

Historical burn analysis has been identified in this literature review as the most common pricing methodology to determine the premium for WII studies, as depicted in Table 9. This pricing methodology has gained significant traction in the literature due to its simplicity and independence from a parametric distribution (Clarke et al. 2012a, b; Taib and Benth 2012; Shah 2016; Miquelluti et al. 2022). This methodology involves calculating historical weather data for at least 30 years for a given location (Darus and Taib 2019). Historical payouts are derived by applying the WII trigger conditions to past weather patterns, identifying occurrences where weather conditions would have triggered a payout. The price of WII product is determined as the average payout generated from historical triggers and is the equivalent of the expected loss over time. Although this method is simple to implement, it has several shortcomings, such as requiring long and consistent weather data, and catastrophic losses may be under or over-represented due to the limited historical observations (Hohl et al. 2021). The robustness of results is also undermined by completeness of data and outliers in weather time series data. This method also assumes that there are no trends in the data and the assumption that the historical loss rate is an appropriate estimator for the future loss rate (Wu et al. 2021). This assumption is increasingly questionable with evidence of unpredictable impacts of climate change (Mortensen and Block 2018).

6.2 Index Simulation

Fitting a probability distribution is another common pricing methodology, as illustrated in Table 9. Parametric distributions, including the gamma, beta, lognormal, and weibull distributions, have been tested in the literature (Hao et al. 2005). Overall, gamma distribution was commonly applied to index data by numerous studies due to its skewed long

Table 9 Summary of WII pricing methodologies

Pricing methodology	Description	Count of studies	Examples of studies
Historical burn rate analysis	Average expected payout from WII realisations on historical index data	22	(Chen et al. 2017) (Clarke et al. 2012a, b) (Dalhaus et al. 2018) (Erec et al. 2012) (Hohl et al. 2021) (Miquelluti et al. 2022) (Shah 2016) (Taib and Benth 2012) (Wu et al. 2021)
Index simulation	Historical index data is fitted to a parametric distribution (e.g. gamma distribution). The index value is simulated using the estimated parametric distribution. The premium is the mean of expected payouts from the simulated index data	14	(Hao et al. 2005) (Husak et al. 2007) (Kath et al. 2019) (Li et al. 2021) (Lu 2021) (Martin et al. 2001) (Poudel et al. 2016)
Time-series models	An autoregressive time series model with seasonality is fitted to daily or weekly index data over a long historical period to capture time dynamics	4	(Darus and Taib 2019) (Shibabaw et al. 2023)
Black Scholes	WII products can be modelled as put options and Black Scholes option pricing formula can be applied to the pricing of WII	3	(Azka et al. 2021) (Baskot and Stanic 2020) (Mazviona 2022)
Copulas	The tail dependence between weather index and crop yield during extreme weather events is modelled using copulas	3	(Bokusheva 2018) (Hidayat and Gunardi 2019) (Kölle et al. 2021)
Other		7	

tail, which is suited to crop yield losses from extreme weather events (Kath et al. 2019; Li et al. 2021; Martin et al. 2001; Poudel et al. 2016). Martin et al. (2001) and Poudel et al. (2016) both fitted a gamma distribution to rainfall data, where maximum likelihood estimation (MLE) was used to estimate parameters. Tests such as chi-square, Anderson-Darling and Kolmogorov-Smirnov test were used to determine the best fitting distribution to empirical data (Erec and Musshoff 2011). Index values were simulated from the estimated distribution to calculate the premium, and for each simulation, the expected payouts were calculated. The fair premium is calculated as the expected payout (Mollmann et al. 2019).

6.3 Black-Scholes Option Pricing

Various studies have applied the Black-Scholes formula to determine the premium of WII (Filiapuspa et al. 2019; Jewson and Zervous 2003; Okine 2014). The Black-Scholes method was traditionally used to price European put options (Black and Scholes 1973). A European put option will trigger the payoff if the share price is less than or equal to the strike threshold at a certain time. Hence, the payout structure of a WII product can be realised as a put option, and thus the Black-Scholes option pricing can be applied to estimate WII premiums. Jewson and Zervous (2003) demonstrated how the Black and Scholes (1973) partial differential equations can be applied to pricing of weather options. Moreover, Okine (2014) applied this methodology to calculate premiums for rainfall index insurance in Ghana. Okine showed that rainfall data distribution approximately followed a lognormal distribution, validating the application of the Black Scholes method. The study also demonstrated the impact of various index triggers on the price of WII premium. A similar study was performed by Filiapuspa et al. (2019) which was applied to rainfall index insurance for rice yield in Banten province, Indonesia. However, the Black-Scholes model requires restrictive assumptions such as assuming the underlying weather index data follows a lognormal distribution, which may not be accurate for all geographic regions (Mazviona 2022; Okine 2014). Alternatively, more suitable methods for pricing WII have evolved in the literature.

6.4 Time-series Models

More sophisticated methods for pricing WII have evolved in the literature, such as autoregressive time-series models which can capture seasonality yet require data over a long historical period. To select the appropriate time series model to use, studies have used the Mann-Kendall trend test to determine if there is a trend component in data and a partial autocorrelation function plot to check if the data is cyclical (Shibabaw et al. 2023). For example, Benth et al. (2007) proposed a seasonal continuous-time autoregressive process to model temperature using 40 years of daily observations in Sweeden. Wanishsakpong and Owusu (2020) successfully fitted auto-regressive integrated moving-average (ARIMA) and the auto-regressive integrated moving average with exogenous variables (ARIMAX) models to predict temperature in Thailand. In addition, there are few comparative studies that have compared the premium from time series models to traditional pricing methods. A study by Darus and Taib (2019) demonstrated that although the continuous-time autoregressive model had a higher WII premium than both historical burn rate analysis and exponential index simulation, it also had a greater probability of getting money back for farmers.

6.5 Copula Models

There have been limited studies exploring copula based WII design. Shah (2016) priced rainfall index insurance in Andhra Pradesh region in India using t copulas, which have a thick tail distribution. The study produced similar results to historical burn analysis. The study concluded that copulas would be better suited to regions with extreme rainfall, since historical burn rate analysis may be unreliable due to scarce data. A similar comparative study was performed by Hidayat and Gunardi (2019) who simulated a thousand data points for price, yield and rainfall index based on both the fitted lognormal probability distribution, as well as the Frank and Joe copula. A study by Bokusheva (2018) utilised three types of Archimedean copulas for grain farms located in Kazakhstan. This study discussed that complex pricing methodologies such as copulas which require many observations in the tail of the distribution are limited by the seasonality of agricultural data which typically has only one or two annual observations of crop yield. Kölle et al. (2021) discovered that the Gumbel copula which has a strong dependence structure in the left tail of joint distribution was better able to capture the strong relationship between extreme weather and olive oil yield, in comparison to the Gaussian copula. Table 10 provides a summary of the advantages and disadvantages of pricing methodologies.

7 WII Hedging Efficiency

Testing the hedging efficiency of a WII contract is essential to evaluate the risk-reducing capabilities. Almost 50% of studies from this review did not consider the hedging efficiency of their proposed pricing frameworks. Table 11 summarises the hedging efficiency measures applied in the studies that did consider hedging efficiency. Furthermore,

Table 10 Advantages and disadvantages of WII pricing methodologies

Pricing methodology	Disadvantages	Advantages
Historical burn rate analysis	Extensive historical data is required Historical data may be unreliable Trends are not considered Historical data may not cover catastrophic losses	Simple to calculate and easy to understand Minimal modelling assumptions Easy to implement
Fitted probability distribution	Sensitive to distributional assumptions Trends are not considered Dependent on the quality of historical data	Confidence interval of the mean can be determined Span of the confidence interval can be used to quantify the risk loading required Index values outside the range of observed data can be predicted (e.g. catastrophic events)
Black Scholes	Confined to unrealistic assumptions e.g. assumes index data follows lognormal distribution	Simple to calculate Closed-form solution is useful as a theoretical benchmark
Time Series models	Daily or weekly data required Complexity increases with nonlinearity	Model considers the trends and seasonal effects Obtains probabilistic information on index
Copulas	Fewer benchmark studies are available Computationally intensive and requires significant historical data Complex to explain to stakeholders	Ideal for modelling extreme weather conditions Captures nonlinear and tail dependence

Table 11 Metrics to evaluate hedging efficiency in WII products

Hedging efficiency methods	Count of studies
Certainty equivalent income	9
Semi variance	9
Expected utility	7
Mean root square loss	6
Expected shortfall	5
Standard deviation	4
Value at risk	3
Spectral risk measures	2
Claims ratio	2
Coefficient of variation	1
Conditional tail expectation	1
Quantile risk premium	1
Relative volatility	1
Other	4
Total	55

these studies often compared multiple hedging efficiency methods. When performing these hedging efficiency tests, it is essential to test on out of sample (holdout) data to avoid overfitting of fitted parameters and overestimating the risk reduction (Leblois et al. 2014a). Few studies specifically mentioned that hedging efficiency tests were performed on out-of-sample data. Overfitting is when a model fits too closely to noise in the training data rather than underlying weather patterns. Certain studies may misleadingly show exceptional hedging efficiency performance on training data. However on unseen test data, the performance of hedging efficiency is likely to be suboptimal, making direct comparisons across different studies in the literature misleading. Testing hedging efficiency on out-of-sample data is a crucial step to ensure that the model generalises well and ensures the robustness of predictions.

The following section explains various methodologies utilised in the literature to evaluate WII risk reduction.

7.1 Standard Deviation and Semi Deviation

Standard deviation is a simple method to understand risk measures used in WII studies. Studies that used standard deviation often considered other sophisticated risk measures as well (Erec and Musshoff 2011; Erec et al. 2012; Kusuma et al. 2018). However, standard deviation is a realistic risk measure only if losses follow a normal distribution. In reality, crop yield losses will adhere to an asymmetric distribution and farmers are likely to be risk averse. Measures such as semi variance are superior to standard deviation, as they consider only downside risk. This measure has been frequently applied in WII studies (Miquelluti et al. 2022; Sun 2022a, b; Sun et al. 2018).

7.2 Utility Functions

Utility functions have also been used in WII to evaluate performance. The choice of utility function should be carefully selected to derive sensible results. WII studies generally investigated the expected utility using either the exponential function (Conradt et al. 2015), or the power utility function (Xiao and Yao 2019). The power utility function represents constant relative risk aversion (CRRA), while the exponential function represents constant absolute risk aversion (CARA). Some studies used fieldwork to calibrate the risk aversion parameters to the specific study region (Leblois et al. 2014a), while other studies relied on the literature to determine sensible parameter values. Additionally, most studies input a range of coefficients of risk aversion into these functions to test various scenarios from risk-neutral to very risk-averse (Dalhaus et al. 2018; Dalhaus and Finger 2016).

7.3 Certainty Equivalent

Another method of testing hedging efficiency is to employ a utility function to calculate the certainty equivalent (CE). Certainty equivalent is defined as the guaranteed return that a farmer would accept, rather than taking a gamble at a higher, but uncertain return.

The certainty equivalent function is defined in Eq. 1 (Vinel and Krokhmal 2017):

$$\boldsymbol{CE} = \boldsymbol{U}^{-1}\left(\mathbb{E}\left[\boldsymbol{U}\left(\boldsymbol{X}\right)\right]\right) \tag{1}$$

In Eq. 1, CE represents the certainty equivalent of an uncertain loss X and U is the utility function. A rational investor should be indifferent between accepting CE value or the uncertain X (Vinel and Krokhmal 2017).

This was the most common method applied in the literature review (Leblois et al. 2014a; Martin et al. 2001; Vedenov and Barnett 2004; Xiao and Yao 2019). The CE measure is again highly dependent on the choice of a sensible utility function. A study by Leblois et al. (2014a) calculated CE using two utility functions, the exponential function and the power utility function.

7.4 Value at Risk and Expected Shortfall

In financial economics, Value at Risk (VaR) is used to measure the maximum expected loss with a specified probability level. It has also been used in WII to calculate hedging efficiency (Erec et al. 2012; Vedenov and Barnett 2004). For example, a study by Erec et al. (2012) calculated hedging efficiency using a 90% confidence level for VaR.

VaR at a confidence level of α% is defined in Eq. 2 (Jorion 1996):

$$\boldsymbol{P_r}(\boldsymbol{R} < \boldsymbol{VaR_\alpha}) = \boldsymbol{\alpha} \tag{2}$$

where, R is the density function of wealth.

However WII studies have argued that VaR can be misleading since it does not capture the distribution of the loss in the tail. Two portfolios can have the same VaR but very different extreme losses.

7.5 Expected Shortfall

Expected shortfall (ES) overcomes the shortcomings of VaR. ES is the conditional expectation of loss given that the loss is beyond the VaR threshold.

ES at a confidence level of α% is defined in Eq. 3 (Acerbi 2002):

$$\boldsymbol{ES_\alpha} = \mathbb{E}\left[\boldsymbol{R}\middle|\,\boldsymbol{R} < \boldsymbol{VaR_\alpha}\right] \tag{3}$$

where, R is again the density function of wealth.

Several WII studies have used ES (Bokusheva 2018; Conradt et al. 2015; Mollmann et al. 2019) in calculating hedging efficiency.

7.6 Spectral Risk

Both VaR and ES do not consider the degree of risk aversion of the farmer. VaR only provides a point estimate while ES assumes farmers are risk neutral because losses that exceed the VaR threshold are equally weighted (Miquelluti et al. 2022). Hence, Acerbi (2002) proposed the use of spectral risk measures to overcome these limitations. Spectral risk is defined in Eq. 4 (Acerbi 2002):

$$\boldsymbol{M_\theta} = \int_0^1 \boldsymbol{\theta}\ (\boldsymbol{w})\,.\boldsymbol{q_w}\boldsymbol{dw} \tag{4}$$

where, q_w is the quantile function for wealth and $\theta(w)$ is the weighting function which captures the risk aversion of farmers.

For example, if the weights follow an exponential function, then larger weights are applied for higher levels of the cumulative probability distribution which represent extreme losses. In addition, the exponential parameters can be adjusted according to the degree of risk aversion of farmers. Farmers with higher risk aversion will have weights that increase more rapidly as losses increase. Although the spectral risk measure is superior, this literature review has only identified two studies where this risk measure has been utilised (Conradt et al. 2015; Miquelluti et al. 2022).

8 Machine Learning Applications in WII Product Design

Various machine learning algorithms have been applied in WII design including; random forests, support vector machines (SVM), artificial neural networks (ANN), and XGBoost. The performance of these algorithms vary depending on data structure, data heterogeneity, outliers, temporal and spatial resolution (Agarwal and Tarar 2021;

Table 12 Comparison of selected machine learning algorithms for WII product design

Algorithm	Strengths	Limitations	Data requirements	Interpret-ability
Gradient Boosting Machine (GBM)	Interpretability via SHAP/feature gain Simple due to fewer hyperparameters Customisable loss functions	Sensitive to overfitting in noisy weather datasets	Moderate	Moderate
XGBoost	Accurate and efficient Interpretability via SHAP/feature gain Handles imbalanced classification problems e.g. predict extreme crop yield failure	Sensitive to overfitting in noisy weather datasets Less transparent	Moderate	Moderate
Artificial Neural Network (ANN)	Effective for modelling complex non-linear relationships between weather and crop yield Scalability with large weather datasets Effective for high-dimensional weather datasets	Very sensitive to overfitting in noisy weather datasets Require hyper parameter tuning to mitigate overfitting Computationally intensive	High	Low
Support Vector Machine (SVM)	Effective for high-dimensional weather datasets Suited for binary classification	Poor scalability for large granular datasets Sensitive to hyperparameters	Low–Moderate	High
Random Forest (RF)	Robust to overfitting in noisy weather data Ability to handle missing data (common in weather station data) Generally lower performance compared to other algorithms	Challenging to model temporal dependencies	Moderate	Moderate

Table 13 Summary of WII studies with machine learning applications

WII Design	Description	Studies
Reducing Basis Risk	Reduction of basis risk in WII design utilising machine learning algorithms.	Schmidt et al. (2022) Chen et al. (2024)
Index Development	Determine which factors are most predictive to use as an index utilising machine learning models.	Cesarini et al. (2021) Biffis and Chavez (2017) Blakeley et al. (2020)
Insurance Payout	Optimal functional form of insurance payout using machine learning.	Chen et al. (2024)
Climate Change	Utilisation of machine learning models to design WII as an adaption strategy for climate change.	Zhang et al. (2022)
Plant Phenology	Determine plant phenological growth stages, as well as improve predictive capabilities of machine learning models utilising phenological data.	Zou et al. (2024) Afshar et al. (2021a, b)
Spatial Downscaling	Generate reliable high resolution climate data with large geospatial coverage using machine learning.	Eltazarov et al. (2023)
Interpretable Index	Development of a transparent and interpretable WII index using machine learning.	Wijesena and Pradhan (2024)

Osisanwo et al. 2017; Nitze et al. 2012). Crop yield is dependent on the complex non-linear relationships between weather variables such as temperature, precipitation, soil conditions and agronomic management practises (Debnath 2024; Sidhu et al. 2023; Bali and Singla 2022). Advanced machine learning algorithms such as gradient boosting machine models can effectively capture these interactions in crop modelling (Anakal et al. 2025; Leo et al. 2021). It was found that XGBoost was able to further enhance the predictive capabilities of gradient boosting machine model with greater efficiency and optimisation, though this requires larger weather datasets to observe a material improvement (Li et al. 2023; Gnanavel and Nandhini 2022; Shahhosseini et al. 2021). On the other hand, random forests have been noted to be robust to noisy weather data and perform well where there is large variation in weather and soil conditions, which is often the case due to limited historical data (Sheth et al. 2022). The gradient boosting machine, XGBoost and random forest also provide interpretability which is useful for drawing insights for WII product design (Gupta et al. 2022). ANN is suitable for modelling highly complex time series and high resolution remote sensing data with non-linear relationships (Osisanwo et al. 2017). A comparative summary of selected machine learning algorithms in WII product design is presented in Table 12.

Limited studies have investigated the potential of machine learning in WII design. A summary of the WII studies with machine learning applications in the literature is summarised in Table 13. Existing research has investigated the potential of machine learning in a variety of domains; from index development, payout structure optimisation, integration of phenological data, and climate change. The development of predictive weather indices is the most common application of machine learning models (Cesarini et al. 2021; Blakeley et al. 2020; Biffis and Chavez 2017), whereas the application of machine learning to optimise other WII contract parameters and premium rating remains a prospective area for future research.

Machine learning algorithms require large datasets to train effectively. Insufficient records may lead to overfitting, where the model captures random noise rather than the true underlying weather patterns, which is especially common for more complex machine learning models such as neural networks. This weakens generalisation when the model is applied to different weather seasons and regions. If the relationship between weather and yield is poorly predicted, it can lead to basis risk, impacting the farmer's confidence in WII. These challenges can be overcome by adopting interpolation and satellite derived data as discussed previously. In addition, data augmentation and crop simulation modelling are other strategies, however have not been widely explored in the literature. A study by Afshar et al. (2021a, b) utilised a crop simulation model to overcome data scarcity by generating a database of synthetic rice yield data for Odisha, India. A robust WII product can be developed, as the APSIM (Agricultural Production System sIMulator) crop model enables the generation of rice yields across diverse weather conditions and management practices. Similarly, a study by Wijesena and Pradhan (2025) also utilised data augmentation to generate 10 random neighbourhood values for crop yield, increasing coverage of the domain space elevenfold, and enabling the development of a more robust WII product.

9 Adapting WII To Diverse Agricultural Systems

It is evident from Fig. 5 that there is a disproportionate number of WII studies based in China, Germany and United States. This regional clustering is likely attributed to the prevalence of high resolution weather and crop yield data and institutional support for research data. The remaining studies are widely distributed across diverse regions such as Sub-Saharan Africa, South America and Southeast Asia. There are fewer studies in these regions due to data constraints and limited agricultural research funding. The diverse agroecological conditions in these regions introduce heterogeneity, highlighting the need for caution when generalising findings from the literature to smallholder farmer contexts. Similarly Fig. 4 highlights the focus of WII studies on cereal grains such as wheat, corn and rice, reflecting their global economic importance. Hence this underscores the necessity for localised WII contracts with WII parameters calibrated to the variability in weather patterns, terrain, and agricultural practices of underrepresented regions and crops (Poudel et al. 2016; Vedenov and Barnett 2004). The following section explains how WII design and pricing could be tailored to different regions and agricultural systems, to enable optimisation of risk mitigation to agricultural communities.

9.1 Developing Countries

Remote sensing data has vast potential for developing countries which lack a network of reliable weather station infrastructure, particularly Sub-Saharan African nations which face challenges in data collection due to inadequate infrastructure and political instability (Black et al. 2016; Enenkel et al. 2018; Masiza et al. 2022; Tadesse et al. 2015). These countries may not have reliable long term historical crop yield and meteorological data, and should hence rely on simpler methods for premium modelling such as historical burn analysis or index simulation. Leveraging more sophisticated methodologies such as machine learning may lead to overfitting due to limited data points.

In addition, metrics which evaluate hedging efficiency should be adapted to the socioeconomic circumstances of the agricultural community in the study region. For example famers in developing countries would have a higher level of risk aversion, in comparison to farmers in developed countries due to limited liquid assets and savings available to absorb catastrophic crop yield losses. Therefore, in order to capture the vulnerabilities of these agricultural communities, metrics such as spectral risk measure should have parameters calibrated to reflect high risk aversion.

9.2 Temporal Variation

Premium rating methodologies can be tailored to the study region. Since historical burn analysis and index simulation employ a long-term historical average and do not dynamically adjust to present weather patterns, they are not appropriate for application in regions with significant temporal changes in weather. Time series modelling or machine learning techniques that can dynamically calibrate to recent weather patterns is more suitable for these regions. This is applicable to countries such as the United States which have diverse weather patterns, where the Mid-West experiences distinct seasonal changes, while West coast has milder weather conditions (Wang et al. 2016). Similar certain countries such as India (Singh and Agrawal 2020) and China (Xu et al. 2013) experience a Monsoon season which causes temporal variation between dry and wet conditions.

Similarly, countries which are expansive in size, are also susceptible to diverse weather conditions such as Australia which is impacted by El Nino and La Nina climate phenomena, with distinct weather conditions in south and north (Kath et al. 2019).

Several crops also exhibit variability in sowing and harvest dates year on year. For instance, rice crop has significant variability in sowing and harvesting dates due to variability in rainfall in Southeast Asia (Afshar et al. 2021a, b; Ward and Makhija 2018). Similarly corn and soybean is also impacted by weather patterns in precipitation and temperature (Osei et al. 2023; Wijesena and Pradhan 2024). Crops and regions which are susceptible to temporal fluctuation in sowing and harvest date, would particularly benefit from phenological data to reduce temporal basis risk.

9.3 Spatial Variation

Countries with significant spatial variability in climate conditions should design and price WII at a more granular level to account for these localised weather patterns. For instance Australia has significant spatial heterogeneity due to its vast size which spans multiple climate zones and diverse topography (Kath et al. 2019). While the north of the country has more tropical conditions, the middle of the country has more arid conditions and the south has a more pronounced seasonal variation. Consequently, premium setting, weather index development and setting strike and exit thresholds should be implemented at an appropriate regional granularity which have more homogenous climate conditions.

9.4 Catastrophic Weather Events

Lastly the strike and exit thresholds should be adapted to localised weather patterns. In geographical regions is susceptible to low frequency, yet high severity weather events which impact crop yield, then a higher strike threshold is more suitable. For instance certain countries are more susceptible to catastrophic natural disasters such as bushfires in Australia (Wittwer and Waschik 2021), droughts in USA (Lu et al. 2020), cyclones in Bangladesh (Rahaman and Esraz-Ul-Zannat 2021), and typhoons in Philippines (Yuen et al. 2022). A higher strike threshold ensures that WII provides protection from catastrophic events, while maintaining an affordable premium for farmers. Alternatively, regions that are impacted by milder weather events, such as excessive precipitation or flooding, which only have a moderate but recurring impact on crop yields, would be more suited to a lower strike threshold. Strike and exit thresholds should be carefully designed to optimise risk protection according to local weather conditions.

10 Conclusions and Future Research Direction

Despite advancements in WII, several critical research gaps remain. Key challenges include reliance on simplified index structures, limited integration of remote sensing data and multi-peril indexes. Methodological challenges persist in optimising contract parameters, pricing premiums, aligning coverage with crop phenology, and reducing basis risk. Additionally, few studies have explored integrated end to end frameworks for WII product design, pricing and evaluation. Interpretable machine learning methods are also required to address the trade-off between model complexity and the need for transparency in real-world implementation. These research gaps are discussed further in the following section.

1. Remote Sensing Data Based Weather Indexes.
   WII primarily focuses on simple variable rainfall-based indexes, constrained by limited weather station data. There is potential to further expand into drought indexes, which have been extensively used in drought monitoring as they capture long term water deficits rather than short term precipitation trends. Furthermore, remote sensing data offers the benefit of high-resolution and real-time data with broader coverage, offering potential for development of more accurate indexes and scalable WII products.

2. Multi Peril Weather Indexes.
   There is potential to develop more multi-faceted indexes which capture this impact of multiple perils on crop yield, rather than reliance on single variable indexes. One of the greatest challenges in developing a multi-variable index is precisely determining how to combine the various indexes to form a single index. Machine learning offers significant potential to develop a highly accurate index since it naturally handles multidimensional data and captures non-linear relationships.

3. Quantitative WII Contract Parameter Optimisation.
   Few studies have leveraged a quantitative approach for parameter optimisation of contract parameters such as strike, exit, and payout structures. There has been a greater focus on developing accurate weather indexes, while methodologies to optimise contract parameters and minimise basis risk have generally been overlooked.

4. WII Basis Risk: Spatial, Temporal and Design.
   As regional weather indexes cannot perfectly capture localised weather patterns, basis risk is an inherent limitation of WII. Further research is required to decompose

basis risk into spatial, temporal, and design basis risk to better monitor and evaluate the WII product's hedging efficiency. Innovative hybrid product design features should be considered to maximise risk protection for farmers.

5. Phenological Crop Data.
Few studies have investigated the potential of phenological crop data to enhance WII product design, enabling stronger alignment of contract dates with critical crop growing stages. Crops undergo multiple phenological stages, each with different sensitivities to weather perils. Certain phenological growth states may resist particular weather perils, while others may be more susceptible. Phenological data becomes increasingly important with climate change, as it may shift phenological stages and increase susceptibility to extreme weather events. Therefore, phenological data should be considered to better align contract dates to crop growth and reduce temporal basis risk.

6. Advanced Premium Setting Methodologies.
Premium setting is an important consideration for insurer's solvency and profitability, as well as the accessibility of WII. Overpriced products are likely to face poor demand. However, most WII studies rely on historical burn rate or index simulation to calculate premiums rather than exploring more sophisticated pricing models such as time series, copulas, and machine learning. These methods offer the potential to better capture tail risks, dependency structures, and non-linear dynamics, resulting in more accurate and fair premium estimates.

7. Trade-off Between Model Complexity and Transparency.
Future research areas should consider the trade-off between increased model complexity and the transparency of WII product design to end beneficiaries during commercial implementation. Transparency in WII design enables farmers to make informed decisions, understand insurance coverage, and gain confidence that insurers will be committed to delivering their promises during adverse times. By promoting transparency, both the insurer and farmers will benefit mutually. Maintaining transparency is particularly important if machine learning becomes more prevalent in WII design, as machine learning models are often perceived as "black boxes".

8. Integrated WII Framework.
Few studies have proposed an integrated WII framework, encompassing parameter optimisation, premium modelling, and performance evaluation. Many studies tend to focus on one component of this framework, rather than taking a comprehensive end-to-end approach. Developing a framework would support the implementation of coherent and scalable WII products.

As machine learning and remote sensing data continue to advance, these future research areas will enable the development of data driven, robust and transparent WII products. Reliable risk management tools will reduce income volatility associated with extreme weather. This may facilitate greater investment in innovative technology such as fertilisers and irrigation systems to improve agricultural productivity. Consequently, not only will WII enhance the resilience of farming communities, but also improve the productivity of the agricultural industry, leading to improved long term food security and economic stability.

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Declaration

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