Review article: Design and Evaluation of Weather Index Insurance for Multi-Hazard Resilience and Food Insecurity

Marcos Roberto Benso[1], Gabriela Chiquito Gesualdo[1], Roberto Fray Silva[2], Greicelene Jesus Silva[1], Luis Miguel Rápalo[1], Fabrício Alonso Richmond Navarro[1], Patrícia Angelica Alves Marques[3], José Antônio Marengo[4], and Eduardo Mario Mendiondo[1]

University of São Paulo, São Carlos School of Engineering, São Carlos, Brazil

University of São Paulo, Institute of Advanced Studies, São Paulo, Brazil

University of São Paulo, Luiz de Queiroz College of Agriculture

Centro Nacional de Monitoiramento e Alerta aos Desastres Naturais, Coordenacao Geral de Pesquisa e Desenvolvimento

Correspondence: Marcos R Benso (marcosbenso@gmail.com)

Abstract. Weather index insurance has gained growing attention in the literature. Several approaches have been employed to determine indices, model losses and calculate fair premium rates, however, little attention has been given to define generalized approach that analyzes multi-hazard risk for insurance design. Therefore, this paper aims to provide a review of weather index insurance design, thereby including methods for natural hazards' indices calculation, vulnerability assessment and risk pricing. Our primary focus is considering a multi-hazard approach and selecting studies in food security, since is the most researched topic in the weather index insurance literature. We applied the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) using the Scopus database. First, 364 peer-reviewed articles from the year 2010 to the present were screened for a bibliometric analysis and then, the 34 most cited articles from the past five years were systematically analyzed. Our results demonstrate that despite a great research effort on index insurance, the majority of them focused on crop insurance, leaving behind other topics such as forestry, nature conservancy, floods and energy. Also, climate change and basis risks were found highly relevant for weather index insurance, but weakly developed. Special focus was given to droughts, while other hazards such as temperature variation, excessive rainfall and wildfires were poorly covered. Also, current literature lacks methods for incorporating multi-hazard risk evaluation in vulnerability assessment and risk pricing. Most studies considered only single-hazard risk, and the multi-hazard risk studies assumed independence between hazards. Thus, we proposed a study case for a multi-hazard weather insurance index for soybean production in south Brazil highlighting index selection, loss modeling and empirical risk analysis for determining pure risk premiums. Despite the great focus on food security, emerging fields such as hydrological and sustainable energy were found promissory for index insurance and will require further systematization.

1 Introduction

The increased frequency and magnitude of extreme weather and climate events have been evidenced in many regions of the globe, and it has been widely attributed to global warming climate change (IPCC, 2022). In the past years, extreme weather events have caused significant losses and damages in many climate-sensitive sectors affecting urban and rural areas. Insurance is an essential tool to provide economic sustainability to vulnerable sectors and improve recovery from catastrophic climate events. Kraehnert et al. (2021) argue that insurance itself is not an adaptation measure and depends on several characteristics and factors such as living standards, economic well-being, the availability of safety nets for poor people, characteristics of the sector, and the type of the risks the sectors are exposed to (FAO, 2014).

Insurance has been pointed as a tool for safeguarding population and properties to climate change (UNEP, 2012). Re (2021) predicted non-life insurance premiums to rise 10% above the pre-pandemic state and acknowledges that climate change might have an even more significant impact on the insurance industry. They propose that increasing underwriting policies against climate-related disasters is vital to tackle this problem. Nonetheless, the challenge might be more significant in developing countries with lower insurance coverage. In one hand, the premiums per capita (hab) of the US and Canada were 7,270 USD/hab, much higher than the world average of 809 USD/hab and the Eurozone average of 2,723 USD/hab. On the other hand, in Latin America and the Caribbean, and emerging Europe and Asia presented 203, 159 and 215 USD/hab respectively. The numbers were much lower in Africa and the Emerging Middle East, representing 45 and 93 USD/hab (Re, 2020).

Index-based insurance policy is a solution to improve insurance coverage, especially in low-income areas (Raucci et al., 2019). The term index insurance started being used for crop yield insurance policies based on area-yield indices as firstly described by Halcrow (1949) and then further revisited by Miranda (1991). The area-yield insurance model was adopted in the US in the early 90s, dividing agricultural areas in the crop domain into Group Risk Plans (GRP). Indemnities were triggered when forecasted crop yields would fall under a certain threshold whithin each GRP (Skees, 2008).

Area-yield contracts depend on data availability and technical capacity to evaluate and monitor the group risk units, which can be costly and impractical in many poor and developing countries. To overcome this challenge, researchers proposed contracts based on weather indices. In the financial and actuarial literature, weather derivatives have been used to associate the financial frustration of a business with a weather index (Müller and Grandi, 2000). Contracts based on weather indices have helped policyholders to hedge against adverse conditions in the clothing business (Štulec et al., 2019), hydropower plants (Foster et al., 2015), and solar energy systems (Boyle et al., 2021). Crop yield contracts based on rainfall have been used due to their simplicity and data availability (Yoshida et al., 2019). The method uses rainfall from weather stations nearby farms to predict losses, and the threshold is usually defined according to an index in the growing season.

This type of contract almost eliminates the need for in-site verification of losses, reducing administrative costs and improving the transparency of insurance products (Shirsath et al., 2019). Insurance companies also benefit from reducing moral hazards since crop losses are estimated from indices provided by third-party agencies (Ghosh et al., 2021). Moreover, due to reduced costs, contracts based on weather indices have been used for microinsurance contracts in poor rural areas to improve protection against adverse climate conditions and prevent smallholder farmers from falling into poverty traps (Skees, 2008). Despite the advantages, index insurance has a particular side effect called basis risk, which is a mismatch between actual losses and predicted losses (Ghosh et al., 2021).

As is expected from the relevance of agriculture in the insurance industry, most of the literature reviews focus on understanding index insurance and microinsurance for agriculture (Leblois et al., 2014; Sarris, 2013). Zara (2010) proposed a systematic review on the role of weather derivatives in the wine industry. Akter (2012) focused on reviewing problems of microinsurance in Bangladesh, looking for evidence for insurance demand, how to approach the market, and design challenges to improve the safety of the vulnerable population, especially for smallholder farmers.

Several studies have been reported on single hazard risk insurance design. Considering only one hazard does not include the expression of risk due to interactions among different hazards (Gill and Malamud, 2014; Hillier et al., 2020). The insurance risk assessment and climate change impacts have been recently reviewed by Lyubchich et al. (2019). The authors review several adverse events such as floods, hail and excessive wind, but the interaction effect between hazards was little discussed.

Sekhri et al. (2020) proposed a framework for multi-hazard risk management. However, their model was too specific for mountainous regions and a broader risk management strategy. Komendantova et al. (2014) introduced a framework for participatory risk governance, allowing for feedback from stakeholders. Nevertheless, the model does not generalize more specific risk management strategies. An extensive review of the possible index insurance applications for agriculture was conducted by Abdi et al. (2022). The authors summarize indices and methods for designing index insurance with possible applications for multi-hazard risks. However, the implementation of multi-hazards has not received nearly as thorough investigation as single-hazard problems.

Although significant advances have been made in index insurance design, very little further attention appears to have been given to a generalized approach. Moreover, less work has been performed on multi-hazard risk insurance than on single hazard risk. This paper provides insight into a generalized approach to designing index insurance for single and multi-hazard risks. The systematic review was designed to answer the following questions: In the context of index insurance, 1) What indices are used to assess and monitor extreme weather events? 2) What functions and methods are used to assess the vulnerability of food production to extreme weather events? 3) How to determine risk premiums?

2 Methodology

This section describes the methodology used in this work, and is divided in the following subsections: 2.1 describes the criteria used in the systematic review and the definitions of the most important concepts considered; and 2.2 describes the study case to validate the proposed framework, considering the data used and the techniques implemented.

2.1 Systematic review

A systematic review was conducted to better define the state-of-the-art in using multi-hazard index-based insurance in agricultural environments and to identify the main gaps of the current techniques and models. The Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) protocol Liberati et al. (2009) was applied, and the Scopus database was used for data collection. This database was chosen due to its wide cover of relevant events and scientific journals related to climate change, agriculture, insurance design, multi-hazard frameworks and techniques, among other relevant topics. It encompasses a wide range of subjects in the fields of technology, science, social sciences, medicine, humanities, and arts (Scopus, 2022). To analyze the data, we used a double-step analysis to analyze the data. First, a bibliometric analysis was performed on the selected papers of the last 10 years, using the Bibliometrix R package (Aria and Cuccurullo, 2017). Then, a critical analysis of the most cited papers of the last 5 years was performed to derive fundamental research topics and guidelines for index insurance design and evaluation and to identify the main gaps in the literature.

The systematic review process was divided into four steps (Figure 1). The first consisted of the definition of the search strings based on the three research questions in this work. Our search string was composed of keywords in the English language, and we have searched the most important keywords, their synonyms according to the authors' experiences, and a search string using the Boolean operators according to Scopus standards for title, abstract, and keywords. The following criteria were considered:

– English keywords: multi-risk weather index insurance.

– English synonyms: multi-risk, risk, weather, climate, index, parametric, insurance, microinsurance, derivative.

– Search string: TITLE-ABS-KEY ((risk (multi AND risk) OR portfolio) OR (index OR parametric) AND (insurance OR microinsurance OR derivative) AND (weather OR climate)).

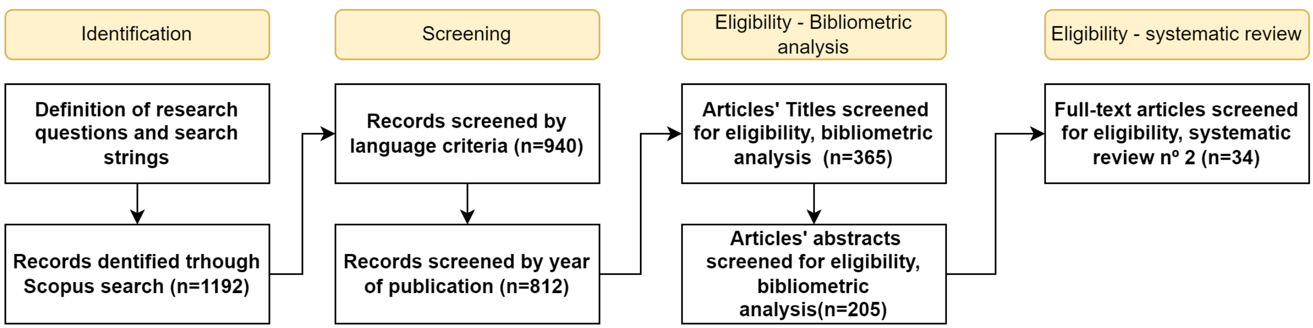

Figure 1. Methodological steps of PRISMA statement

The first step was the screening process, applied to select scientific articles in English, Portuguese or Spanish. Review articles, books, book chapters, and conference proceedings were excluded from the analysis, following the methodology used in other systematic reviews in the literature. From this first step, 1192 documents were selected.

In the second step, studies from 2010 to 2022 were selected using the following inclusion criteria: a complete application of an index insurance or weather derivative design. This refined selection was performed based on the articles' titles and abstracts. Many studies on the evaluation of index insurance demand and on traditional insurance models were excluded. The 365 studies screened in the second step were used in the bibliometric analysis.

To perform a critical review - the third step - the most cited papers from the text from works published in the last 5 years were analyzed in depth . This evaluation excluded papers that did not provide information on index insurance design. Finally, in the fourth step, we performed a critical review of the 34 remaining studies. This review was divided into (i) hazard identification, (ii) vulnerability analysis , and (iii) financial method and risk pricing analyses. This process was adapted from three modules presented in the works by Guzmán et al. (2020); Mohor and Mendiondo (2017); RIGHETTO et al. (2007).

The main index-related concepts that were used for evaluating the works in steps 2-4 were:

– Hazard: “A dangerous phenomenon, substance, human activity or condition that may cause loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage” (Nations, 2009). In this paper, we specifically refer to hazards derived from extreme weather and climate events.

– Multi-hazard: “[...] all possible and relevant hazards and the valid comparison of their contributions to hazard potential, including the contribution to hazard potential from hazard interactions and spatial/temporal coincidence of hazards, while also taking into account the dynamic nature of vulnerability to multiple stresses" (Gill and Malamud, 2014). In this paper we refer to. . . .

– Vulnerability: “The conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards” as defined by the Hyogo Framework for Action (UNDRR, 2014). For this paper, the concept of vulnerability was focused on the physical damages and losses derived from the realization of an extreme weather event. We are utilizing, therefore, a classical approach to quantify the vulnerability of risk-averse individuals, which considers that the greater the losses, the more the vulnerability. Even though this traditional definition has been questioned as a reducer of solely the economic sphere of a issue that permeates social, politic and environmental dimensions, this is ultimately a practical approach of widespread use (Machado et al., 2005).

– Resilience: “The ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions” Nations (2009). In the context of this paper, and as described primarily by Mohor and Mendiondo (2017) and Guzmán et al. (2020), in the resilience module of an index insurance schema, the risk premium is an indicator of the resilience of a sector for coping with weather and climate extreme events.

2.2 Study case

A study case was developed to illustrate the main aspects of the framework proposed, encompassing all steps from problem definition and data collection to index calculation, and loss evaluation for several cities and a specific crop. It is important to note that both the methodology used and the code developed can be adapted and used for different years, areas, countries, hazards, and crops.

The 42 biggest soybean producing municipalities in the Brazilian state of Paraná were chosen for evaluation in this case study. The 22 years of soybean first cycle production from 1996/1997 to 2019/2020 growing seasons were derived from the official statistical yearbooks (Parana). According to the Brazilian insurance authority (Brazil), droughts and excessive rainfall are the hazards that most affect farmers in the studied region. Therefore, we analyzed both hazards, both with uni and multi-hazard models. The multi-hazard risk insurance design was developed by applying the widely used machine learning algorithm random forest (Breiman, 2001; Amit and Geman, 1997). The following four key steps were used in the case study:

1st step: Data collection and processing: Selection of climate extreme index variables and statistical analysis for feature engineering. The following indices were considered, based on the extensive literature review conducted in section 3: pmax, SPI and TX90p over the soybean growing season. The period was chosen due to the highest impacts of extreme weather events on productivity in the region. The target variable considered was crop losses, as it can be used as a proxy for the impact of the extreme weather events. The crop yields were detrended following the the linear procedure used in Bucheli et al. (2021) $\hat{y_i} = y_i + (year_{end} - year_i) * \beta$, where $\hat{y_i}$ is the detrended crop yield series y_i the raw crop yield data in the year i, β is the linear regression coefficient of the equation $y_i = \alpha + \beta * year_i$.The losses were then determined following the equation: $Loss = max(0, (K - \hat{y_i})/K)$. The K variable is the crop yield threshold value. It can be understood as the threshold that divides unfavorable crop yields for farmers (values below K and favorable crop yields (values above K);

2nd step: Data clustering: The kmeans clustering method (MacQueen, 1967), a widely used clustering method, was implemented to better understand the data. The clustering was applied for four relevant variables: maximum daily rainfall event over growing season ($pmax$), 3-month Standardized Precipitation Index (SPI), number of days where daily precipitation is higher than the 90th percentile over growing season ($TX90p$), and crop yield. The elbow method was used to define the optimal value of clusters (also referred to as hyperparameter κ). This is the most used method in the literature for defining κ. The method was implemented in R Environment using the package stats (R Core Team, 2022);

3rd step: Crop loss prediction modeling: Two crop loss prediction models were evaluated, following a supervised learning approach and using the random forest algorithm: (i) M1: using SPI and $TX90p$ as inputs; and (ii) M2: using SPI, $TX090p$, and $pmax$ as inputs . Those options were chosen due to the results observed both on the exploratory data analysis and the cluster analysis conducted in step 2. A standard cross-validation method was applied, following the best practices for machine learning workflows presented in the literature. The models were built using the R-package randomForest (Liaw and Wiener, 2002);

4th step: Risk analysis: The risk analysis is performed to determine pure risk premiums using stochastic methods. Historical burn analysis was performed on detrended crop yields to determine reference pure risk premium values. Then, a stochastic analysis of premiums for M1 and M2 were determined considering $P = E[Loss]$. The expectation of loss $E[Loss]$ was determined using generation of 50 synthetic scenarios of weather data. A multi-site multi-variable (daily precipitation and temperature) weather simulation . The method applies a wavelet-based algorithm for multiple sites and requires. The method was applied using the R-package PRSim (Brunner et al., 2021).

3 Results and Discussion

3.1 Bibliometric analysis

An increasing number of studies can be observed in recent years, with about 50% (n=198) of the articles being published since 2018. The average number of citations per year per paper demonstrate an increasing impact of the weather index insurance in the literature (Figure 2a). However, the global distribution is concentrated in Europe, USA/Canada, and Asia being involved in 42, 26 and 20% of the papers published, respectively. The role of Latin America/Caribbean, Australia/New Zealand/Oceania and Africa are much lower representing 3, 7, and 2%, respectively. International collaboration is a critical factor for high-impact scientific studies. In Russia, more than 90% of highly cited papers were written in an international setting (Pislyakov and Shukshina, 2014). Similarly, in China, 47% of highly cited papers were written in an international collaborative form. The international cooperative background coming from these countries is, in general, a door for more innovative research in the field. These papers highlight those partnerships with international scientists coming from centers of excellence benefit by increasing the dissemination of the study.

In the scientific collaboration map (Figure 2b), there are strong collaboration networks between the United States, European countries, China, and India. European countries such as Germany, Switzerland, and the Netherlands have played a dominant position in integration and have promoted collaboration with Kenia, Ethiopia, Nigeria, and South Africa. Canada has collaborated with China and Indonesia, besides the United States and European countries. From this analysis, we can conclude that the United States, China, and Germany play dominant positions in scientific collaboration and are the most influential countries.

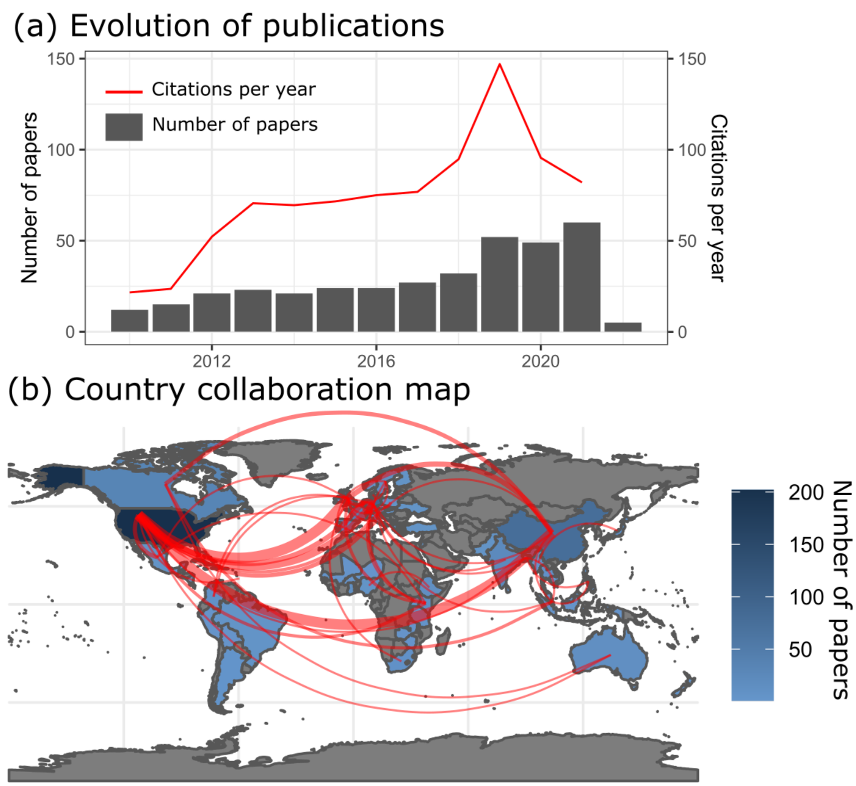

Figure 2. Weather index insurance studies. (a) Temporal distribution from 2010 to 2022. (b) Thematic map representing the global collaboration network, where the countries in blue represent the number of studies produced by scientists. The darker the color, the more affiliations. The world vector map data was provided by https://www.naturalearthdata.com/ under public domain.

Another significant observation is that most developing countries, especially on the South American and African continents, do not have relevant studies in the field. This is somewhat incoherent, as these countries suffer the most from extreme events losses due to their solid economic link with climate-dependent primary activities.

A strategic diagram is presented in Table 1 to analyze themes according to their centrality and density values. According to Cobo et al. (2011), the themes are clusters of keywords. The themes are plotted in a two-dimensional space that is classified in terms of the two parameters (“density” and “centrality”). Density is a measure of the development of the theme, and centrality is the importance of the theme in the development of the whole field of research we analyzed.

Table 1. Thematic mapping of the documents based on the conceptual structure of the author’s keywords divided into seven clusters with word frequency higher than 40 words according to centrality (the relevance of the theme in the development of the field) and density (the development of the field)

Theme	Cluster	Density	Centrality
Motor	Insurance	9	7
	Crop insurance	7	5
Niche	Weather derivative	2	8
Emerging and Declining	Weather index insurance	3	4
	Index-based insurance	5	3
Basic	Basis risk	8	1
	Climate change	6	2

Motor themes: these themes are well developed and relevant for the entire insurance theme. Since they present strong centrality and high density, the clusters “insurance”, “agriculture” and “risk management” and the cluster “crop insurance” are conceptually related to almost all papers gathered in the bibliometric analysis. This result confirms that agricultural and crop insurance are the most explored themes in the index insurance field.

Niche themes: the theme “weather derivatives” is considered a niche theme because it is well developed, but has a marginal impact in the field. The themes have fundamental distinctions and similarities. Derivatives are traded Over the Counter (OTC) or on Chicago Mercantile Exchange (CME). Index insurance is a product offered by insurance and reinsurance companies. They theoretically have a similar principle: a risk-averse individual pays a premium for a risk-bearing individual.

Emerging and declining themes: the themes in this quadrant represent the combination of low level of development and marginal to the entire field of research. This quadrant includes “weather index insurance”, which is a critical issue in terms of impact since extreme weather events trigger significant disasters worldwide. Given the need to manage weather extremes and its importance to a broader geophysical community, we argue that weather index insurance is an emerging topic that will gain more attention in the following years.

Basic themes: these themes are relevant for the field; However, they are weakly developed. This quadrant includes the cluster “index-based insurance”, the cluster “climate change”, and the cluster “index insurance” and “basis risk”. Climate change has been a significant concern for decision-makers, especially risk management. Changes in climate conditions might lead some regions toward higher risk profiles, increasing their vulnerability and the expected losses. Therefore, this theme represents an opportunity for the development of index insurances. Basis risk is a primary topic that requires more development. Even though basis risk is a well-known bottleneck in the field, our analysis suggests room for improvements, and more attention to this topic must be paid in future studies.

Table 1. Thematic mapping of the documents based on the conceptual structure of the author's keywords divided into seven clusters with word frequency higher than 40 words according to centrality (the relevance of the theme in the development of the field) and density (the development of the field).

3.2 Sistematic literature review

We defined agriculture (n=17), hydrologic (n=4), solar and wind power energy (n=3), derivatives (n=4), and multi-hazard risk (n=5) as primary categories of analysis in the systematic literature review (Supplementary material table S1). As expected from the bibliometric analysis, the major focus of the literature was on agricultural insurance, while other emerging topics show potential irrigation, water supply, and energy production applications. Literature has overlooked multi-risk insurance, and our results presented only six studies on this topic. It is worth mentioning that, not all studies in the systematic review could be analyzed in depth, due to the lack of details about their applications. Thus, for the ones with complete information we propose an overview of the application and most relevant characteristics of index insurance in three main categories (i) agricultural, (ii) hydrological, and (iii) sustainable energy production insurance, presented in Table 2.

We observed that the studies evaluated insurance at different spatiotemporal aggregations, e.g. for crop insurance, the studies carried out analysis at the farm level from governmental agencies, insurance companies, or surveys. For instance, in many countries agricultural data is aggregated at regional scale, i.e., municipality, department, state, and country, without standardization. The size of the properties varied greatly, from 5 to 400 hectares and the total coverage was up to 1.6 million hectares. Forestry insurance covers larger areas and uses remote sense data to assessed risk, therefore, spatial discretization is performed at a pixel level. In terms of hydrological insurance, the catchment level was the spatial unit and the coverage took into account all the hydrological processes that occur upstream of the reservoir.

For the sustainable energy insurance - wind and solar power insurance - a unique point, representing the location of the windmills and solar panels, was evaluated. The temporal scale in which the insurance was purchased varied from seasonal to annual scale. Crop insurance is normally contracted before the sowing period and reaches maturity at the end of the crop cycle. Sectors that are continuously exposed to natural hazards are operated on an annual basis. The insurance premiums were represented using different units, however, they focused on premium per unit of area and unit of cost. The crop insurance premium varied from \$6.18 to \$55.26 USD per hectare, this value was affected mostly by the cost of production and the degree of risk aversion of farmers. A value of \$187.29 of USD per ton of crop and 3 to 7% of production costs was also found.

In contrast the hydrological insurance for water supply represents values of \$10.48, and the irrigation insurance ranges from \$212.83 to \$333.07 USD per hectare. The prices for irrigation were inconsistent with the crop insurance and it might be related to the operation costs of the irrigation plant. Sustainable insurance presented premium rates ranging from 0.35 to 0.50 of production costs or a percentage of \$0.033144 per kWh. A detailed analysis of hazard identification, vulnerability analysis, and financial methods of the reviewed paper is presented in sequence.

Table 2. Main topics for index based insurance and specific application

Author	Application	Hazard	Area ha	Type of Area	Time Frame	WTP (Premium)
			Agriculture			
Bucheli et al. (2021)	Crop	Drought	1.0x106	Farm	Seasonal	$34.42
Kapsambelis et al. (2019)	Crop	Multi-hazard	-	Department	Seasonal	$187.29
Guo et al. (2019)	Crop	Multi-hazard	-	Department	Seasonal	$35.29
Shirsath et al. (2019)	Crop	Drought	1.6x106	Farm	Seasonal	$9.88
Vroege et al. (2021a)	Crop	Drought	400	Farm	Seasonal	$23.62-$48.10
Ricome et al. (2017)	Crop	Drought	15.2	Farm	Seasonal	$4.59-$8.44
Sacchelli et al. (2018)	Forestry	Fire, storm	1	Pixel	Annual	$22.90-$44.81
Kath et al. (2019)	Crop	Drought	-	Department	Seasonal	$6.18-$55.26
Furuya et al. (2021)	Crop	Flood	5.57	Farm	Annual	$7.45
Hohl et al. (2020)	Crop	Drought	24	Farm	Seasonal	$7.70
Kath et al. (2018)	Crop	Drought	-	Farm	Seasonal	$8.64-$41.03
Mortensen and Block (2018)	Crop	Drought	-	Department	Seasonal	3%-7%
Kath et al. (2018)	Crop	Drought	-	Department	Seasonal	$6.18*
			Hydrological			
Mohor and Mendiondo (2017)	Water supply	Water deficit	27,700 – 97,200	Catchment	Annual	0.10-0.44
Gómez-Limón (2020)	Irrigation	Water deficit	35.5	Farm	Seasonal	$212.83-$333.07*
Denaro et al. (2018)	Water supply	Water deficit	455.2	Catchment	Annual	$10.48
			Sustainable			
Boyle et al. (2021)	Solar power	Solar energy fluctuation	-	Location	Annual	0.35%-0.50
Rodríguez et al. (2021)	Wind power	Wind speed fluctuation	-	Location	Annual	$0.033144

3.2.1 Hazard assessment

The index insurance literature shows a wider variety of analyzed hazards and employed indices, a summary is presented in Supplementary Material Table S2. Drought is the most frequent hazard (n = 19), followed by temperature variation heat and cold waves (n = 5), excess and heavy rainfall (n = 4), cloud coverage (n = 2), fire (n = 1), storm (n = 1), wind speed fluctuation (n = 1) and, water deficit (n = 1). In Table 2, a overview of the studies including hazard type, index and premium can be visualized. More than half of the studies focused on drought. This is in agreement with the results of the review work of Abdi et al. (2022), in which, studding index insurance for crop production, found drought as being the dominant type of risk. This can be explained by the fact that drought is the most harmful hazard in the agricultural sector, and the sector was the motor theme of the reviewed studies. Our finding is consistent, since, between 1983 and 2009 three-fourths of the global harvested areas experienced drought-induced yield losses (Kim et al., 2019).

Although index insurance is a promising methodology in designing insurance model since it avoids high administration costs, adverse selection and moral hazard issues associated with conventional indemnity-based insurance, its performance in covering losses depend highly on the choice of the index. It is a important step on index insurance modeling, as a mismatch between the index and the actual loss may increase basis risk, which can be a source of uncertainty and low demand for index insurance (Chen et al 2019). In the following section, we briefly present indices utilized in the revised papers and discuss some criteria behind their selection.

The variability of a hazard can be characterized by the behavior of an index. The indices utilized in the studied articles concerning each hazard are described in this section in Figure 3, the main types of hazard and associated index can be visualized.

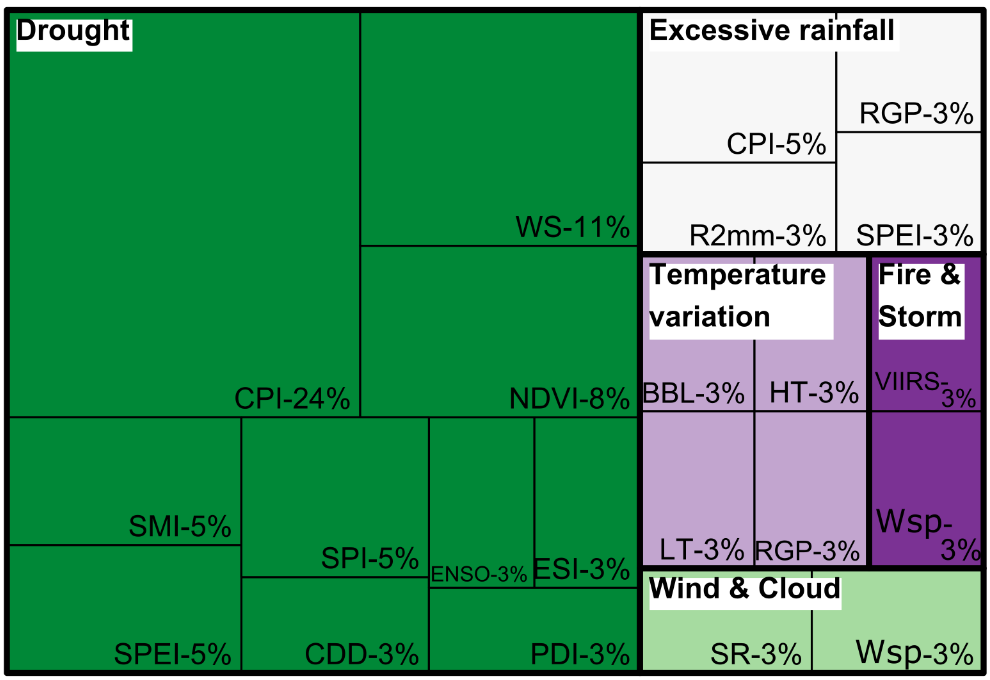

Figure 3. Tree map showing the proportion and percentage of indices applied for different hazards in the reviewed studies. Drought: Cumulative Precipitation Index (CPI); Water Storage (WS); Normalized Difference Vegetation index (NDVI); Soil Moisture Index (SMI); Standardized precipitation evapotranspiration index (SPEI); Standardized Precipitation Index (SPI); Consecutive Dry Days (CDD); El Niño Southern Oscillation (ENSO); Evaporative Stress Index (ESI); Ped Drought Index (PDI). Excessive rainfall: Cumulative Precipitation Index (CPI) ; Ribéreau-Gayon and peynaud hydrothermal scale (RGP); R2mm; Standardized precipitation evapotranspiration index (SPEI). Temperature variation: Berman and Levadoux (BBL); High Temperature (HT); Low temperature (LT); Ribéreau-Gayon and peynaud hydrothermal scale (RGP). Fire and Storme: Visible Infrared Imaging Radiometer Suite (VIIRS); Wind Speed (WSp). Wind and Cloud: Solar Radiation (SR); Wind Speed (WSp).

About 29% of the reviewed studies approached rainfall-based drought index to indicate drought and excessive rainfall hazard (Awondo, 2019; Kraehnert et al., 2021; Bokusheva, 2018; Bucheli et al., 2021; Kath et al., 2019; Turvey et al., 2019; Ward and

Makhija, 2018; Shirsath et al., 2019). It consists of a very straightforward and simple strategy to indicate drought conditions since it only needs precipitation data. The index has the advantage of representing both water deficit and water excess. In the agricultural sector, rainfall indices could significantly represent low-yield events by the occurrence of extreme weather events, in both deficit or excessive forms that would correlate well with low-yields (Abdi et al., 2022).

There are four essential basic criteria in choosing the drought index: the period must be appropriate to the problem being analyzed, the index must allow for a quantitative measure against large-scale and continuous drought conditions, the index must be applicable to the problem being studied, long and accurate information about the index must be available or computable (Zargar et al., 2011). Indices such as the SPI have the advantage of allowing their determination even with the existence of breaks in the data. However, the application of the SPI is limited when factors that are part of the water balance must be taken into account in the analysis of the problem. As an alternative to this problem, the Standardized precipitation evapotranspiration index (SPEI), although capable of reflecting the combined effect of rainfall and temperature variations on drought, requires data for radiation, temperature, and relative humidity, which can be very challenging for developing countries, where the density of weather stations is low.

With the advances in modeling techniques and remote sensing, the more complex indices, like Soil Moisture Index (SMI), and the Normalized Difference Vegetation Index (NDVI), also the use of El Niño Southern Oscillation (ENSO) have become more common. This popularization is already reflected in the current review since 16% of the studies adopted them.

In addition to the factor influencing the index choice, we can list the easiness in calculating the indices as relevant. Furthermore, Yihdego et al. (2019) list problems of scarcity of reliable and long-term databases in countries in the process of developing drought monitoring activities. Likewise, the Standardized Precipitation Index (SPI) and SPEI are more complex indices that incorporate weather statistics in the analysis. Beyond its complexity in calculation, these indices need a database of at a least 30 years. Indices coming form modeling techniques and remote senses are even more complex in terms of data acquisition and determination. On the other hand, we can state that indices such as CPI, Consecutive dry days (CDD), Water Storage (WS) are more common due to their simplicity in the calculations and input data.

According to Abdi et al. (2022), the ease in calculating the index benefits the design and marketing of the insurance products to the potential purchases. Although we noticed in the present work, a preference for simple and one-input indices , there was no clear indicator of a single optimized index for drought hazard. These results corroborate with the study of Bucheli et al. (2021), where they tested several indices in different farms in Germany, and concluded that they are optimized for particular regions rather than regionally accepted as optimal. Customized indices can be used in situations where the relationships between droughts and losses and damages are very specific. Such as the Ped Drought Index (PDI), developed to address this problem by incorporating site-specific information into the CPI (Bokusheva, 2018).

In this section, through a brief presentation of indices, we thus briefly discussed the factors influencing the choice of an index. It is important to note that no index is absolutely superior to the other, depending on the database, degree of drought monitoring and time resources available to its determination, as long as the uncertainties, in which basis risks are a reflection, are under control.

Temperature variation, fire, storm, wind, and cloud hazard indices Other types of hazards encompass temperature variation, fire, storm, wind, and cloud hazard issues. In terms of temperature variation, fire, storm, wind, and cloud hazards represent 12% of the reviewed studies, and the temperature variation is half of that. Thermal hazard has been an emergent subject of interest for human health, crop production, forestry, and the environment. Similar to rainfall, temperature extremes can also explain satisfactory yield losses (Abdi et al., 2022). Given the topic's relevance, it is anti-climax to conclude that we have found only three papers on temperature variation insurance. High Temperature Index (HTI) and Low Temperature Index (LTI) were proposed by Guo et al. (2019) that focused on computing the number of days the temperature was higher or lower than a certain threshold. In general, we had a total of one study per index regardless of the hazard. This represents the heterogeneity of these themes and the lack of in-depth studies regarding the specific hazards - temperature variation, fire, storm, wind, and cloud.

Similarly, in the multi-hazard theme, a unique study was found on fires and storms' impact on forestry in Italy (Sacchelli et al., 2018). Both forest wildfires (Flannigan et al., 2006) and storms (Hettiarachchi et al., 2018) are considered emerging hazards due to climate change. Sacchelli et al. (2018) described forest fires using the Visible Infrared Imaging Radiometer Suite (VIIRS) and explored the effects of strong winds through wind speed (Wsp). It is known that multi-hazards and compound events are increasingly intense and significant, and the finding of only one study related to the theme represents a large gap in the literature.

3.2.2 Vulnerability analysis

The vulnerability analysis focused on the physical damages and losses from the occurrence of an extreme weather event. Thus we presented a summary of the Expected Loss Amount (ELA) and Expected Annual Damage (EAD) models applied in the reviewed papers, available in Supplementary material table S3. The deterministic models were applied for income reduction impacts, especially for crop insurance. In addition, the majority of applied models were related with a unique explanatory variable (index) (Aizaki et al., 2021; Bokusheva, 2018; Bucheli et al., 2021; Hohl et al., 2020; Kath et al., 2019; Mortensen and Block, 2018; F et al., 2020; Vroege and Finger, 2020; Ward and Makhija, 2018). Due to their simplicity of application and understanding, these models are expected to be the most common, however, there is the disadvantage of contemplating only one hazard.

In contrast, the Generalized Additive Linear Models (GALM) and stepwise regression added the possibility of evaluating more than one index, the possibility of a multi-hazard approach (Awondo, 2019; Kath et al., 2018; Matsumoto and Yamada, 2021; Shirsath et al., 2019).A multi-hazard approach requires understanding the frequency of each hazard and its interaction. These interactions are complex, and a few papers tried to tackle this challenge (Decker and Brinkman, 2016; Gill and Malamud, 2014). The multi-hazard risk index insurance papers presented combinations of drought and excessive rainfall for crop insurance (Kapsambelis et al., 2019; Shirsath et al., 2019), fire and storms for forestry insurance (Sacchelli et al., 2018), temperature variation and excessive rainfall for crop insurance (Martínez Salgueiro, 2019) and high and low temperatures for crop insurance (Guo et al., 2019). The assumption of independence was considered prior knowledge by Martínez Salgueiro

(2019) and Guo et al. (2019). However, the authors did not provide a mathematical proof of this choice, instead, they prioritized hazards according to their frequency and magnitude using existent risk maps.

Another possibility to incorporate hazard interactions is through Copulas. This have been incorporating in the loss modeling by Kapsambelis et al. (2019) and Martínez Salgueiro (2019). The copula theory (Nelsen, 2006) is widely used for multi-hazard analysis since it derives joint probability distributions from marginal distributions. Briefly, the marginal distributions are not required to follow the same probability distribution model, giving flexibility and robustness to analyze the interaction of more than two marginal distributions. A simpler approach against the more complicated multivariate probabilistic models.

Machine learning techniques are still emerging in loss models, and here we have reviewed only a very recent paper (from 2020) that used this kind of technology in a loss model. The paper provides evidence that machine learning techniques improve loss modeling from different sources and present different time and spatial scales (Eze et al., 2020). Another example of ELA models is empirical functions that can be used when vulnerability studies for specific sites are not available. Mohor and Mendiondo (2017) presented empirical functions for predicting the impact of water shortage on water supply, irrigation, livestock, and ecological sectors. In summary, linear regression was the most popular model applied to assess the expected losses in the reviewed papers. This may be due to its simplicity, however, this method allows the evaluation of only one hazard. Therefore, we can say that machine learning models and copulas may become more common in future studies, once the multi-hazard assessment is incorporated.

3.2.3 Financial methods and risk pricing

The impact provided in the vulnerability module can be translated as expected values of damage, income reduction, or business interruption by financial methods. In the reviewed papers, we found burning rate, probabilistic fit, and index modeling as the most popular risk pricing models. They commonly use the mean historical losses to estimate expected future losses for similar sectors (Sant, 1980). The expected losses are called pure risk premiums and are the major concern in index insurance papers. The historical losses are converted into payouts considering two critical variables (i) strike value K, and (ii) degree of coverage dc. The k is the index value that triggers payouts, proportional to risk aversion, which in turn is proportional to the degree of coverage. The risk aversion is reflected in the degree of coverage, e.g. dc ranging from 0 to 1, being 0 with no protection and 1 with full protection. These variables represent the behavior and aversion of policyholders towards a particular risk and will be the key to defining the premium and indemnity values.

The loss expectation can be determined using the historical burn rate method (HBR), which is the mean historical losses (Guerrero-Baena and Gómez-Limón, 2019; Hohl et al., 2020; Mortensen and Block, 2018; Shirsath et al., 2019).This method is widely applied in the insurance industry, however, requires sufficient data in order to be accurate. For smaller datasets considering uncertainty, expected values can be evaluated by fitting loss data to a probability density function (Aizaki et al., 2021; Bokusheva, 2018; Bucheli et al., 2021; Eze et al., 2020; Kath et al., 2019; Martínez Salgueiro, 2019; Sacchelli et al., 2018; Vroege et al., 2021b; Ward et al., 2020). This procedure helps to improve pure risk premium rates by accounting for the probability of extreme events that have not been recorded. The probability distribution of loss data presents distortions in the tails, leading to underestimating pure risk premiums. Moreover, insurance companies present nontraded assets that add costs to final premium rates. This can be overcome by a transformation proposed by Wang (2002), and the methodology was applied for pricing premiums by Boyle et al. (2021); Denaro et al. (2018).

Other approaches for defining contract payouts are based on a probabilistic fit. Bokusheva (2018) applied the Marginal Expected Shortfall (MES) method, which is a conditional probability modeling where payouts are given when the target variable exceeds the strike value. In contrast, Eze et al. (2020) used cluster analysis associating NDVI and weather variables with higher yield observations. It is well known that climate variables present a certain degree of uncertainty (only if they were predictions) that needs to be considered when estimating losses caused by climate-related losses (Smith and Matthews, 2015). A stochastic approach based on Monte Carlo simulations is used in the literature to address the problem. A Monte Carlo simulation is the basis of index modeling method applied by Alexandridis et al. (2021); Berhane et al. (2021); Gómez-Limón (2020); Gülpınar and Çanakoḡlu (2017); Guo et al. (2019); Kapsambelis et al. (2019); Salgueiro (2019); Mohor and Mendiondo (2017); Rodríguez et al. (2021). The generation of synthetic weather time series enhances understanding the climate uncertainty in terms of confidence intervals. A summary of the risk pricing methods is described in Supplementary Material table S4.

Econometric models provide values that guide decision-makers in understanding the price of the risk. However, it is fundamental to evaluate the risk reduction performance of index insurance. The simulation of cash flows allows an understanding of the hedging effectiveness of the insurance policy. Nonetheless, this efficiency depends on the point of reference adopted by the modeler. The effectiveness problem arises when policyholders and insurance companies have different objectives. On the one hand, policyholders want to increase the protection of their assets at risk to prevent going out of business, on the other hand, insurance companies want to maximize profit to comply with the interests of their investors and shareholders. Since information asymmetry and moral hazards are allegedly minimized in the case of index insurance (Barnett et al., 2008; Mußhoff et al., 2018), the costs associated with moral hazards can be neglected from premium rates pricing.

The cash flow equation is a standard tool for evaluating the capital of companies and people. The simulation of cash flows using expected revenue and payouts as assets and premiums as liability for policyholders is used for evaluating the effectiveness of the index insurance policy (Bokusheva, 2018; Boyle et al., 2021; Kath et al., 2019; Salgueiro, 2019; Ward and Makhija, 2018). For insurance companies, the cash flow changes the direction, i.e., premiums are considered assets, and payouts as a liability. This was used for calculating the loss ratio (Mohor and Mendiondo, 2017).

Other authors have applied the utility theory to evaluate insurance policies. The utility theory accounts for the behavior and individual preferences in economic analysis and is based on some assumptions that apply to a group of individuals (Kahneman and Tversky, 1979). Some authors (Bucheli et al., 2021; Eze et al., 2020; Furuya et al., 2021; Ricome et al., 2017; Vroege et al., 2021a; Ward and Makhija, 2018) used the concept of risk-averse utility functions for policyholders, where the asset's utility at risk is concave or diminishing. Detailed information about the insurance policy evaluation methods is in Supplementary material table S5.

3.3 Conceptual framework and study case

3.3.1 Conceptual framework

The increased frequency of extreme climate events has been forcing insurers to increase premium rates and threatens coverage availability. Therefore, risk assessment should take measures to minimize the need of risk re-assesment (Cremades et al., 2018). First of all, losses and damages associated with extreme events might have multiple drivers (Zscheischler et al., 2020). This indicates that losses are likely to have multiple thresholds and are associated with multiple variables. Second of all, this thresholds vary with time and space (Hoek van Dijke et al., 2022).

We suggest a conceptual framework that focuses on understanding current weather insurance paradigms found in the literature while proposing how the problem of multi-hazard risk and increasing risk premiums due to increasing climate shocks can be minimized (Figure 6). The first step should be evaluating data and hazards relevant to a site. From that, it is possible to derive thresholds using statistical methods such as copulas, clustering or principal component analysis (PCA).

As it was discussed in the vulnerability section, the selection of thresholds and consequential loss modeling consist in evaluating historical events. This creates a system we call Stationary System State, which is characterized by fixed thresholds even in the case when multiple hazards are considered. The second case is the Non-stationary System State, in which the frequency and severity of hazards are changing over time and the thresholds are dynamic, which can indicate both improvements or worsening in resilience over time.

The optimization process takes into account future scenarios which can help to avoid risk re-assessment by anticipating and diluting potential severe climate shocks. Shifts frequency and severity of extreme events are evaluating using the Representative Concentration Pathways (RCP) (Van Vuuren et al., 2011) that indicate possible changes in risk exposure and the Shared Socioeconomic Pathways (SSP) (Riahi et al., 2017) will helps us to understand risk in different vulnerability trajectories, i.e., increasing resilience, fixed resilience, decreasing resilience.

3.3.2 Study case

The conceptual framework illustrated in Figure 4 was applied to a case study for soybean production in South Brazil, following the methodology described in section 2.2. The main objective of this case study was to illustrate the main steps of the framework, focusing on Stationary System State considering static resilience. The data collected and the processing conducted were described in step 1 of the case study (subsection 2.2). Figure 5 illustrates the results of the clustering analysis.

Figure 5 illustrates the cluster plots for $pmax$ and $TX90p$, very relevant indices for identifying the occurrence of events related to heavy rain and floods. First, it is important to note that: (i) six clusters were identified; (ii) the clusters present considerable intersection, illustrating that rarely only one variable (and, therefore, only one extreme weather event) presented extreme values for the regions evaluated; (iii) cluster 1 covers the biggest area in both plots, pointing out its high variance; and (iv) using the cluster labels for identifying events may be a better option than considering a traditional rule (such as that droughts occur when SPI is lower than -1.0).

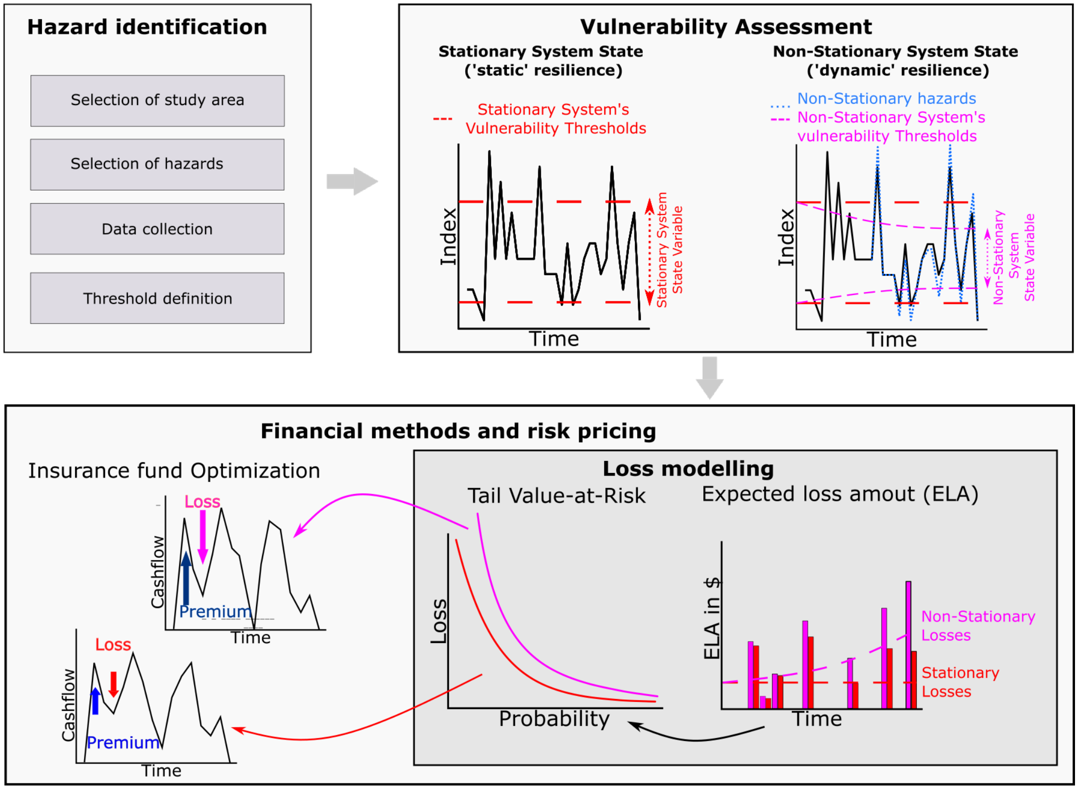

Figure 4. The multi-hazard risks weather insurance design framework. The framework illustrates the process of selecting and prioritizing hazards, defining index thresholds, modeling losses and optimizing insurance risk premiums. The vulnerability assessment presents two types of systems: (a) Stationary System State, where both thresholds and hazards are stationary and represent an analysis based on historic observed information and (b) Non-stationary System State where both indices and hazards are non-stationary and reflect a combination of observed historic and projected data. The non-stationary system anticipates potential increase in risk and optimizes risk premiums.

Table 3 illustrates the mean values for each variable and the percentage of losses for each of the identified clusters. Based on the analysis of Figure 3 and Table 3, we derived three scenarios that reasonably explained around 70% of soybean crop losses for the region and period studied. Cluster 2 represents years where losses were predominantly driven by precipitation deficit. Cluster 4 represents years where losses were driven by precipitation deficit and thermal stress. Cluster 6 is associated with rather normal years in terms of SPI, but with heavy rainfall events and slightly higher temperatures. The underlying structure of the other clusters (1, 3, and 5) are unknown and can be related to other factors such as land use and management, as well as to other factors that are not directly relevant for the present analysis. Additionally, those clusters were the ones that presented the lower crop losses.

Figures 6 and 7 illustrate the results of the fourth step of our case study methodology: the risk analysis. It is possible to observe in Figure 6 that: (i) seven multi-hazard events were identified, based on different values of the considered indices; (ii) the lowest impact event occurred in 2000 (2% average crop loss); (iii) the highest impact event occurred in 2012 (54%

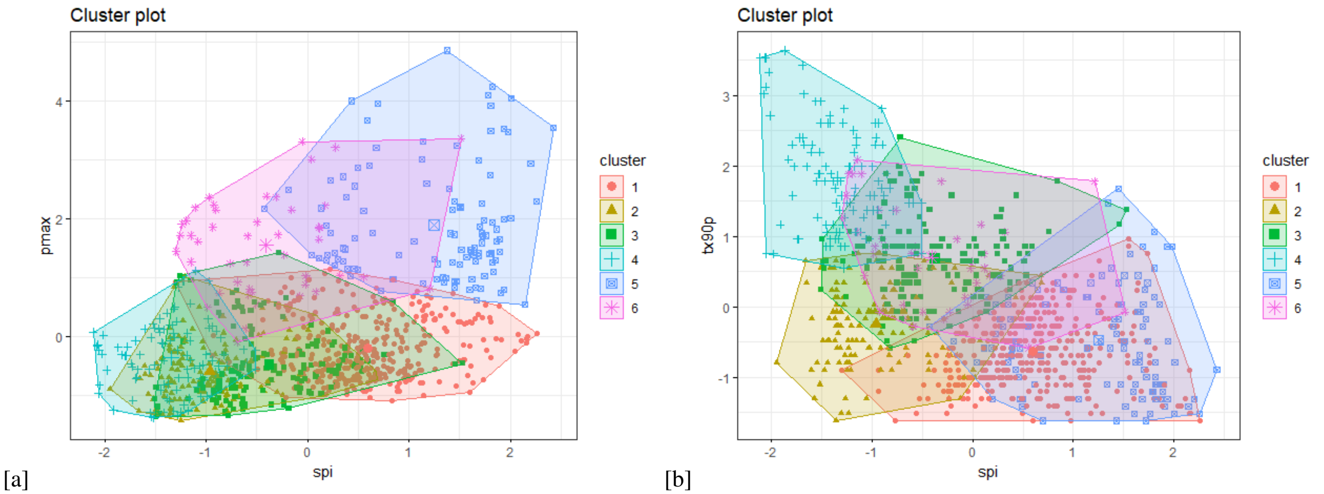

Figure 5. Results of the clustering analysis using the K-means algorithm. Legend: (a) illustrates the clusters for Standardized Precipitation Index SPI and heavy rainfall $pmax$; (b) illustrates the clusters for SPI and the number of days daily maximum temperature exceeds the 90th percentile $TX90p$.

Table 3. Description of each cluster identified

Cluster	Nº of obs	% of Losses	SPI	$pmax$	$TX90p$
1	389	14.4%	0.702	42.4	9.55
2	**153**	**86.3%**	**-0.941**	**36.1**	**13.4**
3	162	19.1%	-0.320	37.9	22.4
4	**106**	**96.2%**	**-1.340**	**39.8**	**33.4**
5	110	27.3%	1.390	76.5	11.1
6	**46**	**95.7%**	**-0.357**	**70.9**	**22.5**

average crop loss, with excessive values for TX90p and SPI); (iv) the variable that presented the lowest number of occurrences outside the defined boundaries was pmax; (v) the variable that presented the lowest number of occurrences outside the defined boundaries was the SPI; (vi) the last year on the dataset (growing season 2019/2020) presented extreme values for all three variables; and (vii) although more studies are needed, considering more extensive periods and climate indices, we can infer that the occurrence of multi-hazard events seems to be increasing in the region studied.

Those observations are in line with the literature, as explored in the systematic review in this work. Additionally, the use of the framework and the methodology proposed allowed for the identification of interesting insights, such as: (i) the nature of the effects of extreme weather events on crops, which seems to be of a more diverse nature (demanding the use of multi-hazard analysis and prediction models); (ii) the difficulty to identify the occurrence of specific events (addressed in this work by using a clustering method instead of a fixed rule for defining the occurrence of extreme weather events such as floods and droughts);

and (iii) the diverse visualization options that can be used to illustrate the results obtained by applying the proposed framework, which may improve decision-making and allow for new insights in comparison to traditional methods (such as evaluating only one hazard at a time; only a group of climate indices; or of only conducting statistical analysis of past crop losses to identify potential trends in the data).

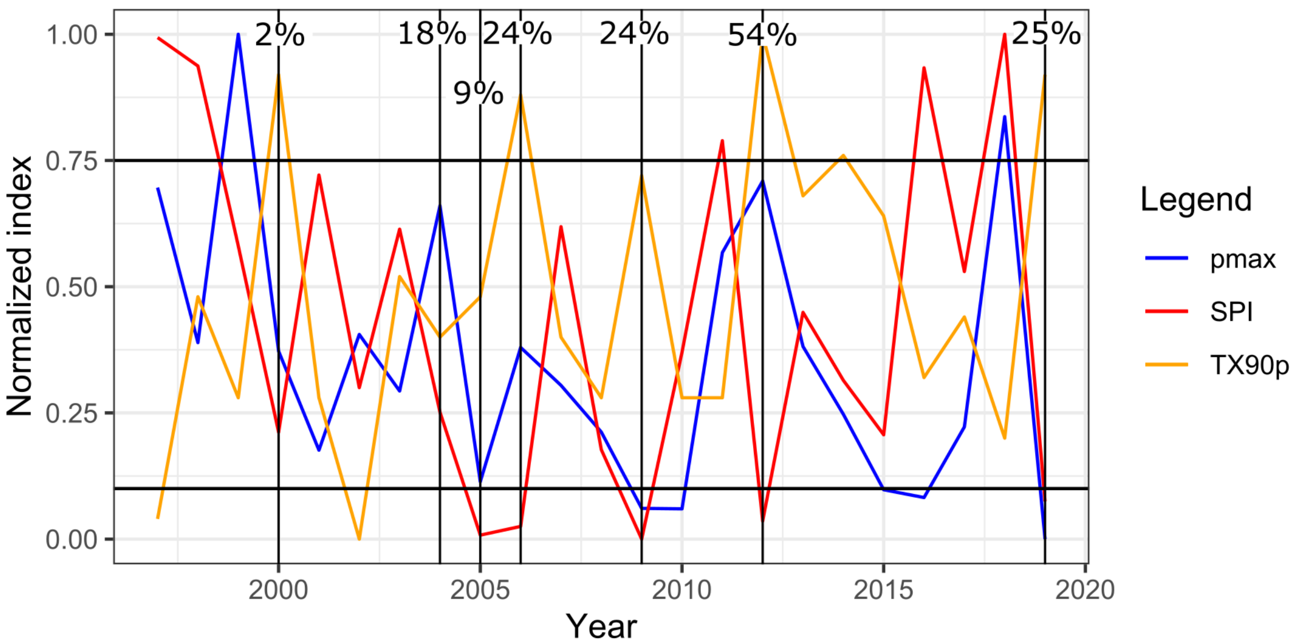

Figure 6. Results of the clustering analysis using the K-means algorithm. Legend: (a) illustrates the clusters for $pmax$; (b) illustrates the clusters for $TX90p$. Each point illustrates the growing season of a specific year and location.

Figure 7 concludes the risk analysis for a specific city (Toledo), which is very relevant for soybean production and is heavily affected by extreme weather events. It is possible to observe that: (i) Toledo had considerable losses on the multi-hazard periods illustrated in Figure 6 (especially 2012); (ii) that both models presented satisfying results for predicting crop losses on the different periods; (iii) that the models identified different aspects of the data, indicating that maybe a model ensemble would present the best results; (iv) that, although M1 better suited the data (presenting a lower mean absolute error), M2 better predicted the worst year (2012), providing more evidence that an ensemble approach could present better results; (v) considering a sum of the models (gray line in subfigure b) presented the lowest overall error in comparison to the observed crop loss, providing further evidence of the importance of using ensembles for predicting crop loss probability.

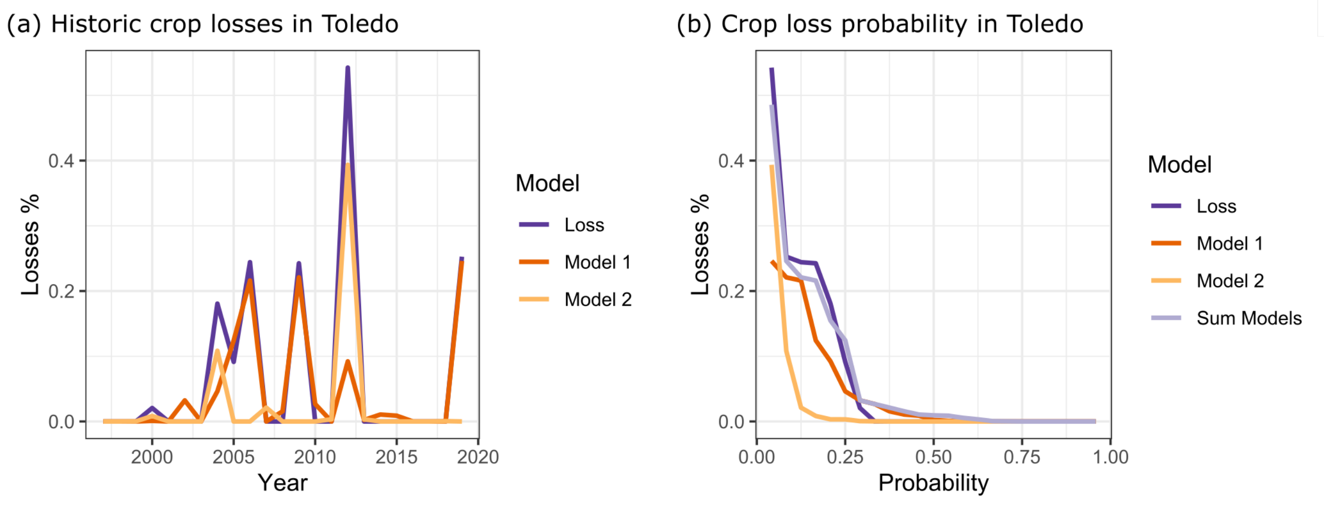

Figure 7. Risk analysis module applied to one specific location. Legend: (a): historic crop losses in the studied period for the city of Toledo; (b) crop loss probability in the studied period for the city of Toledo.

The study case conducted in this subsection illustrates one possible application of the framework, considering several analyses and visualizations that a stakeholder could use to better understand the impacts of extreme weather events over time on agricultural productivity, considering both the historical values and the crop loss probability. This data could be used for both better insurance policy design and for better understanding the current situation in different regions. Generating charts such as the ones illustrated in Figure 7 for multiple regions, on a dashboard, would allow for a better overview of the impacts of weather events on different crops and regions, and be used to better guide investment decisions.

Table 4. Summary of pure risk premiums in terms of percentage of expected crop yields

	Min	Mean	Max
Historical Burn Analysis	2.745 %	5.873 %	9.722 %
Model 1 Synthetic scenario generation	2.894 %	3.253 %	3.630 %
Model 2 Synthetic scenario generation	0.519 %	0.997 %	2.506 %

4 Conclusions

This study reviewed the development and design of index insurance focusing on multi-hazard risk analysis and food security. We summarised main methods for hazard analysis and index calculation, loss modeling and risk pricing. We observed that the lack of studies in multi-hazard risks is the main gap in the literature, therefore we proposed a conceptual framework and a study case to give suggestions for future work in the field.

By performing a bibliometric analysis of relevant studies from 2010 to 2022, we observed a low academic interaction between Latin American countries and the world. Moreover, a co-word analysis of the keywords demonstrated that agriculture and crop insurance are well-developed themes with a high impact on index insurance. The analysis showed that climate change and basis risk are essential in developing index insurance. However, they are weakly developed. Developing countries in Latin America, such as Brazil, Argentina, and Mexico play a critical role in global food production (Baldos et al., 2020).

Furthermore, tropical countries are more likely to experience a reduction in food production due to climate change (Rosenzweig and Parry, 1994). These results outline the importance of developing index insurance in tropical countries, including Latin America, for climate change adaptation. The systematic literature review focused on the most cited papers in the last five years to understand the most recent methods used and potential gaps in the field. The analysis focused on three modules: hazard, vulnerability, and financial. Drought is the most studied hazard; this is explained by the impacts of droughts on agriculture. The index insurance was first intended to use in agriculture (Miranda, 1991; Skees, 2008) and, as the concept has gained attention, a broader range of applications might be proven feasible. The analysis of hazards suggests potential applications such as hydrological and sustainable energy production insurance.

We proposed a conceptual framework for considering multi-hazard risk analysis and two types of vulnerability: static resilience and dynamic resilience. The static resilience refers to a stationary state system and most papers represent this case. The dynamic resilience refers to a Non-Stationary State System and considers both changing hazard patterns and changing vulnerability thresholds. Considering a Non-Stationary State System helps to anticipate increasing patterns of losses, therefore optimizing risk premiums to accelerate adaptation and resilience of farmers against climate change.

In the study case, we provide an example of multi-hazard risk weather insurance design considering a static system, due its simplicity. We follow a four-steps procedure including: (1) Data collection and processing: to select indicators and pre-process data, i.e., remove trends from crop yield data. We consider three hazards: drought SPI, heavy rainfall $pmax$ and excessive temperature $TX90p$. (2) Data clustering: we applied the kmeans method for determining potential multi-hazard scenarios. We found three major scenarios: prevalence of water deficit, water deficit combined with extreme temperature, and extreme precipitation combined with extreme temperature. (3) Crop loss prediction: we applied the widely used machine learning algorithm random forest to predict crop losses using two models M1 for drought and excessive temperature and M2 for heavy rainfall. (4) Risk analysis and pricing: we performed a stochastic modeling of losses using a wavelet-based weather (daily temperature and precipitation) generator to calculate premium rates.

The study case we presented helped to assess the and model the impact of different multi-hazard risks. This offers to decision-makers more risk management options and to tailor solutions according what hazard combinations are more relevant to a particular area. We focused on crop productions, however this approach can be performed to other segments of food production value chain, such as transportation, storage and retail.

Author contributions. Conception and design of the work: MRB. Data collection: MRB. Systematic Literature review: MRB, GCG, GJS, LCR, FARN, RFS. Discussion and analysis: MRB, GCG, GJS, LCR, FARN, RFS, EMM. Drafting the article: MRB. Critical review of the article: MRB, GCG, GJS, LCR, FARN, RFS, EMM, JAM, PAAM. Advisor: EMM

Competing interests. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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