Using the Vulnerability Index for Assessing How Can Weather-Related Risk Factors Affect Crop Insurance Pricing in Egypt

By

Dr. Ahmed Samy Said El Azab

Department of Insurance and Actuarial Science, Faculty of Commerce, Cairo University

ahmed_samy@foc.cu.edu.eg

Dr. Raghda Ali Abdelrahman Hussein

Department of Insurance and Actuarial Science, Faculty of Commerce, Cairo University

raghda.ali.abd@foc.cu.edu.eg

Dr. Zahraa Salah Eldin Gomaa

Department of Insurance and Actuarial Science, Faculty of Commerce, Cairo University

z.saladdin@foc.cu.edu.eg

Scientific Journal for Financial and Commercial Studies and Research (SJFCSR)

Faculty of Commerce – Damietta University

Vol.6, No.1, Part 1., January 2025

APA Citation:

El Azab, A. S. S.; **Hussein**, R.A.A. and **Gomaa**, Z. S. A. (2025). Using the Vulnerability Index for Assessing How Can Weather-Related Risk Factors Affect Crop Insurance Pricing in Egypt, ***Scientific Journal for Financial and Commercial Studies and Research***, Faculty of Commerce, Damietta University, 6(1)1, 525-552.

Website: https://cfdj.journals.ekb.eg/

Using the Vulnerability Index for Assessing How Can Weather-Related Risk Factors Affect Crop Insurance Pricing in Egypt

Dr. Ahmed Samy Saeed Al Azab; Dr. Raghda Ali Abdelrahman Hussein

and Dr. Zahraa Salah Eldin Gomaa

Abstract

Crop insurance is increasingly impacted by weather-related risks such as high temperatures, drought, water scarcity, diseases, and pests, leading to higher claims and the need for updating the risk assessments and pricing mechanism is essential. As global temperatures rise and weather patterns become more erratic, insurers must adapt by refining underwriting practices, incorporating climate data, and responding to new regulations. In Egypt, these changes will likely affect the insurance market, necessitating sustainable practices and innovative solutions to manage risks and protect agricultural productivity.

This paper used the index-based insurance for crop pricing mechanism, which compensates for weather-related losses based on predetermined indices like temperature, humidity, and rainfall, reducing operational costs compared to conventional indemnity insurance. A likelihood-impact assessments conducted, ensuring transparency and consistency, and helps determine financial premiums for crop insurance based on the crop vulnerability index.

The vulnerability index is calculated based on weights assigned for each weather-related risk factors using the principal component analysis, and the risk premium is adjusted based on the risk score and its vulnerability.

The paper examined the effects of the weather-related risk factors on three economic crop productions in Egypt using a panel data and finds that cotton is the most vulnerable crop due to its high sensitivity to temperature. Rice and sugarcane show medium vulnerability across all factors, with temperature and water availability being the key risks. This will lead to higher pricing for cotton to account for the increased costs of irrigation, pest control, and reduced yields.

Keywords

Generalized Additive Model, Index-based pricing, Principal Component Analysis, Weather-related risks, Vulnerability Index.

1. Introduction

The insurance industry is consistently affected by a variety of climate-related events, including hurricanes, floods, wildfires, and other extreme weather phenomena. Events such as severe storms, heatwaves, and changing rainfall patterns can have significant implications for insurers, leading to increased claims, shifts in risk assessments, and adjustments in pricing.

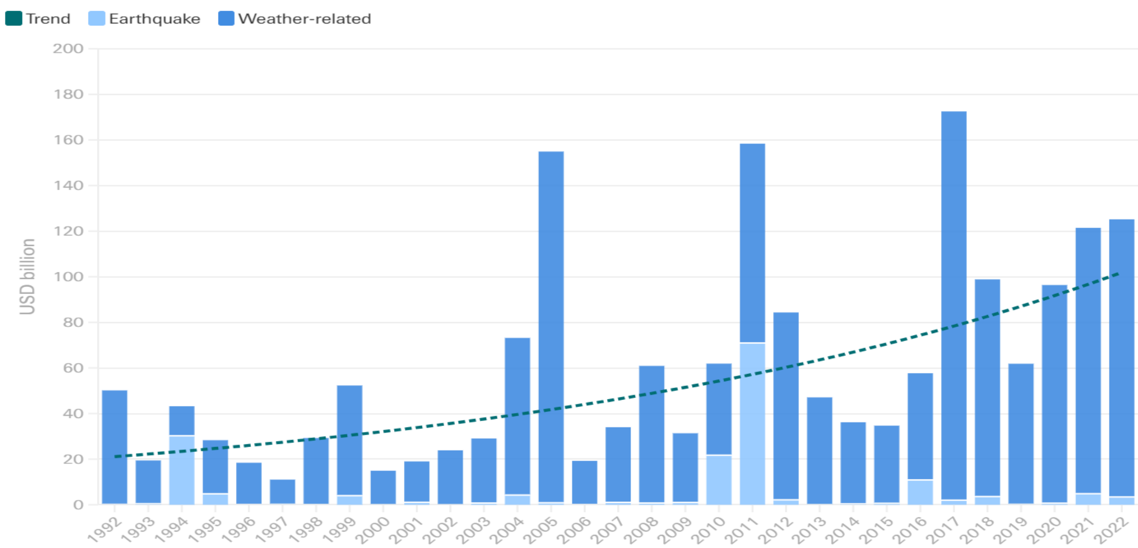

Figure 1. Growth in insured losses due to global climate-related risks (2022 prices)

Source: Swiss Re Institute

For several decades, the financial losses covered by insurance policies due to natural catastrophes have shown a consistent upward trajectory. From 1992 onwards, the average annual growth rate of these insured losses has ranged between 5% and 7%. Although there was a temporary decline observed between 2012 and 2016, the past six years have witnessed a return to the previously mentioned growth trend in annual average losses. Despite variations in year-to-year fluctuations, the projections indicate that insured losses are expected to persistently increase in line with the established trend, even when factors such as inflation diminish. (Re, 2023)

Even in European Union (EU), climate-related extreme events have the potential to cause significant economic disruption. Over the period from 1980 to 2022, direct cumulative catastrophe losses in the EU reached approximately €500 billion. (EEA, 2019) Projections suggest that even in a scenario where global warming is limited to 1.5°C, losses associated with these events within the EU are expected to nearly double by 2050. Moreover, the costs are anticipated to escalate significantly under scenarios featuring a 2°C or 3°C average temperature increase. (Gagliardi, et al., 2022)

As global temperatures rise, and weather patterns become increasingly unpredictable, financial institutions and markets find themselves navigating a landscape fraught with new challenges and uncertainties. From the escalating frequency and severity of natural disasters to the transformation of industries in response to climate-related regulations, the financial sector is confronted with unprecedented risks and opportunities. This introduction delves into the intricate relationship between climate change and the financial sector, exploring the ways in which environmental shifts reshape economic landscapes, influence investment strategies, and necessitate innovative approaches to risk management in our rapidly evolving world.

The potential increase in the insurer's paid losses can be due to:

- Increase in the frequency and severity of extreme weather events like hurricanes, floods, wildfires, and storms. This elevated risk leads to a jump in insurance claims and higher payouts for damages.
- The increase in the frequency and severity of weather-related events result in elevated claims costs for insurers, prompting potential increases in premiums for policyholders as insurers aim to mitigate their financial risks.
- Climate change intensifies extreme weather events, increasing the risk of damage to properties and critical infrastructure. This presents challenges for property insurance, especially in regions susceptible to flooding, hurricanes, or wildfires.
- Adjust the underwriting practices to address evolving climate change risks, potentially revising risk assessment models and incorporating climate data to account for heightened potential losses. This adaptation is crucial for managing the impact of changing environmental conditions on insurance portfolios.

- Climate change affects reinsurance companies, impacting their risk management capabilities due to the increasing number of claims from severe weather events. This could result in elevated costs for insurers and, consequently, policyholders.
- Governments and regulatory bodies may respond to the increased risks associated with climate change by implementing new regulations and standards. Insurers must adapt to these changes, which may include stricter disclosure requirements and sustainable insurance practices.
- Climate change can affect public health, presenting challenges for health insurers due to a potential rise in claims related to climate-induced illnesses, including heat-related conditions, vector-borne diseases, and other health impacts.
- Insurance companies, with significant investment portfolios, face long-term risks from climate change. Exposure to industries susceptible to climate-related impacts or policy changes can potentially affect the performance of these investments.
- An increase in temperature can significantly affect crops and agricultural systems. Here's how it impacts crops:

Reduced Crop Yields:

- Higher temperatures can lead to heat stress in plants, reducing their ability to photosynthesize efficiently.
- Certain crops, especially those sensitive to heat (e.g., cotton, rice, and sugarcane), may experience lower yields as a result.

Altered Growing Seasons:

- Warmer temperatures can shift the timing of planting and harvesting seasons, shortening the growth period for some crops. This may result in smaller harvests or poor-quality yields.

Water Stress:

- Increased temperatures often lead to higher rates of evaporation and greater demand for water by crops.
- This can exacerbate water shortages in regions already facing limited water supply, leading to drought stress and reduced productivity.

The Egyptian insurance market is likely to undergo changes in risk assessment practices, product offerings, and pricing models. Collaboration with government agencies, regulators, and international organizations becomes essential in developing strategies to mitigate the impacts of climate change on the insurance sector. This includes exploring sustainable insurance practices, incorporating climate risk into underwriting, and promoting innovative solutions to address emerging challenges.

Given the critical role of agriculture in Egypt, any disturbance in this sector could carry socio-economic implications, where fluctuations in temperature and rainfall patterns can influence agricultural productivity. Instances of extreme heat and shifts in growing seasons may affect crop yields, posing a potential threat to food security. As noticed that there is a huge in temperature increase compared to the previous years future waves & never get back as before.

2. Crop Insurance in Egypt

Agricultural activities are most vulnerable to climate fluctuations due to changes in temperature and rainfall, which affect the land and water regimes and eventually affect agricultural production and small increase in temperature, decreases agricultural production (Parry, et al., 2007)

Given, agriculture is considered one of the main pillars of the Egyptian economy, employing approximately 20% of Egypt's workforce in 2021, which represents the highest share in economic sector employment. Agriculture contributes around 11% to the country's Gross Domestic Product (GDP) in Egypt, but there is a huge decline in this sector compared to 30% at 1960 (see Figure 2) that can be resulted from the climate change and the increased population size.

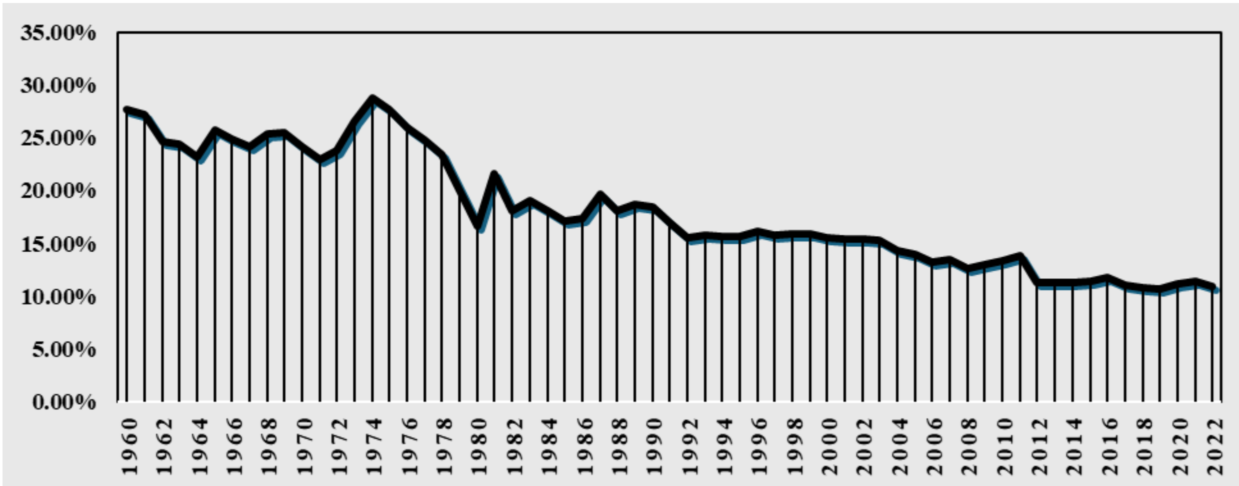

Figure 2. Agriculture, forestry, and fishing, value added (% of GDP)

Data source: World Bank

Crop insurance can play a role in climate change adaptation by safeguarding farmers against fluctuations in crop yield and prices, fostering the adoption of inventive risk management tools, collaborating with the government through partnerships between insurers and public agencies, conducting information and risk/hazard analysis, and offering financial incentives to encourage investment in relevant mitigation strategies

The coverage of agricultural crop insurance in the Egypt has not reached the level seen in agricultural coverages worldwide in general, and particularly in developing countries.

Despite the significant size of the agriculture sector and land reclamation in Egypt, along with the advancements in investments in the food industries sector, this crucial insurance branch has not yet saturated with suitable insurance products. The Egyptian market still operates primarily through traditional insurance policies for agricultural insurance, livestock mortality, and recently, policies covering damage to greenhouses and crops due to natural disasters and pandemics. The need for these policies arose with Egypt's expansion in implementing agricultural greenhouse projects.

Besides that, the Egyptian parliament officially approved the Unified Insurance Law recently. This comprehensive law incorporates an insurance policy specifically designed to protect agricultural crops from damages caused by natural hazards, such as floods, droughts, temperature fluctuations that harm crops, humidity, pests, and diseases.

There are two main types of agriculture crop insurance policies, either Conventional Indemnity insurance or Index-Based insurance: (Ceballos & Kramer, 2019)

- ***Conventional-Indemnity insurance:*** this policy will provide indemnification for the insured in case of loss in production, income, etc. that resulted from natural hazards or others, in this case a loss assessment report will be required case by case.
- ***Index-Based Insurance:*** this policy will be based on an index (e.g. rainfall-based index, temperature-based index, etc.). In this case, the insured will be compensated for losses resulted from weather- related events via payouts based on a predetermined index and site visit will not be require which will reduce the operational costs in return.

Consequently, in order to have a successful agriculture and crop insurance policy that increase small farmer's financial inclusion, some aspects should be considered, among them: (Nshakira-Rukundo, et al., 2021)

- Develop appropriate agricultural insurance products for small-scale farmers that do not heighten their vulnerability, for instance, by reducing dependence on mono-cropping.
- Employ clearly defined and standardized insurance criteria, such as index-based insurance, instead of indemnity insurance.
- Inclusion of agricultural insurance is essential within an all-encompassing national strategy for managing climate change risks.

This paper will concentrate on creating a weather-related Vulnerability Index (VII) that include temperature, humidity, and rainfall and can be used as an adaptation tool to provide more flexible premiums and claims settling process.

3. Climate Change, Adaptation, and Insurance Vulnerability

Over the course of two decades, various disciplines have conceptualized vulnerability in diverse ways, employing it as a synonym for concepts such as resilience, risk, marginality, adaptability, and exposure (Liverman, 1990).

The third assessment report of the United Nations Intergovernmental Panel on Climate Change (IPCC) describes vulnerability as “The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity.” (Parry, et al., 2007).

The weather-related Vulnerability Index (VI) is a method for hedging against climate change that has seen widespread use since the 1990s, especially in developing countries where agriculture is heavily reliant on climate conditions. VI is economically attractive due to its ability to tackle persistent challenges such as moral hazard, adverse selection, and low administrative costs, along with the simplicity of processing claims for indemnities (Tadesse, et al., 2015).

(Schneider, et al., 2001) outlined three key aspects of vulnerability to climate change:

- **Physical Environment**: This encompasses the impact of climate change on the environment, including changes in agricultural productivity and the distribution of disease vectors.
- **Socioeconomic Dimension**: This refers to a region's ability to adapt to long-term changes and recover from extreme events.
- **External Assistance Dimension**: This relates to the extent to which a region can receive support from allies and trading partners in its efforts to adapt to climate change (Füssel, et al., 2006)

VI offers the advantage of conducting impact assessments based on real meteorological data instead of relying on production damage evaluations. Additionally, since it relies on weather data from official weather stations, there is a high level of consistency and transparency (Binswanger-Mkhize, 2012).

The VI typically measures how much a crop is exposed to risks like climate change, pests, diseases, and economic instability, and pricing agriculture crops should be subject to the following key factors: (Helgeson, et al., 2013)

- **Climate Exposure**: How vulnerable a crop is to temperature increases, droughts, or heavy rainfall.
- **Water Availability**: Crops that require more water are more vulnerable in regions facing water scarcity.
- **Soil Health**: Regions with degraded soils may lead to reduced yields and higher costs to maintain productivity.
- **Market Instability**: Price fluctuations due to supply-demand imbalances or market access issues.
- **Pests and Disease**: Higher vulnerability to pests and diseases can increase the cost of production due to more intensive pest management.
- **Infrastructure and Logistics**: The cost of transporting crops from farm to market can be influenced by infrastructure quality, affecting the final price.
- **Socioeconomic Factors**: Farmer access to credit, insurance, and social safety nets, which can affect their ability to cope with vulnerability.

To **increase the risk premium for each crop based on its vulnerability index**, the paper will follow a systematic approach that quantifies risk factors and translates them into financial premiums based on the following steps in the next section.

4. Steps to Price Crops Using a Vulnerability Index:

a) Calculate the Risk Score for Each Risk Factor

To calculate a **risk score** for use in the vulnerability index of a crop, a structured approach will be followed that evaluates the various risk factors affecting the crop. The **risk score** quantifies the degree of risk a crop faces from specific categories, such as climate, pests, market conditions, etc. This score is typically based on historical data, probability assessments, and expert analysis. (Hazell, et al., 2010)

The **risk score** for each risk factor is calculated by multiplying the **likelihood** by the **impact**:

Each risk is assessed in terms of **likelihood** (how likely it is to occur) and **impact** (how severe the consequences would be if it happens). This is often done using a **risk matrix** or similar scoring system (McIntosh, et al., 2013):

Likelihood Scale:

- **1**: Very unlikely (occurs less than once in 10 years)
- **2**: Unlikely (occurs once in 5-10 years)
- **3**: Possible (occurs once in 3-5 years)
- **4**: Likely (occurs once in 1-3 years)
- **5**: Very likely (occurs annually or more frequently)

Impact Scale:

- **1:** Negligible impact (little or no effect on crop yield or quality)
- **2:** Minor impact (small reduction in crop yield or quality)
- **3:** Moderate impact (moderate reduction in crop yield or quality)
- **4:** Significant impact (large reduction in yield or quality, affecting profitability)
- **5:** Severe impact (crop failure or major losses in profitability)

Not all risk factors affect all crops equally. Some crops may be more vulnerable to drought, while others may be more sensitive to market volatility. Therefore, **weights** should be assigned to each risk factor based on the crop type and the region it is grown in. These weights reflect the relative importance of each risk to the overall vulnerability.

b) Assign Weights for Each Risk Factor

The quantitative assessment of vulnerability entails creating a vulnerability index constructed from multiple risk factors. An index is a numerical scale calculated from a set of variables that are representative of each risk factor. The data is arranged in an $\boldsymbol{m} \times \boldsymbol{k}$ matrix, representing the different k risk factors for m observations.

Data for k risk factors and m observations

Observations	**Variables / Indicators**				
	1	**2**	**...**	***j***	***K***
1	X_{11}	X_{12}	$\vdots$	X_{1j}	X_{1K}
2	X_{21}	X_{22}	$\vdots$	X_{2j}	X_{2K}
$\vdots$	...	...	$\vdots$	...	...
$\boldsymbol{i}$	X_{i1}	X_{i2}	$\vdots$	X_{ij}	X_{iK}
$\boldsymbol{m}$	X_{m1}	X_{m2}	$\vdots$	X_{mj}	X_{mK}

Source: Researchers

When formulating the vulnerability index, data for each risk factor will be normalized where normalization plays a crucial role in multivariate statistical analysis due to the varying ranges of different risk factors. As some variables exhibit a large range of variances while others have a smaller range, employing a normalization technique becomes essential. This technique involves transforming the dataset to a specific range, typically between 0 and 1. The application of normalization is instrumental in establishing a more robust relationship among the dataset, and it is used to normalize residuals through various transformation methods (Quackenbush, 2002).

The normalization process is implemented to prevent the undue influence of one risk factor on others within the dataset. This approach aligns with similar methodologies employed in the creation of indices such as the Human Development Index and Life Expectancy Index (Coulibaly, et al., 2015), (Piya, et al., 2012), and (UNDP, 2007)

In this context, two potential types of relationships exist:

- When vulnerability decreases with a decrease in the value of a variable, the following formula is employed to standardize the scores:

$$M_{ij} = \frac{X_{ij} - X_{min}}{X_{max} - X_{min}} \tag{1}$$

- When vulnerability increases with an increase in the value of the variable, the following formula is utilized to standardize the scores:

$$N_{ij} = \frac{X_{max} - X_{ij}}{X_{max} - X_{min}} \tag{2}$$

Where, M_{ij} and N_{ij} are normalized scores, X_{max} is the highest value in the same array, and X_{min} is the lowest value in the same array. After normalizing the values of all factors.

The literature suggests three approaches for weight assignment to variables: (1) through expert judgment (Brooks, et al., 2005) and (Moss, et al., 2001); (2) employing equal weighting (Lucas & Hilderink, 2005) and (o'Brien, et al., 2004); and (3) utilizing statistical methods like Principle Component Analysis (PCA) or factor analysis (Cutter, 2003) and (Thornton, et al., 2006)

Assignment of weights to the selected risk factors is a key issue in the vulnerability assessment model (Brooks, et al., 2005). The vulnerability index was derived Principal Components Analysis (PCA). PCA approach is used in modelling correlated random variables and known as eigenvalue decomposition. The PCA approach describes the difference from the mean for each variable as a weighted average of a number of independent volatility factors.

Mathematically, PCA relies on Eigenvector-based multivariate analysis (Abdi & Williams, 2010). PCA can be performed through either eigenvalue decomposition of a data covariance (or correlation) matrix or singular value decomposition of a data matrix. The outcomes of PCA are typically expressed in terms of component scores, also referred to as factor scores, which represent the transformed values of variables associated with a specific data point. Additionally, loadings, which are the weights used to multiply each standardized original variable to obtain the component score, are integral to the interpretation of PCA results (Wold, et al., 1987).

The next step is to compute the covariance matrix $\sum$ from the standardized data, where $\sum$ is the $m \times k$ covariance matrix.

$$\sum = \mathrm{Z} \times Z' \tag{3}$$

The matrix Z is lower triangular – in other words, all elements above and to the right of the diagonal are zero:

$$Z = \begin{pmatrix} Z_{1,1} & 0 & \cdots & 0 \\ Z_{2,1} & Z_{2,2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ Z_{m,1} & Z_{m,2} & \cdots & Z_{m,k} \end{pmatrix} \tag{4}$$

The transpose, Z', is therefore upper triangular. Each element of Z can be calculated using the following formula:

$$Z_{i,j} = \begin{cases} 0 & if\ i < j \\ \sqrt{\sigma_{i,i} - \sum_{u=1}^{i-1} Z_{i,u}^2} & if\ i = j \\ \frac{1}{Z_{j,j}}\left(\sigma_{i,j} - \sum_{u=1}^{j-1} Z_{i,u}\, Z_{u,j}\right) & if\ i > j \end{cases}$$

(5)

Where $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, k$. This means that if the elements above and to the left of a particular element are known, the element itself can be evaluated, so the matrix must be evaluated from the top left corner downwards, either by column or by row.

For this matrix, there exists an orthogonal matrix **V** that can convert the covariance matrix into a diagonal matrix, **Λ**:

$$\Lambda = V' \times \sum \times V \tag{6}$$

$$\begin{pmatrix} \Lambda_1 & 0 & \cdots & 0 \\ 0 & \Lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Lambda_k \end{pmatrix} = \begin{pmatrix} V_{1,1} & V_{2,1} & \cdots & V_{m,1} \\ V_{1,2} & V_{2,2} & \cdots & V_{m,2} \\ \vdots & \vdots & \ddots & \vdots \\ V_{1,k} & V_{2,k} & \cdots & V_{m,k} \end{pmatrix} \times \begin{pmatrix} \sigma_{1,1} & \sigma_{1,2} & \cdots & \sigma_{1,k} \\ \sigma_{2,1} & \sigma_{2,2} & \cdots & \sigma_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m,1} & \sigma_{m,2} & \cdots & \sigma_{m,k} \end{pmatrix}$$

$$\times \begin{pmatrix} V_{1,1} & V_{1,2} & \cdots & V_{1,k} \\ V_{2,1} & V_{2,2} & \cdots & V_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ V_{m,1} & V_{m,2} & \cdots & V_{m,k} \end{pmatrix}$$

Matrix V is, like $\sum$, an $m \times k$ matrix. It contains k column vectors, each of length m, the K eigenvectors of the covariance matrix $\sum$. The diagonals of Λ are the eigenvalues of $\sum$. The combination of each eigenvector and eigenvalue is a principal component. This means that the first eigenvector, column vector V_1, and the first eigenvalue, Λ_1, form the first principal component of the data, such that:

$$\Lambda_1 = V_1{}' \times \sum \times V_1 \tag{7}$$

$$\begin{pmatrix} V_{1,1} & V_{2,1} & \cdots & V_{1,k} \end{pmatrix} \times \begin{pmatrix} \sigma_{1,1} & \sigma_{1,2} & \cdots & \sigma_{1,k} \\ \sigma_{2,1} & \sigma_{2,2} & \cdots & \sigma_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m,1} & \sigma_{m,2} & \cdots & \sigma_{m,k} \end{pmatrix} \times \begin{pmatrix} V_{1,1} \\ V_{2,1} \\ \vdots \\ V_{m,1} \end{pmatrix}$$

The process for finding the second principal component is the same as for the first, except that the covariance matrix is replaced with a new matrix:

$$\textstyle\sum_1 = \sum - \Lambda_1 \times V_1 \times V_1' \tag{8}$$

For each observation, the weighted vulnerability index is calculated by multiplying the standardized values of the risk factor by their respective weights and summing the results:

$$VI = \sum_{j=1}^{k} \Lambda_j \times Risk\ Score_j \tag{9}$$

This vulnerability index (VI) represents a composite measure of vulnerability for each observation, combining information from the k risk factors based on their contributions to the first k principal components.

c) Link the Vulnerability Index to Risk Premium

Based on the vulnerability index, a **risk premium** can be added to the pricing model. This premium compensates farmers for the extra risks they face due to environmental challenges. Crops in high-risk areas should have a higher premium, while those in more stable environments will have a lower one.

To determine how much to increase the risk premium, you need to create a **scaling factor** that converts the vulnerability index into an additional cost or premium for the crop. This could involve setting **thresholds** for the vulnerability index that trigger increases in the risk premium. (Eze, et al., 2020)

For instance:

- **Low Vulnerability (VI < 3)**: No additional premium.
- **Moderate Vulnerability (3 ≤ VI < 5)**: 5-10% increase in base crop price.
- **High Vulnerability (VI ≥ 5)**: 10-20% increase in base crop price.

This ensures that crops with higher vulnerability indices receive a **proportional risk premium** to compensate farmers for increased risks and potential losses.

Next, data analysis and result will be presented to address the suggested method for adapting crop insurance pricing to the climate change.

5. Analysis and Conclusions

The quantitative assessment will be completed through creating the VI. This index is constructed by several risk factors chosen by the researchers based on literature and data availability. All risk factors chosen are related to climate change category.

Temperature Data, including maximum and minimum temperatures was obtained from the General Meteorological Authority of Egypt for the period from 1995 – 2022. This data is collected for different climate division across delta area which include the production of the most key crops. The climate division data was obtained for the growing season only, which runs from March through September.

Similar to temperature data, humidity and rainfall data were collected from 1995 to 2022, based on climate division data for the growing season.

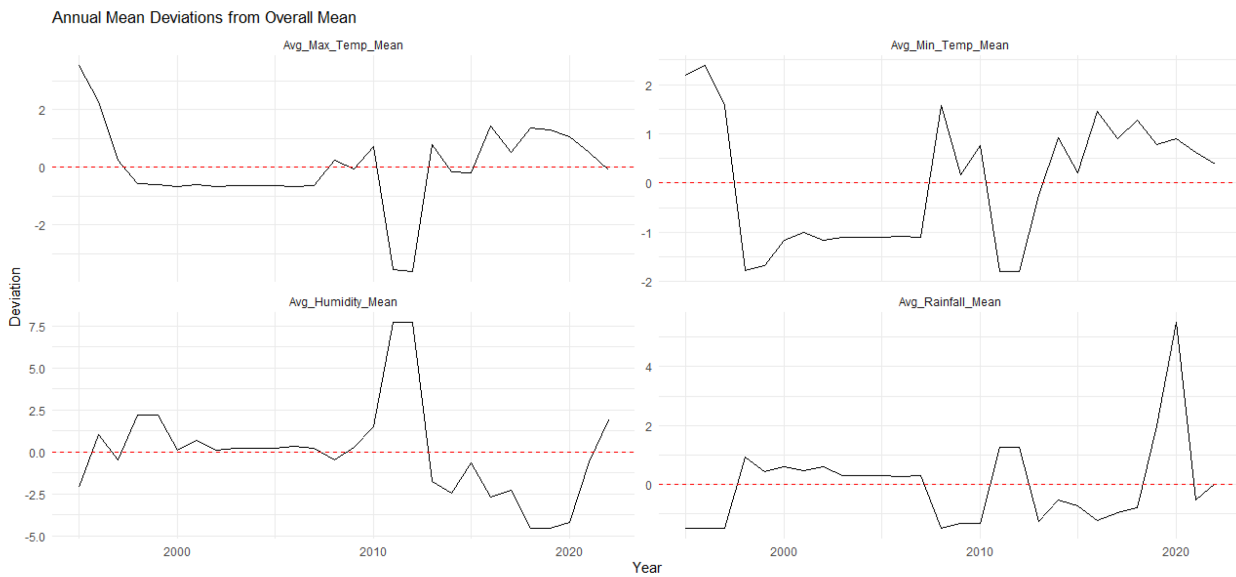

Figure 3. Climate change risk-indicators variability (1995 – 2022)

The summary statistics shows that the average maximum temperatures range from 17.30 C^o to 46.50 C^o during the period of the study with mean equal to 30.56 C^o, given the average minimum temperatures ranges to 31.30 C^o with a median of 21.30 C^o. the maximum rainfall were 82.9 mm., and the humidity at some region and years reached 82%.

Data on the cultivation area and production volume of Cotton, Rice, and Sugarcane were gathered from the Egyptian Ministry of Agriculture and Land Reclamation (MALR) for the years 1995 to 2022. Cotton, Rice, and Sugarcane are selected as key economic crops within a sector highly vulnerable to the effects of climate change and cultivated in the growing season.

The production volume was measured in tons. In instances where specific crop production data was unavailable for a particular year, a straightforward interpolation formula was employed to generate the data for those specific years.

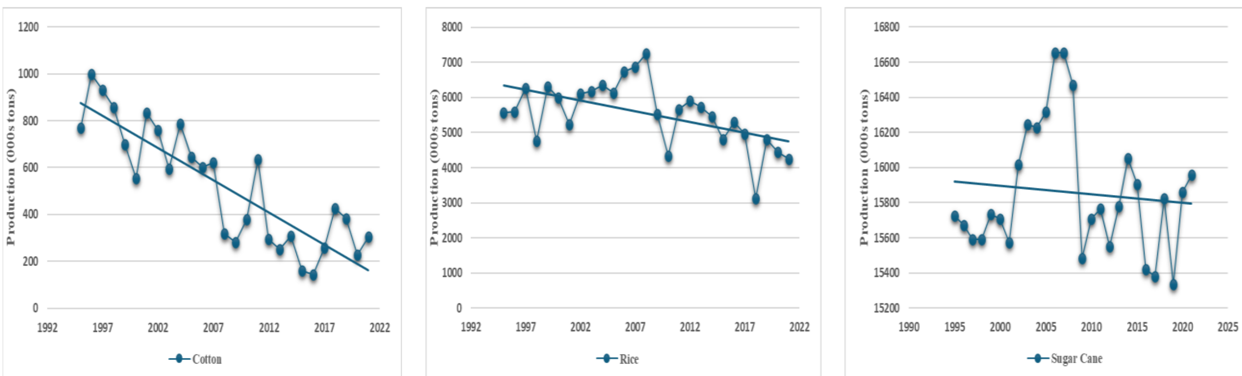

Figure 4. Trends of the Economic crops' productions in Egypt

The figure shows that Egypt is facing a huge decline in the main economic crops due to many reasons among them the climate change and its effect on the cultivated area available especially that Egypt is facing a problem of Desertification, this is clear for the cotton production where there is a decline with around -152% in year 2021 compared to 1995.

In order to analyze the relation between the weather-related risk factors and the crops production, the Generalized Additive Model (GAM) is used that allow for **non-linear and smooth effects** of independent variables on the dependent variable, without pre-specifying the form of the relationship. The analysis shows the following:

Table 1. Weather-related risk factors vs. Cotton crop (GAM) analysis

Terms	*EDF*	*Ref. DF*	*F-Value*	*p-value*
s(Max_Temp)	1.000	1.000	12.559	0.00324 **
s(Min_Temp)	2.455	2.939	1.492	0.25249
s(Humidity)	4.046	4.542	4.690	0.01252 *
s(Rainfall)	5.922	6.767	6.502	0.00191 **
Intercept				<2e-16 ***

- **Adjusted R-squared**: 0.833
- **Deviance Explained**: 91.6%
- **GCV (Generalized Cross-Validation)**: 276,350
- **Scale Estimate**: 133,990
- **Sample Size (n)**: 28

The GAM analysis suggests that the smooth term for maximum temperature is effectively linear, as indicated by its effective degrees of freedom (edf = 1.000). This means that the relationship between maximum temperature and cotton production is close to linear, although modeled as a smooth term. The high F-statistic (12.559) and very low p-value (0.00324) underscore the statistical significance of this term, confirming that maximum temperature has a strong and impactful effect on cotton production.

Other predictors like humidity and rainfall also have significant effects with p-values below 0.05, indicating important non-linear relationships. In contrast, the smooth term for minimum temperature is not statistically significant (p-value = 0.25249), suggesting it does not play a major role in predicting cotton production.

The model explains 91.6% of the deviance in cotton production, demonstrating a high fit, and the adjusted R-squared of 0.833 reflects robust explanatory power. This analysis reveals that while maximum temperature has a significant and nearly linear impact on cotton production, the other variables exhibit more complex, non-linear effects.

Table 2. Weather-related risk factors vs. Rice crop (GAM) analysis

Terms	*EDF*	*Ref. DF*	*F-Value*	*p-value*
s(Max_Temp)	1.000	1.000	0.170	0.0684
s(Min_Temp)	2.545	3.104	3.709	0.0232 *
s(Humidity)	2.460	2.926	2.238	0.0834
s(Rainfall)	1.586	1.914	0.774	0.4237
Intercept				2.55e-13 ***

- **Adjusted R-squared**: 0.596
- **Deviance Explained**: 71%
- **GCV (Generalized Cross-Validation)**: 35,991
- **Scale Estimate**: 24,948
- **Sample Size (n)**: 28

The GAM analysis for rice production reveals varying effects of the predictors. The smooth term for maximum temperature shows an effective degree of freedom (edf) of 1.000, indicating a nearly linear relationship with rice production. However, the F-statistic for this term is 0.170 with a p-value of 0.0684, suggesting that the effect of maximum temperature on rice production is nearly statistically significant in this model. In contrast, the smooth term for minimum temperature is significant with an F-statistic of 3.709 and a p-value of 0.0232, indicating that minimum temperature has a meaningful impact on rice production. The smooth term for humidity approaches significance with a p-value of 0.0834, suggesting a potential influence on rice production that is not quite statistically significant at the 0.05 level. Rainfall does not show a significant effect with a p-value of 0.4237 where in Egypt rice is heavily depends on irrigation from the Nile River.

The model explains 71% of the deviance in rice production, with an adjusted R-squared of 0.596, reflecting a moderate to good fit. The GCV score is 35,991, indicating the model's complexity is well-balanced. The scale estimate of 24,948 provides a measure of residual variance. Overall, the results indicate minimum temperature, and maximum temperature does have significant impact rice production. The model suggests that while some predictors have potential effects, such as humidity, these are not strongly supported by the data in this instance.

Table 3. Weather-related risk factors vs. Sugarcane crop (GAM) analysis

Terms	*EDF*	*Ref. DF*	*F-Value*	*p-value*
s(Max_Temp)	1.000	1.000	1.412	0.250
s(Min_Temp)	1.000	1.000	0.650	0.431
s(Humidity)	1.000	1.000	2.657	0.120
s(Rainfall)	6.481	7.478	2.902	0.030 *
Intercept				<2e-16 ***

- **Adjusted R-squared**: 0.421
- **Deviance Explained**: 62.4%
- **GCV (Generalized Cross-Validation)**: 1.2033e+05
- **Scale Estimate**: 75,286
- **Sample Size (n)**: 28

GAM results for sugarcane production indicate distinct effects of the predictors on the outcome. The smooth terms for maximum temperature and minimum temperature both have effective degrees of freedom (edf) of 1.000, suggesting almost linear relationships with sugarcane production. However, neither term is statistically significant as sugarcane thrives in warm climates, with p-values of 0.250 and 0.431, respectively, indicating that maximum and minimum temperatures do not have a meaningful impact on sugarcane production in this model. The smooth term for average humidity also shows a near-linear relationship with an edf of 1.000 and a p-value of 0.120, which is not statistically significant at the 0.05 level.

In contrast, the smooth term for rainfall has an edf of 6.481 and is significant with a p-value of 0.030. This indicates a complex, non-linear effect of rainfall on sugarcane production. The model explains 62.4% of the deviance in sugarcane production, with an adjusted R-squared of 0.421, suggesting a moderate fit. The GCV score of 120,330 and the scale estimate of 75,286 provide measures of model complexity and residual variance. Overall, the results highlight that rainfall has a significant and complex effect on sugarcane production, while the other predictors do not show statistically significant impacts in this model.

Next, to calculate the Vulnerability index, first, the **risk score** for the climate risks category only will be included given the historical data analyzed previously, probability assessments, and expert judgments, each of these risk scores will be assigned for the 3 economic crops selected based on a scale from 1 – 5. The scores take into consideration the crop yields and quality beside the likelihood of the weather-related risk factors.

Table 4. The Risk Scores for the Cotton Production in Egypt given the weather-related risk factors

	Likelihood	***Impact***	***Score***
Max Temp	5	4	20
Min Temp	2	2	4
Humidity	3	3	9
Rainfall	3	4	12

High maximum temperatures are very likely and have a significant impact on cotton production, as evidenced by the near-linear relationship observed in the GAM analysis. Minimum temperatures have a lesser impact, being possible but less critical. Humidity is also possible and exerts a moderate influence on cotton growth and quality. Rainfall is unlikely due to Egypt's arid climate, but when it does occur, it has a significant impact on cotton yields, underlining the importance of adequate precipitation for optimal production.

Table 5. The Risk Scores for the Rice Production in Egypt given the weather-related risk factors

	Likelihood	***Impact***	***Score***
Max Temp	3	4	12
Min Temp	5	4	20
Humidity	3	3	9
Rainfall	2	3	6

High temperatures are likely to affect rice production with a moderate impact, though not as strongly as on cotton. Minimum temperatures have a significant effect on rice, influencing growth critically. Humidity, especially in the Nile Delta, can moderately impact rice due to disease risks. Rainfall is generally unlikely but significantly affects rice yields, particularly in regions reliant on natural precipitation, highlighting its crucial role in rice cultivation.

Table 6. The Risk Scores for the Sugarcane Production in Egypt given the weather-related risk factors

	Likelihood	***Impact***	***Score***
Max Temp	3	3	9
Min Temp	2	2	4
Humidity	3	3	9
Rainfall	5	4	20

High temperatures are very likely and have a moderate impact on sugarcane, thriving in warm climates but still affected by extremes. Minimum temperatures are possible with a minor impact, as sugarcane is relatively tolerant of temperature variations. Humidity is possible and moderately affects sugarcane quality and disease resistance. Rainfall is unlikely in desert areas but crucial in irrigated regions, with significant impact on sugarcane growth and yield, reflecting its importance for maintaining production levels.

These overall risk scores can then be combined with weights using PCA to determine the vulnerability index and ultimately adjust risk premiums.

R software packages is used to calculate weights for the climate-rated risk factors through normalizing data and using the principal component analysis and the results was as follows:

Table 7. The weight of the weather-related risk factors using PCA

	Eigen Values	***% of variance***
Max Temp	0.16426	69.59
Min Temp	0.04586	19.43
Humidity	0.01965	8.32
Rainfall	0.00628	2.66

In the PCA, we extracted the first principal component, which represent 70% of the total variance (i.e., the input variables were highly correlated).

In order to update the risk premium based on the vulnerability index for each crop complying with the following;

Cotton Crop pricing (Medium Vulnerability):

- Maximum temperature: High (Risk Score = 20, Weight = 0.164)
- Minimum temperature: Medium (Risk Score = 4, Weight = 0.046)
- Humidity: Medium (Risk Score = 9, Weight = 0.020)
- Rainfall: Medium (Risk Score = 12, Weight = 0.006)
- **Vulnerability Index**: (20×0.16426) +(4×0.04586) +(9×0.01965) +(12×0.00628) = 3.72

Risk premium: 7% increase on base price due to moderate vulnerability.

Rice Crop pricing (Medium Vulnerability):

- Maximum temperature: Medium (Risk Score = 12, Weight = 0.164)
- Minimum temperature: Medium (Risk Score = 20, Weight = 0.046)
- Humidity: Medium (Risk Score = 9, Weight = 0.020)
- Rainfall: Medium (Risk Score = 6, Weight = 0.006)
- **Vulnerability Index**: (12×0.16426) +(20×0.04586) +(9×0.01965) +(6×0.00628) = 3.10

Risk premium: 5% increase on base price due to moderate vulnerability.

Sugarcane Crop pricing (Low Vulnerability):

- Maximum temperature: Medium (Risk Score = 9, Weight = 0.164)
- Minimum temperature: Medium (Risk Score = 4, Weight = 0.046)
- Humidity: Medium (Risk Score = 9, Weight = 0.020)
- Rainfall: High (Risk Score = 20, Weight = 0.006)
- **Vulnerability Index**: (9×0.16426) +(4×0.04586) +(9×0.01965) +(20×0.00628) = 1.96

Risk premium: No additional premium is required to the base price due to low vulnerability.

Finally, developing a composite vulnerability index for each crop, based on data from the weather-related risk factors mentioned above quantify how much risk the crop faces due to climate changes, and weights are established for all variables to derive a vulnerability index from PCA and obtained the coefficients for each indicator in order to calculate the final score and find the vulnerability index that will adjust the risk premium, Therefore, the risk premium should be dynamically adjusted as these risks evolve.

6. Recommendations

To enhance crop pricing mechanisms, the following recommendation should be considered:

- **Crop-Specific Climate Assessments**: Focus future studies on farm-level assessments to better capture how specific crops respond to climate stressors like temperature and rainfall. This will enable more targeted climate adaptation strategies.
- **Weather-Based Index Pricing**: Implement weather-based pricing mechanisms that adjust crop prices based on local climate conditions, like droughts or heatwaves. This can help protect farmers and encourage sustainable practices.
- **Dynamic Risk Adjustments**: Adapt risk and premiums seasonally or annually, based on updated climate data. Increase risk scores for crops during forecasted extreme events to better manage climate impacts.
- **Resilience Investment**: Encourage farmers to adopt climate-resilient practices, such as drought-resistant crops and improved irrigation. Support with financial incentives and training to lower long-term vulnerability and costs.
- **Scenario-Based Pricing for Extreme Events**: Adjust pricing in response to extreme weather forecasts, incentivizing farmers to mitigate risks through more sustainable practices, lowering premiums in the process.
- **Local Knowledge Integration**: Use local climate knowledge to refine vulnerability models, ensuring policies are more accurate and relevant to specific regions.
- **Institutional Support**: Improve access to climate data, forecasts, and training for farmers. Help them make informed decisions and adopt resilient farming techniques.
- **Refine Econometric Models**: Improve climate impact models by integrating more variables and accounting for regional and crop-specific differences to better reflect the complexity of climate risks.

References

1) Abdi, H. & Williams, L. J., (2010). Principal component analysis.. *Wiley Interdisciplinary.*

2) Binswanger-Mkhize, H. P., (2012). Is there too much hype about index-based agricultural insurance?. *Journal of Development studies,* 48(2), pp. 187-200.

3) Brooks, Nick, Adger, W. N. & Kelly, P. M., (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global environmental change,* 15(2), pp. 151-163.

4) Ceballos, F. & Kramer, B., (2019). From index to indemnity insurance using digital technology: Demand for picture-based crop insurance.. *International Food Policy Research Institute (IFPRI)..*

5) Coulibaly, et al., (2015). Mapping vulnerability to climate change in Malawi: Spatial and social differentiation in the Shire River Basin. *American Journal of Climate Change,* 4(3), p. 282.

6) Cutter, S. L., (2003). The vulnerability of science and the science of vulnerability. *Annals of the Association of American Geographers,* 93(1), pp. 1-12.

7) EEA, (2019). Economic losses from climate-related extremes in Europe.. *European Environment Agency*.

8) Eze, E., Girma, A., Zenebe, A. A. & Zenebe, G., (2020). Feasible crop insurance indexes for drought risk management in Northern Ethiopia. *International Journal of Disaster Risk Reduction,* Volume 47, p. 101544.

9) Füssel, Hans-Martin & Klein., R. J., (2006). Climate change vulnerability assessments: an evolution of conceptual thinking.. *Climatic change,* 75(3), pp. 301-329.

10) Gagliardi, N., Arévalo, P. & Pamies-Sumner, S., (2022). The Fiscal Impact of Extreme Weather and Climate Events: Evidence for EU Countries. Publications Office of the European Union.

11) Hazell, et al., (2010). The potential for scale and sustainability in weather index insurance for agriculture and rural livelihoods. *World Food Programme (WFP).*

12) Helgeson, J. F., Dietz, S. & Hochrainer-Stigler, S., (2013). Vulnerability to weather disasters: the choice of coping strategies in rural Uganda. *Ecology and Society,* 18(2).

13) Liverman, D. M., (1990). "Drought impacts in Mexico: climate, agriculture, technology, and land tenure in Sonora and Puebla. *Annals of the Association of American Geographers,* 80(1), pp. 49-72.

14) Lucas, P. L. & Hilderink, H. B., (2005). *Vulnerability concept and its application to food security ,* s.l.: RIVM rapport 550015004.

15) McIntosh, Craig, Sarris, A. & Papadopoulos, F., (2013). Productivity, credit, risk, and the demand for weather index insurance in smallholder agriculture in Ethiopia. *Agricultural Economics,* 44(4-5), pp. 399-417.

16) Moss, R. H., Brenkert, A. L. & Malone, E. L., (2001). *Vulnerability to climate change: a quantitative approach,* Washington: Prepared for the US Department of Energy.

17) Nshakira-Rukundo, E., Kamau, J. W. & Baumüller, H., (2021). Determinants of uptake and strategies to improve agricultural insurance in Africa: A review. *Environment and Development Economics,* pp. 1-27.

18) o'Brien, K. et al., (2004). Mapping vulnerability to multiple stressors: climate change and globalization in India.. *Global environmental change,* 14(4), pp. 303-313.

19) Parry, L., M. & ed, (2007). *Climate change 2007-impacts, adaptation and vulnerability: Working group II contribution to the fourth assessment report of the IPCC..* Vol. 4 ed. s.l.:Cambridge University Press.

20) Piya, Luni, Maharjan, K. L. & Joshi, N. P., (2012). Vulnerability of rural households to climate change and extremes: Analysis of Chepang households in the Mid-Hills of Nepal.

21) Quackenbush, J., (2002). Microarray data normalization and transformation. *Nature genetics,* 32(4), pp. 496-501.

22) Swiss Re., (2023). *Natural catastrophes and inflation in 2022: a perfect storm,* s.l.: Sigma 1.

23) Schneider, et al., (2001). Overview of impacts, adaptation, and vulnerability to climate change. *Climate change,* pp. 75-103.

24) Solomon, S. et al., (2007). *IPCC fourth assessment report (AR4). Climate change, 374.,* s.l.: s.n.

25) Tadesse, A., M., Shiferaw, B. A. & Erenstein, O., (2015). Weather index insurance for managing drought risk in smallholder agriculture: lessons and policy implications for sub-Saharan Africa. *Agricultural and Food Economics 3,* Volume 1, pp. 1-21.

26) Thornton, P. K. et al., (2006). Mapping climate vulnerability and poverty in Africa.

27) UNDP, (2007). *Human development report 2007/2008: Fighting climate change: Human solidarity in a divided world,* s.l.: Oxford University Press for UNDP.

28) Wold, S., Esbensen, K. & Geladi, P., (1987). Principal component analysis. *Chemometrics and Intelligent Laboratory Systems,* 2(1-3), p. 37–52.

"استخدام مؤشر الحساسية (Vulnerability Index) في تقييم تأثير عوامل الخطر المرتبطة بالتغييرات المناخية على تسعير تأمين المحاصيل الزراعية في جمهورية مصر العربية"

المستخلص

يتزايد تأثير العوامل المناخية مثل ارتفاع درجات الحرارة، الجفاف، وندرة المياه على التأمين الزراعي، مما يؤدي إلى زيادة المطالبات التأمينية وبالتالي أصبح تحديث تقييمات المخاطر وآليات التسعير تحدياً يواجه شركات التأمين.

يتناول هذا البحث أثر المخاطر المرتبطة بالتغيرات المناخية على التأمين الزراعي، مع التركيز على ضرورة تكيّف شركات التأمين لمواجهة تحديات تغير المناخ. حيث يتعين على شركات التأمين تحسين ممارسات الاكتتاب الخاصة بها في ظل التغيرات المناخية العالمية وارتفاع درجات الحرارة، وذلك من خلال آلية تقوم على دمج بيانات المناخ كمؤشر للتأمين على المحاصيل الزراعية. وتعتمد هذه الآلية على تعويض الخسائر المرتبطة بالتغيرات المناخية وفقًا لمؤشرات محددة مسبقًا مثل درجات الحرارة، نسبة الرطوبة، ومعدلات هطول الأمطار. مما يقلل من التكاليف التشغيلية مقارنة بالتأمين التقليدي الذي يعتمد على تعويض الخسائر الفردية.

وقد تم الاعتماد على دراسة المخاطر المتعلقة بالتغيرات المناخية وتأثيراتها على ثلاثة محاصيل رئيسية في جمهورية مصر العربية، وهم: القطن، الأرز، وقصب السكر، وذلك باستخدام بيانات مقطعية زمنية عن الفترة من عام ١٩٩٥ إلى عام ٢٠٢٢، وتم تحليل هذه البيانات عن طريق (Principal Component Analysis) لتحديد العوامل الأكثر تأثيرًا.

وقد توصلت النتائج إلى أن القطن هو الأكثر عرضه للمخاطر المناخية بسبب حساسيته لارتفاع درجات الحرارة، بينما أظهر الأرز وقصب السكر حساسية متوسطة، وتعتبر المخاطر المتعلقة بدرجات الحرارة وتوافر المياه من أبرز التحديات التي تؤثر على هذه المحاصيل الزراعية. وبناءً على ذلك من المتوقع أن تؤدي هذه المخاطر إلى ارتفاع تكاليف الإنتاج الزراعي، خصوصًا للقطن، وذلك لزيادة التكاليف المرتبطة بالري ومكافحة الآفات وانخفاض الإنتاجية، وبذلك يمكن لشركات التأمين تحسين تقديرات الأقساط المالية للمحاصيل الزراعية بناءً على مؤشر الحساسية.

الكلمات الدالة:

نموذج الإضافات المعمم، التسعير القائم على المؤشر، تحليل المكونات الرئيسية، المخاطر المتعلقة بالطقس، مؤشر الحساسية.