applied sciences

Article

Forecasting Agricultural Financial Weather Risk Using PCA and SSA in an Index Insurance Model in Low-Income Economies

Adriana L. Abrego-Perez *, Natalia Pacheco-Carvajal and Maria C. Diaz-Jimenez

Group for Optimization and Applied Probability (COPA), Industrial Engineering Department, Universidad de los Andes, Bogotá 111711, Colombia
* Correspondence: al.abrego@uniandes.edu.co; Tel.: +57-(601)-339-4949

Abstract: This article presents a novel methodology to assess the financial risk to crops in highly weather-volatile regions. We use data-driven methodologies that use singular value decomposition techniques in a low-income economy. The risk measure is first derived by applying data-driven frameworks, a Principal Component Analysis (PCA), and Singular Spectrum Analysis (SSA) to productive coffee crops in Colombia (163 weather stations) during 2010–2019. The objective is to understand the future implications that index insurance tools will have on strategic economic crops in the country. The first stage includes the identification of the PCA components at the country level. The risk measure, payouts-in-exceedance ratio, or POER, is derived from an analysis of the most volatile-weather-producing regions. It is obtained from a linear index insurance model applied to the extracted singular-decomposed tendencies through SSA on first-component data. The financial risk measure due to weather volatilities serves to predict the future implications of the payouts-in-exceedance in both seasons—wet and dry. The results show that the first PCA component contributes to forty percent of the total variance. The seasonal forecast analysis for the next 24 months shows increasing additional payouts (PO), especially during the wet season. This is caused by the increasing average precipitation tendency component with POERs of 18 and 60 percent in the first and second years. The findings provide important insights into designing agricultural hedging insurance instruments in low-income economies that are reliant on the export of strategic crops, as is the case of Colombian coffee.

Keywords: index insurance; coffee production; low-income economies; Principal Component Analysis (PCA); Singular Spectrum Analysis (SSA); payouts in exceedance (PoE); financial risk measure; Colombia

check for updates

Citation: Abrego-Perez, A.L.; Pacheco-Carvajal, N.; Diaz-Jimenez, M.C. Forecasting Agricultural Financial Weather Risk Using PCA and SSA in an Index Insurance Model in Low-Income Economies. *Appl. Sci.* **2023**, *13*, 2425. https://doi.org/10.3390/app13042425

Academic Editor: Wan-Soo Kim

Received: 9 January 2023
Revised: 29 January 2023
Accepted: 31 January 2023
Published: 13 February 2023

Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Low-income economies are severely affected by climate change, limiting sustainable development [1]. These effects are strengthened in regions with underdeveloped financial services [2,3]. Unusual weather events lead to disruptions in worldwide food security [4]. According to recent studies, the effects of climate change, such as droughts and extreme heat conditions, have reduced the yield of staple crops worldwide by approximately 10% [5,6].

Agriculture in Colombia is one of the most significant socioeconomic sectors, contributing to 7.4% of the GDP [7]. Some of Colombia's main agricultural products are coffee, corn, potatoes, and palm oil, among others. According to the National Agricultural Survey, ENA 2019, the total production recorded was estimated at more than 63 million tons, 67% of which corresponds to the agro-industrial product group [8]. The export of high-value crops such as coffee accounts for a sizeable portion of the GDP total. In 2020, coffee was the third most exported product in Colombia, with a value of $2.54 billion (about $8 per person in the US), and was ranked as the fourth largest coffee-exporting country in the world [9]. Nevertheless, according to the World Bank [10], Colombia is highly exposed to hydrometeorological events, known as El Niño and La Niña. These weather events result in drought or excess rainfall which directly impact the agricultural sector and affect the country's GDP. In 2010/11, La Niña's damages were estimated at 2% of GDP and about 3.5 million people were affected [10]. It is estimated that these changes in the amount of precipitation in the next 30 years will harm coffee crops [11].

Several studies have demonstrated a direct correlation between time series analysis and climate change [12,13]. These studies allow for the identification of ways to mitigate the consequences of climate change on agriculture. Trends in agrometeorological and hydrological data sets are frequently evaluated using the nonparametric Mann–Kendall test [14–16]. This test allows researchers to determine the significance of a time series trend of weather variables [17].

"Agricultural index insurance is a financial tool for risk management that has demonstrated promise for encouraging economic development and resilience" [18]. The main difference between this insurance and standard insurance is that payouts are based on the measure of climate variables such as rainfall and temperature. The values across which indemnity payments are made in this type of insurance are established by set thresholds and restrictions. Thresholds provide the starting point for indemnity payments. Once the threshold is met, the payout grows steadily as the index's value approaches its limit or maximum indemnity [19]. Weather index insurance offers advantages and shortcomings (Table 1).

Table 1. Summary of advantages and disadvantages of index insurance. Sources: Abdi et al. [20], Miranda et al. [21], Miranda et al. [22], Skees et al. [23], Di Marcantonio [24], and the World Bank [25].

Dimensions	Advantages	Disadvantages
Indemnities	It indemnifies policyholders based on the observable value of a specific "index" or some other variable closely related to losses.	Requires research to design accurate thresholds and index selection [20].
Insurance components	Adverse selection and moral hazards are minimized [21].	Basis risk can grow if (1) the index is not correlated with loss, (2) the crop production is far from the data collection, or (3) the statistical method is not adequate to model the loss [20]
Costs and implementation	Index insurance exhibits lower transaction costs than conventional insurance [21]	Offers less reflective individual risk protection [21,22].
Nature and product knowledge	Payments are made in due time [23].	Lack of product awareness [24] and an enabling environment for the time of insurance [25].
Scalability	A generalized need for insurance expansion as climate change poses risks to worldwide crop production [20].	Scalability can be achieved if insurance products are profitable for insurers. It also implies massive investments in infrastructure and delivery channels [24].

To highlight some points, index insurance is advantageous as it overcomes problems of traditional insurance such as moral hazard, adverse selection, and high costs; in addition, it can be measured remotely [26]. Despite these advantages, in index insurance, basic risk arises when the measurement does not match with actual losses because of poorly designed tools [26] or if the distance between the index measurement location and the crop's location is far [20]. One way to handle this risk is by using data or images based on satellites. For instance, payouts can be based on a Normalized Difference Vegetation Index (NDVI), which allows for estimating vegetation conditions from a color map showing relative biomass [27]. Nevertheless, NDVI sometimes does not include site calibration, and so should not be widely used in the design of index-based insurance products [28]. The benefits it offers to individual farmers are limited, so there may be more advantages to using a reinsurance tool used by corporations that have a relationship with many agricultural producers, agricultural banks, or cooperatives [21,22].

Although the insurance index started to be mentioned in the land regime law in 1944, it was not until the crisis caused by the La Niña phenomenon in 1992 that interest was renewed. As a result, Law 69 was approved in 1993, establishing the regulations for agricultural insurance in the country. This law regulates the entities that can be insurers, which can be public, private, or mixed, but must be under the supervision of the financial superintendence [29].

The agricultural insurance market has existed in Colombia since 1998. In 1998, the first program was designed for banana crops, which based its indemnity on verifiable losses. Seven years later, two companies launched the first index insurance program for corn and cotton crops, but the results were poor and fueled producer distrust [10,29]. The main problem with this program was that farmers could choose between different thresholds that triggered indemnity and the premium price varied depending on the trigger level selected [18]. Farmers tended to choose the cheapest premium, which resulted in lower coverage. In practice, when crops suffered damage due to rainfall, the insurance did not activate, so no payment was generated, resulting in distrust among banana producers [30].

By 2017 there was already a presence of public and private traditional insurers in Colombia, which launched programs to underwrite crops, forestry, and livestock. Among the participants are Sura, Mapfre, Seguros Bolivar, Allianz, and Liberty, and also one state insurer, La Previsora. There is also Proagro, which is a Mexican insurance company that was registered in Colombia. This company promotes a range of agricultural insurance products and services to the market [31].

In 2018, an emerging company formed by a consortium of insurers launched its first pilot program of weather-indexed insurance for coffee producers in Caldas, a Colombian department. A year later, it received premium subsidies from the government, which allowed it to cover more production costs at risk and offer its insurance to other coffee producers [32]. In 2020, this program was expanded, reaching approximately 9000 smallholders and 2200 hectares. This can be interpreted as the sustainable success of the program [33]. The insurance offered in the program covers farmers against heavy rains and floods and shortages based on the analysis of available information from weather stations and satellite data. For index-based insurance programs, satellite weather data has been increasingly employed in developed economies [34]. However, in low-income economies, satellite information is difficult to access.

In Colombia, the average penetration rate of crop insurance between 2010 and 2015 was only 1.76% (hectares seeded vs. insured hectares) [35]. The limited traditional compensation processes available for Colombian crops have typically relied on traditional insurance frameworks based on yield loss or damage [11]. Some reasons for the low coverage rates in the country are related to local conditions, such as regional conflict and the resulting insecurity, which makes field inspections difficult [36]. Although there are many studies on weather-indexed insurance in the literature, there is still a lack of research that includes product design in low-income economies [19].

State-of-the-art studies show diverse types of index insurance models where indices are mostly built from mereological, temperature, meteorological drought, hydrological drought, climate, and vegetation indices. For the methods of yield–index relationship estimation, the most common methods used to build indices are regression, correlation, copulas, production functions, and, more recently, machine-learning methods [20]. Regarding the risk evaluation methods, most studies focus on risk-reducing effectiveness evaluation methods, such as variance or semi-variance deviation, value at risk, or conditional value at risk [37–41]. However, few of these methods address the relevance of measuring future financial risks in highly volatile regions. For example, Siebert [42] used a Gerrit Skill Score (GSS) to assess the way indices forecast payouts or non-payouts during loss and non-loss years. This was seen as advantageous, as the GSS score weighs both sides of basis risk, assigning false payout and failure to pay. Recommendations from these state-of-the-art reviews include more in-depth studies emphasizing index derivation during critical crop growth periods and the employment of models to aid in index design that considers future climate conditions. This study addresses these two recommendations.

Referring to the costs for index insurance programs, Kerer [43] states that one of the main shortcomings in these programs is the high cost for low-income farmers in developing countries, as most of their income is absorbed by their basic needs such as food and housing. This results in low uptake of this insurance tool. Di Marcantonio [24] states that while high premium prices for weather index insurance programs are the main constraint when adopting weather index insurance, this is offset by public subsidies and support donors who help to promote insurance expansion. Some studies discuss whether public subsidies are the best way to promote the use of index insurance. Instead, these authors promote the use of credit subsidies and fertilizer subsidies in conjunction or separately. Ricome et al. [44] showed first that the potential benefits of public subsidized weather index insurance are more evident in the driest areas. Second, in zones with extreme precipitation, insurance premiums that are publicly subsidized by 60% induced farmers to adopt insurance; however, this incentive was less efficient than subsidizing credits and technologies such as fertilizers, or just cash transfers. One Colombian index insurance example of expansion is the Cafe Seguro program. In this program, one of the key factors that promote the adoption of index insurance in coffee crops has been the close work by insurers with farmers. Farmers receive clear information about the rationale of the insurance tool, and questions are answered regarding their needs and the expectations of the insurance program. In addition, these insurance programs are successful because of recent public and private subsidies [33].

This paper aims to propose a new methodology based on a data-driven framework that allows us to explore the use of different statistical models in the design of indexed insurance in agriculture. The methodology considers the effect of future changes in precipitation levels in low-income economies such as Colombia. We believe that the results from this research could be useful in the design of new policies that would benefit the actors involved in Colombian agriculture.

2. Materials and Methods

2.1. Conceptual Framework

The methodology (Figure 1) used in this study combines statistical analysis, a PCA reduction process, SSA filtering, and forecasting kernel simulation for index and payout modeling using R [45], by:

(i) Applying a Principal Component Analysis (PCA) to scaled monthly cumulative rainfall data between 2010 and 2019 from 163 weather stations.
(ii) Establishing reliable index parameters that measure the shortage and excess rainfall for coffee production.
(iii) Selecting and extracting the eigenvectors for the signal component.
(iv) Simulating monthly accumulated precipitation values in mm (PTPM) with nonparametric kernel density estimators.
(v) Using a piecewise linear index insurance model consisting of four crucial points based on the amount of rain to simulate crop damage.
(vi) Forecasting the seasonal tendency components to apply a weather risk measure based on the ratio of payouts that exceed or reach the maximum indemnities or POERs.

2.2. Data

The Institute of Hydrology, Meteorology, and Weather Studies (IDEAM by its Spanish acronym) is a public entity of the Colombian government whose functions include monitoring the country's climatic conditions [46]. To carry out this monitoring, it has around nine thousand climate stations distributed in different areas of the Colombian territory. IDEAM, in its databases (publicly available), has information on the accumulated monthly precipitation levels (PTPM) of all stations between 2010 and 2019. We chose this window period as it was the most balanced available data from IDEAM that included the coffee crop zones.

To diminish the basis risk associated with the difference between the data recording and the crop sites, we selected the weather stations near coffee-growing regions. As a result, we obtained data consisting of 163 meteorological stations whose altitude is between 1000 and 1890 m with a median of 1513 m above sea level. The distribution of altitudes is presented below (Figure 2). This graph shows that most stations are close to 1750 m above sea level, and there are fewer stations with an altitude of less than 1400 m.

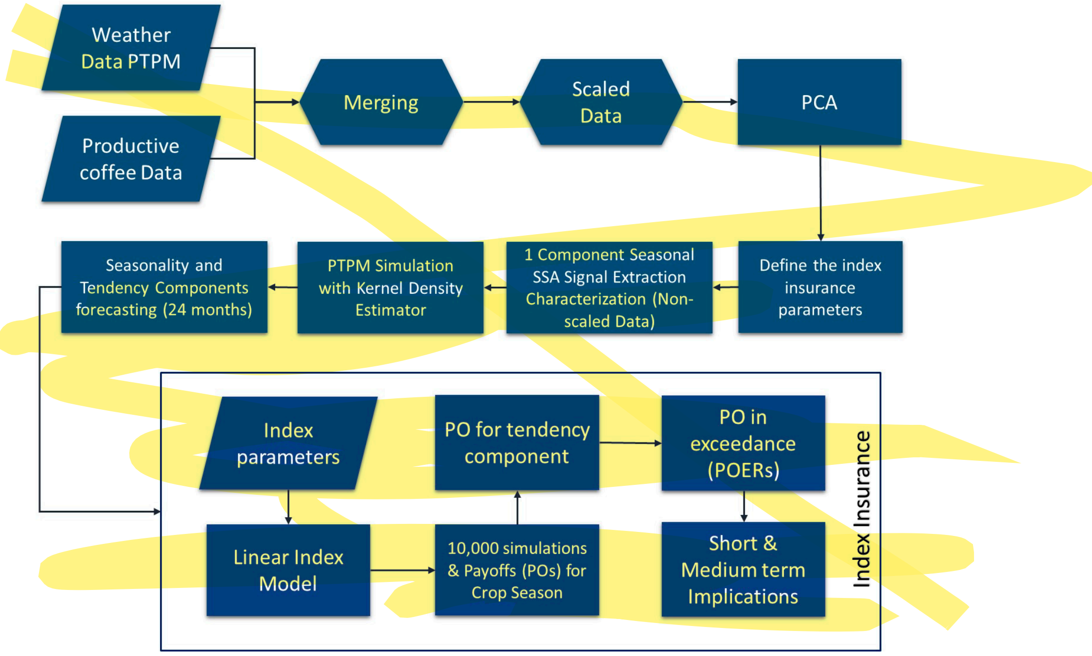


Figure 1. Methodology applied to derive payout rates for each principal component in precipitation index insurance. Source: authors.

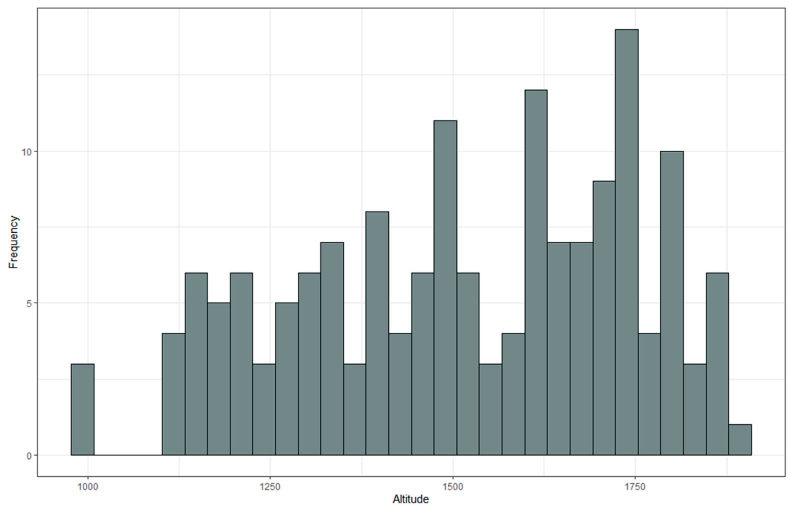


Figure 2. Frequency histogram of altitude for the 163 selected stations. Source: authors' processing.

In Colombia, there are two seasons for coffee cultivation, dry and wet, and four productive zones in the country: eastern north, central north, central south, and south [18–47]. According to the sample data, the mean monthly rainfall in the dry season is 131 PTPM, while in the wet season, the mean is 168 PTPM. In addition, a boxplot shows that the dispersion of the data is similar between the two seasons, and in the case of the dry season, the data are more asymmetric (Figure 3).

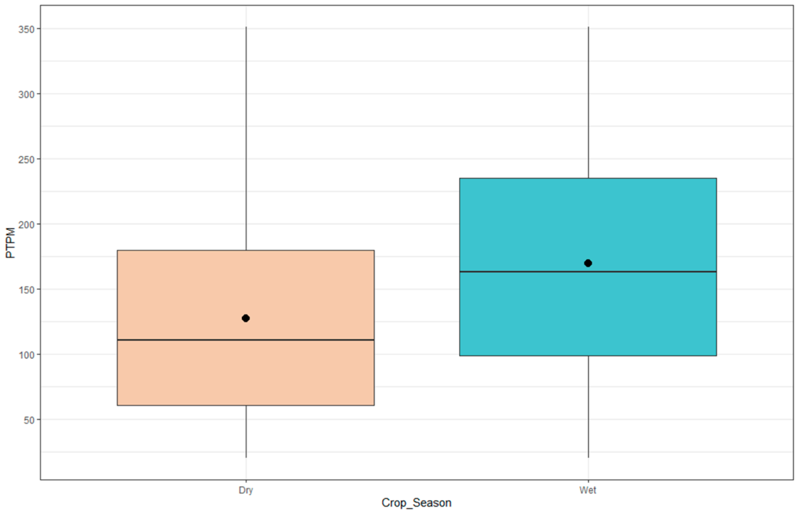


Figure 3. Boxplot of the monthly accumulated precipitation values (2010–2019) in the wet and dry seasons in Colombia without extreme values. Source: author's processing.

The production of coffee crops comprises four stages: the first two stages II and II) are known as the first-growing and flowering phases. In these stages, there is a slow but consistent demand for water. The following two stages are known as the second-growing and filling stages, where the demand for water rises uniformly [48]. The months in which these stages take place vary according to the location of the productive zones in the country and their weather seasons (Figure 4). As stages I and II are highly water sensitive, throughout these stages, ongoing index insurance programs, such as Cafe Seguro, protect against flooding. Whereas during stages III and IV, which comprise the second-growing and filling phases, insurance programs protect against drought. In these programs, the payouts are tailored to the deficit or excess of precipitation [33].

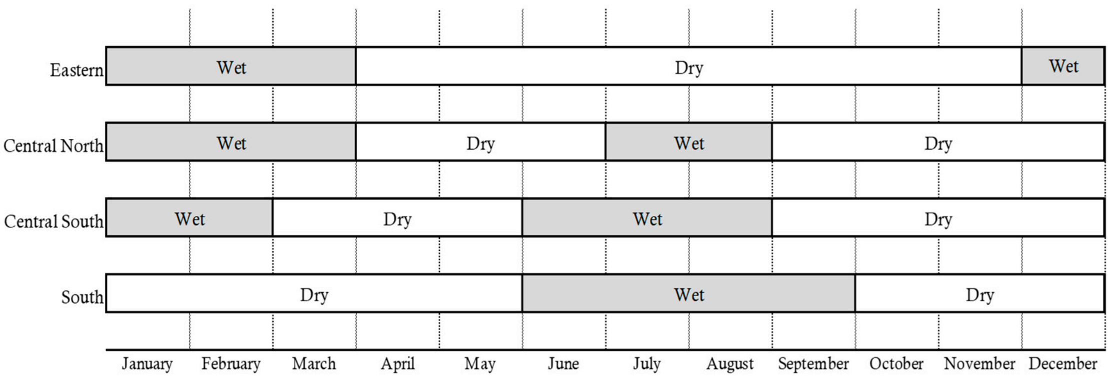


Figure 4. Weather seasons in Colombia per region. Source: Cenicafé, 2016 [47]. Note: eastern: Santander and eastern Cundinamarca; central north: Caldas, Antioquia, Risaralda, northern Tolima, and northern Cundinamarca; central south: Quindío, Tolima, Valle Cauca, and northern Huila; south: Cauca, Nariño, and Huila.

Multiple factors influence coffee quality. Among the most relevant are the amount and distribution of rain, which allows for homogeneous growing stages and, as a result, higher-quality coffee. It is during the growing stage that coffee needs intense but acceptable rainfall. Temperature is another significant factor. Due to climate change, producers have had to move their crops to different altitudes, usually higher [49]. In most of the coffee-producing regions of Colombia, the preferred method for farmers to irrigate their crops is rain; when rainfall levels are adequate, the coffee is of a better quality than that irrigated artificially. According to a study by Ramirez-Builes [48], "Artificial watering is challenging and expensive; it also requires expert knowledge of natural rainfall levels, where excessive water accumulation leads to several diseases in coffee plants such as the coffee leaf rust (or the "Roya disease")".

The average annual area cultivated with coffee in 2021 exceeded 0.911 million hectares. This area was cultivated by more than 500,000 farmers in 72% of Colombia's departments [10]. These crops tend to be cultivated using more traditional techniques. In this area, the departments of Huila (17.2%), Antioquia (13.8%), Tolima (12.7%), and Cauca (11.1%) make up approximately one-third of the total coffee production in the country [50]. Traditional cultivation methods result in the crops being more vulnerable to relatively even shorter adverse weather conditions. An example of this was a 12.8% production drop in 2022 compared to 2021, which was the equivalent of a decrease from 13.4 to 11.7 million bags of coffee beans. This was caused mainly by La Niña, which resulted in excess rainfall [50]. This illustrates how crucial the implementation of index insurance programs that consider weather variables for the most vulnerable coffee producers, small farmers, can be. Analyzing weather variables could also allow the government to plan more accurate financial strategies for extreme events, as there is evidence that appropriate bailouts and tax programs can stabilize farmers' profitability [51].

2.3. *Principal Component Analysis (PCA)*

We applied an unsupervised machine-learning technique to reduce the dimensionality of the database while retaining as much information as possible [52]. The database is a matrix of the dimension $N \times p$, where N is the number of observations and p is the number of variables. In this study, variables are the monthly accumulated rain values from 2010 to 2019 and observations correspond to each station.

The PCA can be thought of as a rotation of the axes of the original variable's coordinate system to a new orthogonal axis. This is done to align these axes with the direction of the data's highest variance [52]. In other words, each principal component corresponds to a linear combination of the original variables. The first principal component (PC1) is the component that allows us to describe the maximum variance of the data set; the second component (PC2) is the component with the second highest variance, and so on. The number of principal components that can be calculated corresponds to $\min(N-1, p)$, but in practice, only a few components collect most of the information.

The procedure to calculate the principal components is as follows [52]:

1. Center the variables by subtracting from each the value of its mean.
2. Generate the variances and covariances matrix.
3. Determine the eigenvector and eigenvalue of the matrix found in step 2.
4. Find the contribution of each variable (loadings) to the principal component by multiplying the transposed eigenvector matrix with the transposed matrix of the centered data.

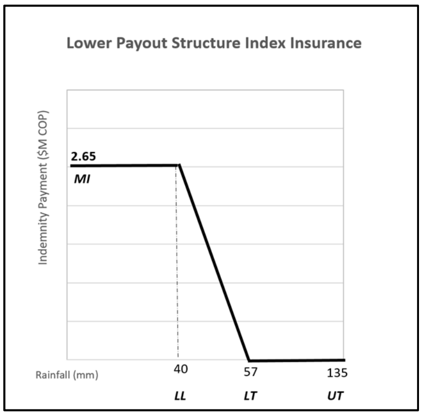
2.4. *Parameters of Index Insurance*

With a similar approach to Hill and Robles [53] and the Nyala Insurance Share Company [54], we established the PTPM as the index variable. To define the parameters, we found the average monthly water requirements for Arabica crops. These requirements rely on different factors including altitude, the quality and humidity of the soil, and the age of the crop [55]. Usually, this type of information is hard to acquire; thus, we used the values recommended by the FNCC (National Federation of Coffee Growers of Colombia), which are based on altitude ranges. In summary, the FNCC establishes optimal average monthly waterings of 57 and 135 PTPM. The upper and lower limits were set following the same procedure established in this study by Abrego-P et al. [18]. The lower limit was established as 40 PTPM and the upper limit as 241 PTPM [55].

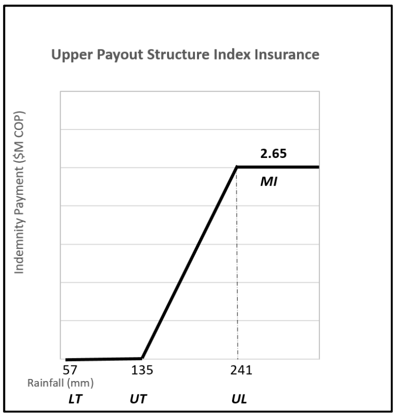
The amount insured was calculated by using a similar methodology as used by Abrego-P et al. [18] and by Hohl [56]. This amount was based on a currency exchange rate of 3478 COP–USD [57] and a reported coffee market price of USD 2427/ton (or 1,055,000 COP) per coffee bag. In the main and Mitaca crop production season, which yields

40% of the first crop season, 30 bags of dried coffee are added annually. For growers to reach maximum indemnity, there must be a maximum production loss of up to 75% caused by extreme weather. Therefore, the maximum indemnity is USD 761 (2.69×10^6 COP/ha), as indemnity is 1.16 USD/kg [58]. In summary, the lower and upper limits are set to 40 and 241 PTPM, respectively. Similarly, the lower and upper thresholds are 57 and 135 PTPM. The sum insured is set at 15 M COP per ha. The maximum indemnity (MI) is 2.7 M COP per ha.

The referenced payout function follows a linear index insurance model [19]. The marginal payouts for low PTPM levels are derived linearly by dividing the maximum payoff or indemnity of 2.7 M COP/ha per one PTPM, by the difference of 40 PTPM (lower limit). The threshold for drought is 57 PTPM (about 2.24 in) (Figure 5a). Similar considerations for the case of high rain levels can be seen in Figure 5b.



(**a**)



(**b**)

Figure 5. Indemnity structure for the lower and upper average PTPM. (**a**) Lower precipitation ranges, (**b**) upper precipitation ranges. Notes: (1) Low and high rainfall index insurance are annually seasonalized. (2) Lower limit (LL); upper limit (UL); lower threshold (LT); upper threshold (UT); and max indemnity (MI) [17]. Source: adjusted according to Abrego-P et al. [18].

We previously derived a simulated kernel distribution of PTPM with $n = 1000$ points from the year time series data for each of the weather stations (2010–2019) to calculate the payments linear function (POs) (3) for wet and dry crop seasons. The pricing linear function follows both PTPM conditions, m_0 (2) and m_1 (3), applied to the first component and season i, where $i \in [1,2]$.

$$PO(PTPM)_i = \begin{cases} M.I.\ if\ PTPM < LL\ or\ PTPM \geq UL \\ m_0\ if\ PTPM \in [LL, LT) \\ 0\ if\ PTPM \in [LT, UT) \\ m_1\ if\ PTPM \in [UT, UL) \end{cases} \quad (1)$$

$$m_0 = PO_{low} = \frac{(LT - PTPM_{value})}{(LT - LL)} * M.I., \quad (2)$$

$$m_1 = PO_{high} = \frac{(PTPM_{value} - UT)}{(UL - UT)} * M.I., \quad (3)$$

$$PO_{total} = \frac{1}{n}\sum_{1}^{n} PO(PTPM_i), \quad (4)$$

The forecasted POs per season i are next calculated by averaging the forecasted fair PO values.

2.5. Singular Spectrum Analysis (SSA)

There are many different methods for studying time series. Many of these methods rely on parametric assumptions; for example, they require linearity or nonlinearity with functional forms. An alternative method that uses nonparametric assumptions and which is neutral to usual requirements such as stationarity, linearity, and normality in data is Singular Spectrum Analysis (SSA). SSA is a relatively new nonparametric method that has demonstrated its useful applications in many different fields, from economics to physics, including meteorology. SSA has two main applications, which are filtering and smoothing and forecasting [59]. In this article, we employed both applications.

For filtering and smoothing, the technique decomposes the original series in the sum of interpretable components. These components are usually slowly varying trends, oscillatory components for seasonality, and noise. The primary SSA method consists of two complementary phases: decomposition and reconstruction. Each phase has two separate steps. In the first phase, the series is decomposed. This phase comprises two steps: embedding and singular value decomposition.

The embedding step can be considered a mapping process that transforms a one dimensional $Y_N = \{y_t; t = 1, 2, \ldots N\}$ time series into a multidimensional series, $X_i = (y_i, \ldots, y_{i+L-1})^T \in \mathbb{R}^L$, where L is the window length and $2 \leq L \leq N/2$. As established by Golyandina [59] and Hassani et al. [60], one of the crucial steps in the technique of SSA is the definition of the window period, which is useful in the embedding step. The product of this step is the Hankel matrix, or trajectory matrix, which is the primary resource for the SVD, and this is the basic difference when applying a traditional PCA procedure to a multivariate time series. The widow period was set at $L = N/2$, as established by Golyandina [59], obtaining the trajectory matrix: $\tau_{SSA}(PTPM) = X$.

In the second step, the SVD of X is performed, which is denoted by $\lambda_1, \ldots \lambda_L$. The eigenvalues of XX^T are arranged in decreasing order $(\lambda_1 \geq \cdots \geq \lambda_L \geq 0)$ and by the corresponding left eigenvectors $(U_1, \ldots U_L)$. The SVD of the Hankel matrix can be defined as the collection of $X = X_1 + \cdots X_L$, where $X_i = \sqrt{\lambda_i} U_i V_i^T$, and $V_i = X^T U_i / \sqrt{\lambda_i}$ (if $\lambda_i = 0$, then $X_i = 0$). The $\sqrt{\lambda_i}$ are the singular values of X, and $\{\sqrt{\lambda_1}, \sqrt{\lambda_2}, \ldots, \sqrt{\lambda_L}\}$ is the spectrum. The collection $(\sqrt{\lambda_i}, U_i, V_i)$ is called the i-th eigentriple, formed by the eigenvalues and the left and right eigenvectors. Therefore, the SVD of the Hankel matrix produces $X = X_1, + \cdots + X_d$. The SSA can be seen as a way of obtaining and analyzing this spectrum of singular values to identify and then distinguish between the signal and the noise, usually by visual techniques in each time series [60].

In the second phase, the series, which is filtered and free from noise, is reconstructed. This phase is formed by two steps as well: grouping and diagonal averaging. The goal of the grouping step is to enable the signal and noise to be distinguished. This is done by splitting the elementary matrices into several disjointed subsets, $I_1, \ldots I_m$, with the representation, $X \equiv X_{I1} + \cdots + X_{Im,}$ which is later summed within each group (tendency or seasonality). The process of choosing the sets $I_1, \ldots I_m$ is called grouping. Then, the series, which can be interpreted as the proxy of the original series, is used for forecasting purposes [59,60]. Finally, the purpose of diagonal averaging is to transform a matrix from the Hankel format to a time series.

The forecasting stage can be implemented once the decomposition is performed. The basic requirement to perform SSA forecasting is that the series satisfies a linear recurrent formula (LRF), where the series $Y_N = \{y_t; t = 1, 2, \ldots N\}$ satisfies an LRF of order $L - 1$ if $y_t = a_1 y_{t-1} + a_2 y_{t-1} + \cdots + a_{L-1} y_{t-L+1}, t = L + 1 + \cdots N$. This means that the series ruled by an LRF follows a natural recurrent continuation since each term of the series is a linear combination of several preceding terms. As in the case of Arima models, the SSA is based on the weighting of previous observations; these weights are obtained based on eigenvectors. As noted by Hassani et al. [60], the LRF does not imply that the series must be linear, but it might be a nonlinear structure ruled by the LRF. In the case of this study, we considered one of the two versions of the univariate SSA algorithm, also known as the recurrent SSA (RSSA). We also used the construction of the bootstrapped confidence intervals to forecast. Another option is the Vector SSA (VSSA). We employed the RSSA package in R for these purposes.

3. Results and Discussion

3.1. PCA

We applied a PCA technique to the standardized data, where the first component captures 40% of the variability (Table 2). This component is considered a case study for the rest of the calculations, as the methodology would be similar for the rest of the components.

Table 2. Summary of the importance of PCA by principal components (PC) for PTPM. Source: author's processing.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Standard Deviation	6.916	4.464	2.023	1.740	1.492	1.460	1.372	1.346	1.286	1.193
Proportion of Variance	0.405	0.169	0.035	0.026	0.019	0.018	0.016	0.015	0.014	0.012
Cumulative Proportion	0.405	0.574	0.609	0.635	0.653	0.671	0.687	0.703	0.717	0.729

The first six PCA components are depicted in Figure 6. Eleven departments are included in Figure 6, and they account for 67% of weather variability (Table 3).

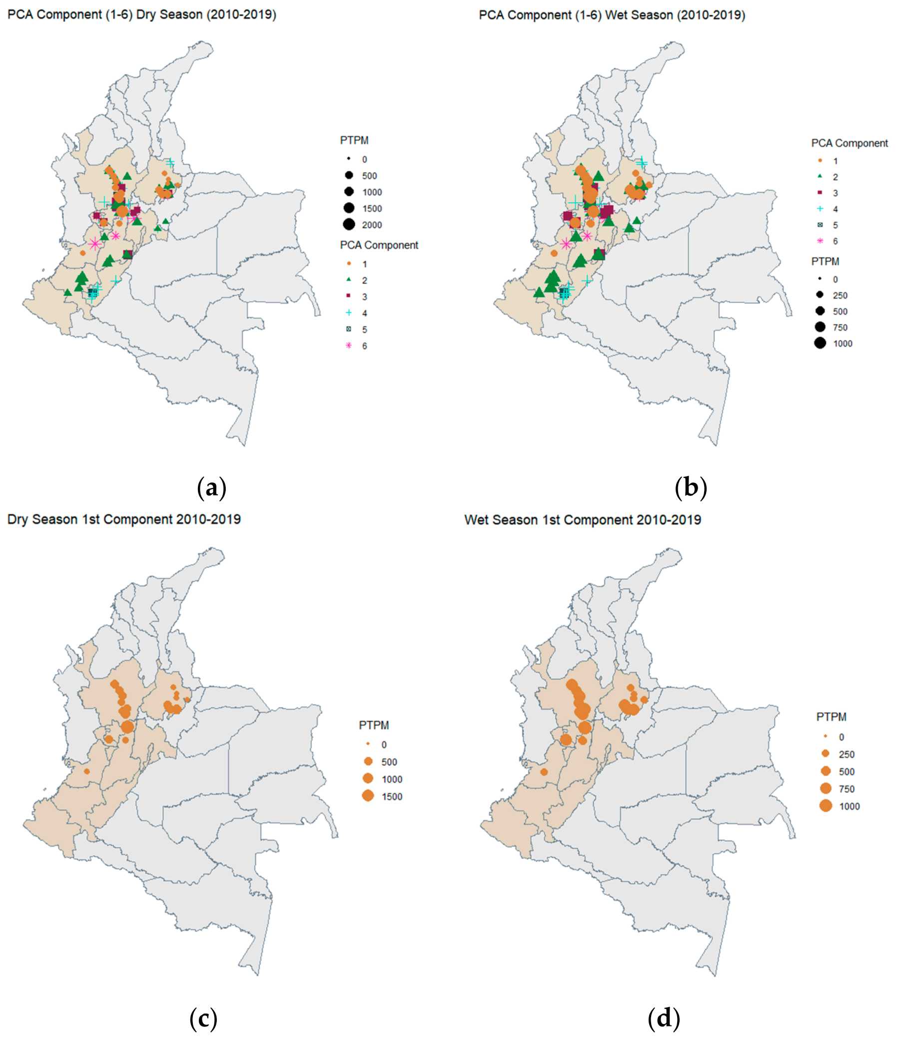


Figure 6. PCA results for seasonal periods (**a**) for dry in 1st–6th components; (**b**) for wet in 1st–6th components; (**c**) for dry in 1st component; (**d**) for wet in 1st component. Source: author's processing.

Table 3. Summary of departments that have the largest contribution to the first six PCs (principal components).

	PC1	PC2	PC3	PC4	PC5	PC6	Total
Antioquia	x	x	x	x	x		5
Caldas	x	x		x	x	x	5
Cauca		x		x	x		3
Cundinamarca		x	x	x	x	x	5
Huila			x	x			2
Nariño		x					1
Quindío		x			x		2
Risaralda			x	x	x	x	4
Santander	x	x	x			x	4
Tolima		x	x		x	x	4
Valle del Cauca	x						1
Total	4	8	6	6	7	5	

A summary of the statistics for the first component shows the range of the altitude of plantations, which covers the entire sample range. For PTPM statistics, the maximum monthly values are near 2000 mm (about 6.56 ft), which exceeds the maximum upper limits considered in the index insurance design (Table 4).

Table 4. Summary statistics PCA for PTPM 1st component.

	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Altitude (m)	996	1280	1440	1447	1550	1850
PTPM (mm)	0	69.95	209.89	258.79	393.30	1995.52

In particular, the first 25 locations for the first component contribute significantly to the cumulative proportion of the component variance (Figure 7).

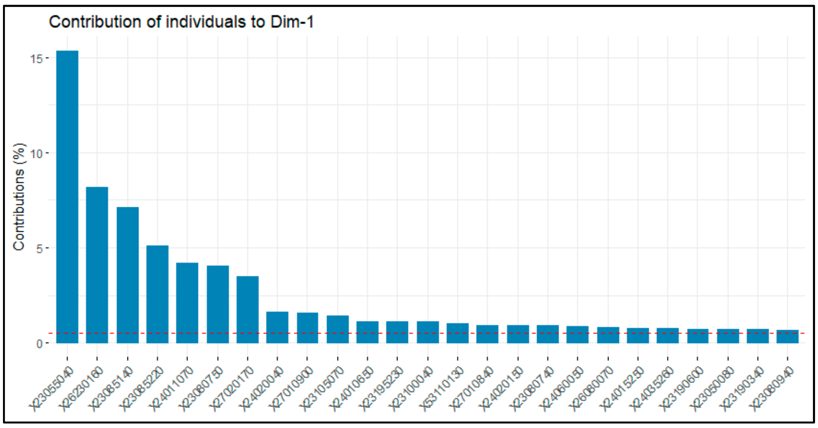


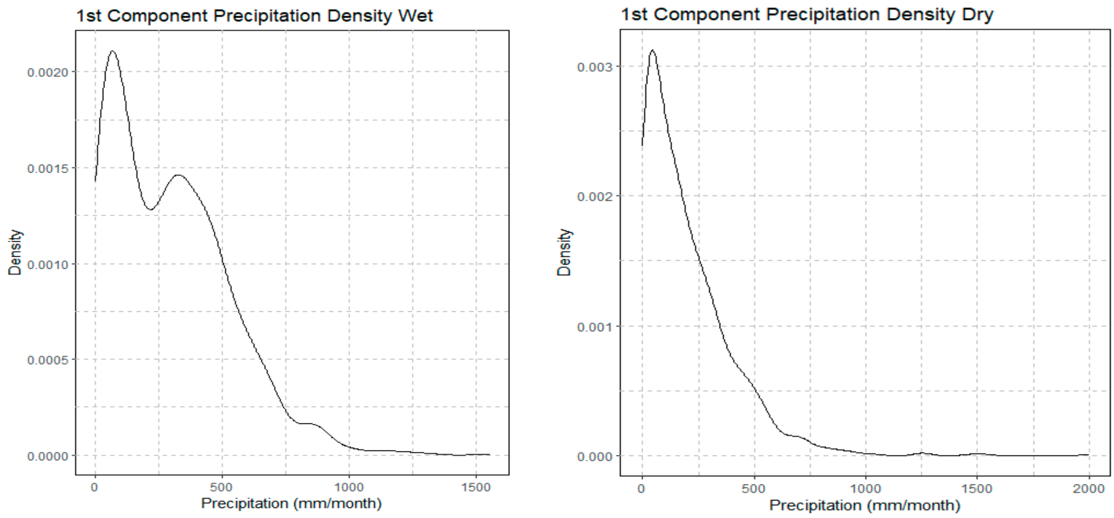
Figure 7. First PCA component contributions of individuals. Here, the weather stations and the percentage of variance contributions are identified. Source: author's processing.

The departments that belong to the first component are Santander, Antioquia, Caldas, and Valle del Cauca (Figure 6c,d). The largest contribution of variance (15.3%) can be found in Samana in Caldas (Table 5 and Figure 7). The next location, with an 8% contribution of variance, is in Briceño, Antioquia, and then it is followed by San Francisco, Antioquia (7.1%), San Carlos, Antioquia (5%), and El Guacamayo, Santander (4%). The locations in Valle del Cauca have less than 1% of the contributions.

Table 5. Information of the region that contributes the most to the first component. Source: author's processing.

Station	Department	Municipality	Latitude (m)	Longitude (m)	Altitude (m)
2305504	Caldas	Samana	5.419	−74.999	1532

Density PTPM distributions per season obtained by kernel simulations show an irregular wet distribution. The dry season shows a significantly positively skewed distribution and extreme PTPM values (Figure 8 and Table 6).



(**a**) (**b**)

Figure 8. Kernel pdfs with n = 1000 points, results for 1st component in the (**a**) wet season and (**b**) dry season of monthly average rainfall values (2010–2019). Source: author's processing.

Table 6. Summary statistics for dry and wet seasons in the 1st component. Source: author's processing.

Season	n	Mean	sd	Median	Min	Max	Skew	Kurtosis	se
Wet	1378	293.69	232.6	267.06	0	1551.74	0.91	1	6.27
Dry	846	201.95	209.05	145.69	0	1995.92	2.42	11.16	7.19

In summary, statistics (Table 6) for the dry and wet seasons show possible adverse conditions to the optimal development of coffee because the second half of the stages for optimal coffee development show lower extreme rain levels [55].

3.2. Singular Spectrum Analysis and Index Insurance

We used the *first* component result from the PCA to obtain its signal using an SSA methodology. With the signal extracted, we calculate the payouts (POs). Next, we determined the expected payments exclusively caused by the tendency components for the next two years (Figure 9). These disbursements represent payments in excess or additional to those that belonged to seasonal patterns. Unlike in dry months, during wet months, an increasing disbursal due to tendency components is expected.

We estimated the average POERs (calculated as future POs for tendency and the maximum indemnity, MI amount) (Table 7) for a common coffee crop producer near each weather station. This was reported in the first component (Table 3) in concordance with each crop season. For instance, during the wet months, it is expected that POs increase to 19% and 60% in the first and second years, respectively, with respect to regular seasonal disbursals (Figure 9). This could be interpreted as extra payments because of the effect of extreme rain conditions.

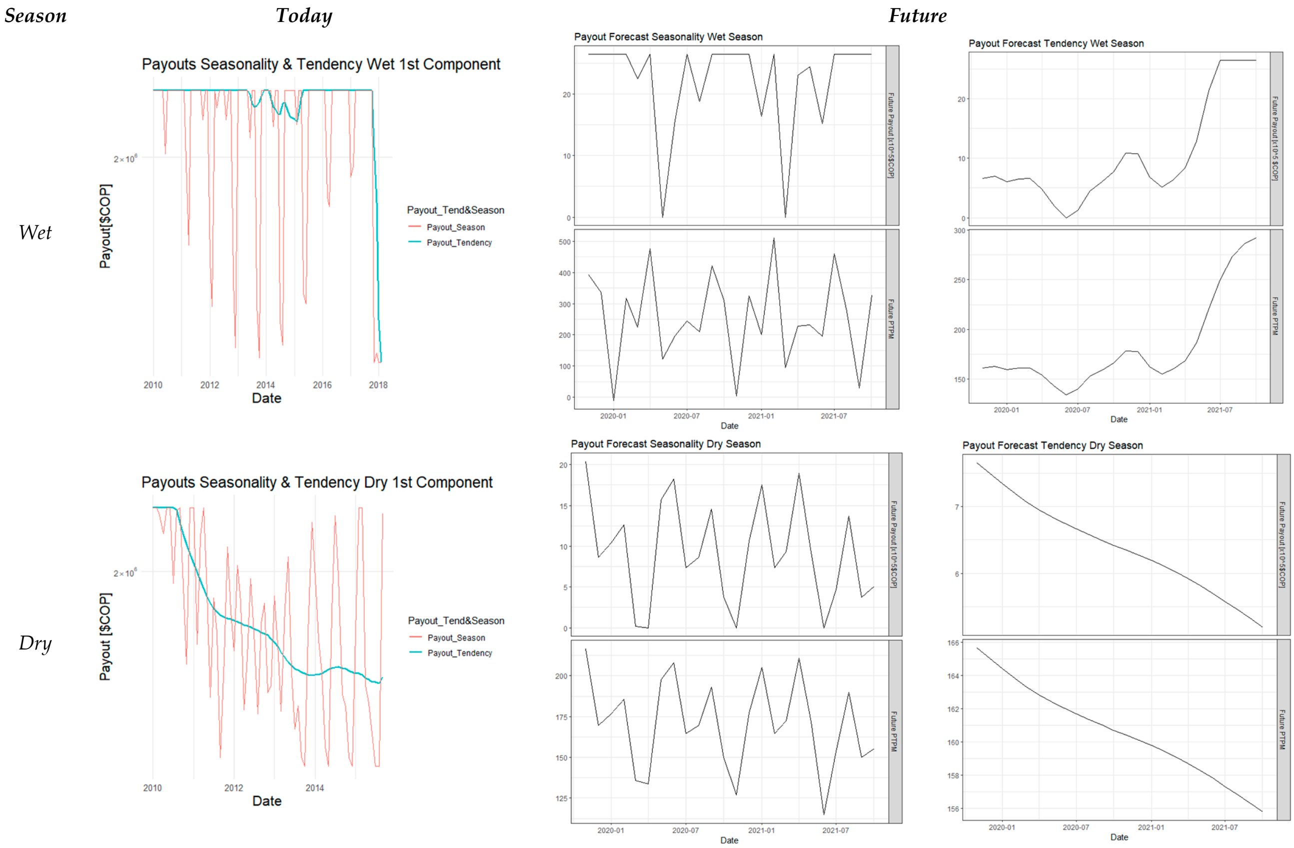


Figure 9. Decomposition of POs for seasonality and tendency in wet and dry months. Source: author's processing.

Table 7. Future payouts in exceedance (PoEs) and ratios (POERs) for 2 years ahead. Note: arrows reflect the direction of the tendency. Source: author's processing.

Season	**Payout Exceedance PoE**		**PoE Ratio (%)**		**POERs Forecast Tendency Direction**
	Year 1 ($COP/Month*ha)	**Year 2 ($COP/Month*ha)**	**Year 1**	**Year 2**	
Wet	491,528.90	1,568,978	18.56	59.27	↑
Dry	695,868.10	582,540.40	26.28	22	↓

We applied a tendency significance test, specifically, the Mann–Kendall test, to the reconstructed tendency series (Appendix A, Table A1). The results show that both seasonal tendencies are significant at 95% confidence. These significant effects can also be identified in the SSA results, where the singular eigenvectors show that the tendency component accounts for most of the variation in the series with 79% and 94% for wet and dry seasons, respectively.

In terms of coffee crop quality, the shapes of the density distributions and the summary statistics (Figure 8, Table 6) indicate that the current and future quality of the crops in the regions of the first component could be at risk. It is at risk as the transition from the flowering to the filling phase usually occurs in the stages of the dry season, and this requires stable irrigation levels that are not happening [55]. This effect can be seen in Figure 9, which depicts the tendency of the dry season.

In Colombia, there are currently coffee index insurance programs that have had positive results. One positive example is Cafe Seguro [33]. Besides the use of weather stations and satellite data these programs use, the reason for their success may be that they promote a closed approach to farmers and cooperatives to narrow gaps regarding their challenges and the needs of the agricultural insurance programs. These programs could be an example to learn from and to promote insurance use by coffee farmers in more productive regions. However, as some of their goods operate in Caldas (e.g., Samana), which belongs to the first component with the greatest levels of POERs, specific approaches should be used to ensure the transfer of risk as well as the development of further adaptation and mitigation strategies, considering the insights of future disbursals according to the methodology presented in this study.

Considering the limitations that satellite data could exhibit for its use in index insurance models, such as the eventual lack of site calibration [28], weather station data has a high potential for this purpose. Index insurance models such as the one proposed here should be used in advance to calculate the expected future payments, which are related to the seasonal and trend components of each crop season. These may result in more efficient solutions for producers and insurers by knowing in advance the expected tendencies of disbursals and, with that, concerted and suitable timely insurance responses [61].

4. Conclusions

This study offers a different methodology to quantify the financial weather risk in agriculture. It is done by using a basic index insurance model to compute future payouts and a ratio of payments in exceedance. This can be applied to short time series precipitation data from weather stations near a crop's productive zones. This new methodology allows us to identify highly volatile weather crop production areas in the current- and mid-term by applying a data-driven approach such as SVD techniques and a financial ratio that accounts for a risk metric. This metric comprises the POERs or payouts in exceedance which could be interpreted as future disbursals due to tendency components.

Studies highlight the need to promote insurance programs to acquire financial resilience, especially in low-income economies whose income relies on agricultural activities. This study suggests a specific methodology to assess financial risk involving future weather instances in crop seasons. This is because state-of-the-art index insurance reviews recommend deeper research to model and assist future index insurance scenarios, as well as an emphasis on index derivation during critical crop seasons. We found that in the mid-term, a hypothetical financial entity would have to disburse from 20 to 60% of payouts in addition to regular seasonal disbursals due to the tendency of weather components in dry coffee seasons.

As is the case for many other countries where a significant part of their productive agricultural activities occurs in risky-weather regions, it is necessary to account for possible extraordinary disbursements or overpayments before losses occur. In the case studied here, these regions are the villages located in (i) Caldas: Samana, Cocorna; (ii) Antioquia: Briceño, San Carlos, and San Francisco; and (iii) Santander: El Guacamayo. Using the POERs measures recently proposed in the literature, it is possible to identify risk regions with an increasing trend of payments that could impact the quality of coffee and the sustainability of ongoing insurance programs.

Public and private subsidies have been successfully implemented and have promoted the expansion of index insurance in the department of Cauca, Colombia. One example is the program Cafe Seguro. One of the key factors of this program's success is the use of public and private subsidies along with fostering a close working relationship with farmers.

This analysis can be implemented and customized in other crops and regions to promote the wider use of index insurance programs. Therefore, programs should consider the implementation of insurance products by maintaining a close work relationship with farmers and by funding programs in order to ensure their adoption and the reduction in costs.

These results could be improved with the inclusion of more weather indices, as well as larger time series to capture climate changes. Crop yield data could be used to enhance the limits and thresholds of the index model. Nevertheless, we believe that this study serves as a point of reference for further debate and the elucidation of Colombia's agricultural development efforts.

Author Contributions: Conceptualization, A.L.A.-P. and N.P.-C.; methodology, A.L.A.-P., M.C.D.-J. and N.P.-C.; software, A.L.A.-P. and M.C.D.-J.; validation, M.C.D.-J.; investigation, A.L.A.-P.; resources, A.L.A.-P. and M.C.D.-J.; writing—original draft preparation, A.L.A.-P. and N.P.-C.; writing—review and editing, A.L.A.-P., M.C.D.-J. and N.P.-C.; visualization, A.L.A.-P. and M.C.D.-J.; supervision, M.C.D.-J. and N.P.-C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the authors.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Mann–Kendall Results for forecasted tendency components in wet and dry seasons (significance level: $\alpha = 0.05$).

CL	Wet	Dry
1	tau = -1 (***) 2-sided p-value = 9.0276×10^{-12}	tau = 0.522 (***) 2-sided p-value = 0.00038958

Signif. codes: 0 '***' 0.001.

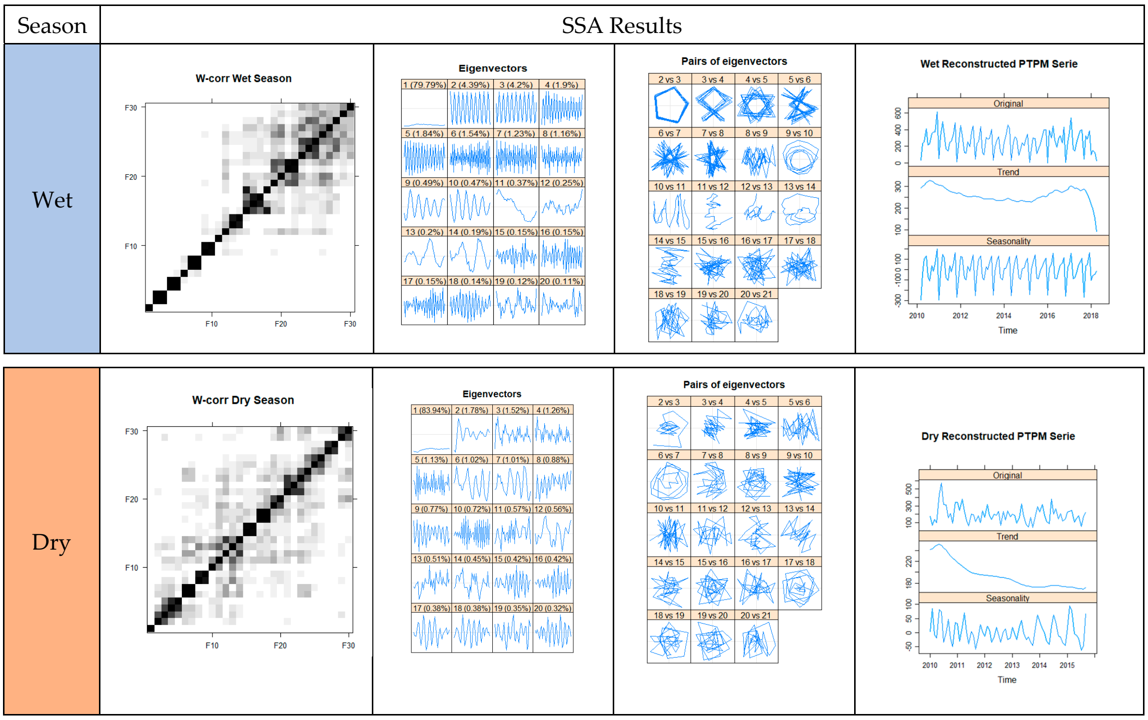


Figure A1. SSA analysis of PTPM time series for the first component. Source: author's processing. Notes: These images aid in deriving the tendency and seasonality signal components from a window length of $=N/2$. The first column depicts the w-correlation plots for wet and dry seasons, which lets us assess the strength of separability, as shown by the pairs that are separated from each other and those that are contaminated by noise. The second column shows the eigenvectors useful to identify through their form, tendency, and seasonal components. The third column identifies the pair of eigenvectors to be chosen by those who form regular polygons. Note: selected vectors: wet: trend = (1,11,12), seasonality = (6:7, 8:9). For dry: trend = (1), seasonality = (6:7, 8:9).

References

1. Jensen, N.; Barrett, C. Agricultural index insurance for development. *Appl. Econ. Perspect. Policy* **2017**, *39*, 199–219. [CrossRef]
2. Collier, B.; Skees, J. Increasing the resilience of financial intermediaries through portfolio-level insurance against natural disasters. *Nat. Hazards* **2012**, *64*, 55–72. [CrossRef]
3. Pelka, N.W. Does weather matter? How rainfall shocks affect credit risk in agricultural micro-finance. *Agric. Financ. Rev.* **2015**, *75*, 194–212. [CrossRef]
4. Vogel, E.; Donat, M.G.; Alexander, L.V.; Meinshausen, M.; Ray, D.K.; Karoly, D.; Meinshausen, N.; Frieler, K. The effects of climate extremes on global agricultural yields. *Environ. Res. Lett.* **2019**, *14*, 054010. [CrossRef]
5. Regan, P.M.; Kim, H.; Maiden, E. Climate change, adaptation, and agricultural output. *Reg. Environ. Chang.* **2019**, *19*, 113–123. [CrossRef]
6. Lesk, C.; Rowhani, P.; Ramankutty, N. Influence of extreme weather disasters on global crop production. *Nature* **2016**, *529*, 283–296. [CrossRef]
7. Agriculture, Forestry, and Fishing, Value Added (% of GDP)—Colombia. Available online: https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?locations=CO (accessed on 27 September 2022).
8. Dane. Encuesta Nacional Agropecuaria (ENA). 2019. Available online: https://www.dane.gov.co/index.php/estadisticas-por-tema/agropecuario/encuesta-nacional-agropecuaria-ena#:~{}:text=La%20Encuesta%20Nacional%20Agropecuaria%20%E2%80%93%20ENA,%25)%2C%204.423.183%20toneladas%20a (accessed on 25 January 2023).
9. Cofffee in Colombia. Retrieved from Product Trade. Exports, Imports, and Tariffs. Available online: https://oec.world/en/profile/bilateral-product/coffee/reporter/col (accessed on 27 September 2022).
10. World Bank Group Agriculture. *Colombia: Policy Note on the Implementation of Catastrophe Agricultural Insurance*; Open Knowledge Repository; The World Bank: Washington, DC, USA, 2017. Available online: https://openknowledge.worldbank.org/handle/10986/29761 (accessed on 1 December 2022).
11. Lau, C.; Jarvis, A.; Ramírez Villegas, J. Agricultura Colombiana: Adaptación al cambio climático. In *CIAT Políticas en Síntesis*; CIAT: Cali, Colombia, 2011; pp. 1–4. Available online: https://cgspace.cgiar.org/bitstream/handle/10568/57475/politica_sintesis1_colombia_cambio_climatico%202.pdf (accessed on 22 November 2022).
12. Asfaw, A.; Simane, B.; Hassen, A.; Bantider, A. Variability and time series trend analysis of rainfall and temperature in northcentral Ethiopia: A case study in Woleka sub-basin. *Weather Clim. Extrem.* **2018**, *19*, 29–41. [CrossRef]
13. Assefa, Z.; Dioha, M. Climate change and trend analysis of temperature: The case od Addis Ababa, Ethiopia. *Environ. Syst. Res.* **2020**, *9*, 27. [CrossRef]
14. Lettenmaier, D.; Wood, E.; Wallis, J. Hydro-climatological trends in the continental United States, 1948–1988. *J. Clim.* **1994**, *7*, 586–607. [CrossRef]
15. Yue, S.; Pilon, P.J.; Phinney, B.; Cavadias, G. The influence of autocorrelation on the ability to detect trend in hdrological series. *Hydrol. Process.* **2002**, *16*, 1807–1829. [CrossRef]
16. Chandler, R.; Scott, M. *Statistical Methods for Trend Detection and Analysis in the Environmental Sciences*; Wiley: Chichester, UK, 2011. [CrossRef]
17. Alhaji, U.; Yusuf, A.; Edet, C.; Oche, C.; Agbo, E. Trend Analysis of Temperature in Gombe State Using Mann Kendall Trend Test. *J. Sci. Res. Rep.* **2018**, *20*, 1–9. [CrossRef]
18. Abrego-P, A.L.; Penagos L, I.G. Mixture modeling segmentation and singular spectrum analysis to model and forecast an asymmetric condor-like option index insurance for Colombian coffee crops. *Clim. Risk Manag.* **2022**, *35*, 100421. [CrossRef]
19. USAID. *Index Insurance for Weather Risk in Lower-Income Countries*; United States Agency for International Development: Washington, DC, USA, 2006.
20. Abdi Raffar, N.; Zulkafli, Z.; Nurulhuda, K.; Rehan, B.M.; Muharam, F.M.; Khosim, N.A.; Tangang, F. Index-based insurance and hydroclimatic risk management in agriculture: A systematic review of index selection and yield-index modelling methods. *Int. J. Disaster Risk Reduct.* **2022**, *67*, 102653. [CrossRef]
21. Miranda, M.J.; Farrin, K. Index Insurance for Developing Countries. *Appl. Econ. Perspect. Policy* **2012**, *34*, 391–427. [CrossRef]
22. Miranda, M.; Gonzalez-Vega, C. Systemic risk, index insurance and optimal management of agricultural loan portfolios in developing countries. *Amer. J. Agric. Econ.* **2010**, *93*, 399–406. [CrossRef]
23. Skees, J.R. Innovations in Index Insurance for the Poor in Lower Income Countries. *Agric. Resour. Econ. Rev.* **2008**, *37*, 1–15. [CrossRef]
24. Di Marcantonio, F. Index-Based insurance challenges and socio-economic considerations: The Ibli-Kenya case. *Geopress. J.* **2016**, *3*, 31–48.
25. World Bank. What Are the Advantages and Disadvantages of Index Insurance? Index InsuranceForum. Global Insurance Facility. 2022. Available online: https://www.indexinsuranceforum.org/faq/what-are-advantages-and-disadvantages-index-insurance (accessed on 19 January 2023).
26. Shirsath, P.; Vyas, S.; Aggarwal, P.; Rao, K. Designing weather index insurance of crops for the increased satisfaction of farmers, industry and the government. *Clim. Risk Manag.* **2019**, *25*, 100189. [CrossRef]
27. Global Index Insurance Facility. Index Insurance Forum. What Are the Different Types of “Crop” Index Insurance? Globla World Bank. Available online: https://www.indexinsuranceforum.org/faq/what-are-different-types-%E2%80%9Ccrop%E2%80%9D-index-insurance (accessed on 2 January 2021).

28. Turvey, C.; Mclaurin, M. Applicability of the normalized difference vegetation index (NDVI) in index-based crop insurance design. *Weather Clim. Soc.* **2012**, *4*, 271–284. [CrossRef]
29. Fasecolda. Seguro Agropecuario. Capítulo 12.7. Federación de Aseguradores Colombianos. Bogotá. Colombia. Available online: https://publicaciones.fasecolda.com/regimen-de-seguros/chapter/p3-c12-7/ (accessed on 1 December 2022).
30. García-Romero, H.; Molina, A. Agriculture and Adaptation to Climate Change: The Role of Insurance in Risk Management: The Case of Colombia. *IDB Tech. Note* **2015**. [CrossRef]
31. Fasecolda. Estadísticas del Ramo. Compañías Autorizadas. Federación de Aseguradores Colombianos: Bogota, Colombia. Available online: https://fasecolda.com/ramos/seguro-agropecuario/companias-autorizadas/ (accessed on 29 October 2019).
32. Blue Marble. Blue Marble Microinsurance. Available online: https://bluemarblemicro.com/ (accessed on 2 January 2021).
33. Mughal. Crop Insurance for Coffee Smallholders. Available online: https://www.sustainability.nespresso.com/crop-insurance-coffee-smallholders (accessed on 4 November 2021).
34. Enenkel, M.; Osgood, D.; Anderson, M.; Powell, B.; McCarty, J.; Neigh, C.; Wooten, M. Exploiting the convergence of evidence in satellite data for advanced weather index insurance design. *Weather Clim. Soc.* **2018**, *11*, 65–93. [CrossRef]
35. PNUD. Análisis del Gasto Público y Privado e Institucionalidad para el Cambio Climático—Caso de Colombia. DNP, GCF. Available online: https://www.uncclearn.org/es/recursos/biblioteca/analisis-del-gasto-publico-e-institucionalidad-para-el-cambio-climatico/ (accessed on 27 September 2022).
36. The World Bank. *Seguro Agropecuario Catastrófico en Colombia: Estudio de Factibilidad*; Borrador; The World Bank: Washington DC, USA, 2017.
37. Vedenov, D.; Barnett, B. Efficiency of weather derivatives as primary crop insurance instruments. *J. Agric. Resour. Econ.* **2004**, *29*, 387–403.
38. Dalhaus, T.; Finger, R. Can precipitation data and pheneological observations reduce basis risk of weather index-based insurance? *Weather Clim. Soc.* **2016**, *8*, 409–419. [CrossRef]
39. Kusuma, A.; Jackson, B.; Noy, I. A viable and cost-effective weather index insurance for rice in Indonesia. *Geneva Risk Insur.* **2018**, *43*, 186–218. [CrossRef]
40. Conradt, S.; Finger, R.; Bokusheva, R. Tailored to the extremes: Quantile regression for index-based insurance contract design. *Agric. Econ.* **2015**, *46*, 537–547. [CrossRef]
41. Conradt, S.; Finger, R.; Spörri, M. Flexible weather index-based insurance design. *Clim. Risk Manag.* **2015**, *10*, 106–117. [CrossRef]
42. Siebert, A. nalysis of index insurance potential for adaptation to hydroclimatic risks in the west African Sahel. *Weather Clim. Soc.* **2016**, *8*, 265–283. [CrossRef]
43. Kerer, J. Backgroud Paper on the Situation of Agricultural Insurance in Kenya with Reference to International Best Practices. Adaptation to Climate Change and Insurance (ACCI). 2013. Available online: https://www.rfilc.org/wp-content/uploads/2020/08/ACCI_Insurance-Background-Kenya_6-2013.pdf (accessed on 1 January 2023).
44. Ricome, A.; Affholder, F.; Gérard, F.; Muller, B.; Poeydebat, C.; Quirion, P.; Sall, M. Are subsidies to weather-index insurance the best use of public funds? A bio-economic farm model applied to the Senegalese groundnut basin. *Agric. Syst.* **2017**, *156*, 149–176. [CrossRef]
45. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2021. Available online: https://www.R-project.org/ (accessed on 26 January 2023).
46. IDEAM. Instituto de Hidrología, Meteorología y Estudios Ambientales. Available online: http://www.ideam.gov.co/ (accessed on 1 January 2021).
47. Cenicafe. Epocas Recomendadas para la Siembra del Café en Colombia. Nota Técnica No. 465. 2016. Available online: https://biblioteca.cenicafe.org/bitstream/10778/703/1/avt0465.pdf (accessed on 19 January 2023).
48. Ramirez-Builes, V. La fenología del café, una herramienta para apoyar la toma de decisiones. *Avences Técnicos Cenicafé*. 2014, pp. 1–8. Available online: https://www.researchgate.net/publication/263162623_La_fenologia_del_cafe_una_herramienta_util_para_apoyar_la_toma_de_decisiones (accessed on 24 November 2022).
49. Perfect Daily Grind. ¿Por qué Florecen los Cafetos y Qué Significa para los Productores? Available online: https://perfectdailygrind.com/es/2021/08/24/por-que-florecen-los-cafetos-y-que-significa-para-los-productores/ (accessed on 24 August 2021).
50. FNCC (No Date) Informe del Gerente, Federación Nacional de Cafeteros. Available online: https://federaciondecafeteros.org/app/uploads/2022/12/Informe-del-Gerente-D.pdf (accessed on 25 January 2023).
51. Li, L.; Liu, Z.; Chen, J.-Y.; Wu, Y.-C.; Li, H. Enhanced Agriculture Insurance with Climate Forecast. *Sustainability* **2022**, *14*, 10617. [CrossRef]
52. James, G.; Witten, D.; Hastie, T.; Tibshirani, R. *An Introduction to Statistical Learning: With Applications in R*; Springer: Boston, MA, USA, 2022.
53. Hill, R.; Robles, M. Flexible Insurance for Heterogeneous Farmers: Results from a Small-Scale Pilot in Ethiopia. 2011. Available online: https://www.ifpri.org/publication/flexible-insurance-heterogeneous-farmers (accessed on 1 January 2023).
54. Dercon, S.; Vargas Hiil, R.; Clarke, D.; Outes-Leon, I.; Seyoum, A.T. Offering rainfall insurance to informal insurance groups: Evidence from a field experiment in Ethiopia. *J. Dev. Econ.* **2014**, *106*, 132–143. [CrossRef]
55. Ramirez-Builes, V.; Jaramillo-Robledo, Á.; Arcila-Pulgarin, J. Rangos adecuados de lluvia para el cultivo de café en Colombia. *Avences Técnicos Cenicafé*. 2010, pp. 1–8. Available online: https://biblioteca.cenicafe.org/bitstream/10778/364/1/avt0395.pdf (accessed on 23 February 2021).

56. Hohl, R.; Jiang, Z.; Tue, M.; Srivatsan, V.; Liong, S.-Y. Using a regional climate model to develop index-based drought insurance for sovereign disaster risk transfer. *Agric. Financ. Rev.* **2020**, *ahead-of-print*. [CrossRef]
57. Bloomberg. USDCOP:CUR. Available online: https://www.bloomberg.com/quote/USDCOP:CUR (accessed on 10 January 2022).
58. FNCC. Tabla de Precio Interno de Referencia para la Compra de Café en Colombia. Available online: https://federaciondecafeteros.org/app/uploads/2019/10/ (accessed on 8 January 2021).
59. Golyandina, N.; Zhigljavsky, A.; Korobeynikov, A. *Singular Spectrum Analysis with R*; Springer: Berlin/Heidelberg, Germany, 2018. [CrossRef]
60. Hassani, H. ; *Rahim. M. Singular Spectrum Analysis Using R*, 1st ed.; Palgrave Macmillan: London, UK, 2018; ISBN 1-137-40951-7.
61. Raju, K.N. *Transforming Weather Index-Based Crop Insurance in India: Protecting Small Farmers from Disasters*; Status and a Way Forward; Research Report IDC-8; ICRISAT Development Center: Hyderabad, India, 2016. Available online: http://oar.icrisat.org/id/eprint/9761 (accessed on 18 November 2022).

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.