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MODELO DIFUSO PARA LA CARACTERIZACIÓN DE RIESGOS EN CULTIVOS DE AGUACATE PARA LA CONFIGURACIÓN DE SEGUROS INDEXADOS

Title Fuzzy Model for Risk Characterization in AvocadoCrops
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Fuzzy Model for Risk Characterization in Avocado Crops for Index Insurance Configuration

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Abstract.

Climate change has caused strong variations in agro-climatic parameters such as precipitation, temperature, and relative humidity, accelerating the phytosanitary conditions associated with agricultural crops, mainly in insect pests, since these generate an alteration in their life cycle and an increase in their population. This causes significant economic damage to important crops such as the Hass avocado, which has had a growing development and demand in national and international markets, which has generated significant income for small and medium-sized farmers and exporters of this fruit in the country. To mitigate the impacts of climate change on agricultural production, it is possible to implement digital agriculture technologies. These technologies allow estimating the incidence of climate variations on crops through the monitoring of agro-climatic and phytosanitary variables that affect fruit growth. Therefore, a variable dispersion model with fuzzy characterization is proposed that seeks to establish a correlation between rainfall and the aggregate distribution of losses in the Hass avocado crop. In order to analyze and validate the proposed model, the random variables related to phytosanitary risk were taken and characterized. Subsequently, the frequency and severity random variables were modeled as linguistic random variables using fuzzy logic concepts. The results indicate that rainfall is the key variable to correlate in the search for an index insurance model based on agricultural risk, as well as in the characterization of qualitative and quantitative risks, promoting the improvement of financial and environmental sustainability by reducing agricultural losses through better crop management.

Keywords: Phytosanitary, Agroclimatic, Fuzzy Logic, Productivity, Insurance, Indexing.

1 Introduction

Precipitation is a component that, if not measured or studied, can significantly affect the avocado crop; 90% of the water requirement is obtained from rainwater, and only 10% is supplied by irrigation, which increases the vulnerability of the sector due to the alteration of precipitation regimes as a result of climate change [1]. Climate

change has caused strong variations in agro-climatic parameters such as precipitation, temperature and relative humidity, accelerating the phytosanitary conditions associated with agricultural crops, mainly in insect pests as they generate an alteration in their life cycle and an increase in the population, reducing the effectiveness of control methods and decreasing the presence of natural control organisms. In addition, the appearance of new pests and the increase of weeds that can become potential foci for new pests is observed. This causes significant economic damage to important crops such as Hass avocado, which has had a growing development and demand in national and international markets, which has generated significant income for small and medium farmers and exporters of this fruit in the country [2-5].

Phytosanitary risk management provides an ideal opportunity to improve and rigorously evaluate the efficiency of current integrated pest and disease management (IPPM). In addition, it allows the articulation of new strategies in phytosanitary management provided by precision agriculture, with the objective of improving the environmental and financial sustainability of production systems. The use of digitized tools plays a fundamental role in the efficient management of agricultural activities, fostering an innovative interaction between man and machine. These tools make it possible to optimize activities such as pest monitoring in the field, through the use of heat maps with geographic information systems (GIS), spectral and satellite images [6]. Likewise, unmanned aerial vehicles (UAVs) are used to carry out spraying and fertilization [7], and Internet of Things (IoT) networks are designed for monitoring and differentiated management of crop units using environmental variables [8].

The agricultural sector in Colombia is a little studied environment in relation to the quantification of data and quantitative measurements of agricultural production, being a little digitized sector [9]. In recent years, avocado cultivation, specifically the Hass variety, has experienced a significant expansion in Colombia. This is due to its high yield in production and its late ripening capacity compared to other varieties. The Hass variety is highly valued for its nutritional potential and has desirable morphological characteristics, such as a resistant skin, adequate size and long storage capacity. These qualities make Hass avocado a highly attractive product for the Colombian export market [10].

During the period between January and April 2022, Colombia has positioned itself as the second largest supplier of avocados in Latin America, with exports reaching approximately 876,754 tons. These shipments were mainly destined to countries such as the Netherlands (56%), the United Kingdom (12%), Spain (9%), the United States (5%), Belgium (4%) and France (4%), among others, with smaller shares [11]. Glo- bally, it is estimated that there are around 407,000 hectares dedicated to avocado culti-vation, which translates into a total production of 4,000,000 tons. Colombia contributeswith 14.2% of the planted hectares, equivalent to a total of 312,615 tons [12]. These figures demonstrate the relevance of avocado as an income generator for small and medium farmers in the country.

The use of fuzzy logic modeling in agriculture, in general, offers a series of significant benefits that contribute to improving the efficiency and sustainability of agricultural production. One of the key advantages is its capacity to handle uncertainty and imprecision present in agricultural and environmental data, where factors such as weather, and strengthen avocado crop production and, ultimately, promote a more resilient and sustainable agricultural development.

Author Wenner [22] emphasizes that agriculture is a risky economic activity, subject to climatic, biological, and geological impacts. Traditional risk management strategies and emergency relief have not been sufficiently effective in preventing serious economic losses or enabling rapid recovery. In developing countries, producers are exposed to the vagaries of weather and have little access to formal agricultural insurance to transfer risks. Despite this, agricultural insurance has re-emerged as a necessity to improve competitiveness in integrated markets and address technological, economic, and educational asymmetries.

In Latin America, actions have focused on reactive and emergency responses to adverse climatic events, which is insufficient. A comprehensive risk management strategy is required that includes prevention, mitigation, and risk transfer, with the participation of the public and private sectors in coordination and mutual agreement [23].

In addition, it is essential to recognize the importance of collecting and measuring climatic data on a crop as an essential tool to prevent economic losses. Accurate monitoring of climatic conditions, such as temperature, humidity, precipitation, and solar radiation, allows farmers to make informed decisions and anticipate potential adverse climatic impacts.

The collection and measurement of climate data also plays a crucial role in agricultural risk management. Real-time and historical weather data allows assessing the risks associated with extreme events, such as droughts, floods, or frosts. This information helps farmers make proactive decisions to minimize the impact of these events, protect their crops and minimize expected economic losses. In addition, access to reliable and up-to-date weather data is essential for agricultural insurance. Weather-based agricultural insurance provides a way to transfer the risk of economic losses associated with adverse weather events. Farmers can use the collected weather data to demonstrate the occurrence of damaging weather conditions and thus claim compensation for the losses suffered [22].

3 Methodology

3.1 Case study

The research project focuses on the Hass avocado production system, one of the main fruit trees exported nationally. To guarantee quality and meet export standards, itis necessary to effectively manage and control agricultural practices. However, this system is affected by insect pests that affect yields and fruit quality during harvest. Two of the most relevant insect pests are the chinch bug (*Monalonion velezangeli*) and the marceño beetle (*Phyllophaga obsoleta* Blanchard), especially problematic in the eastern region of Antioquia. We selected a crop located in the northwestern part of Colombia, which has been affected by the aforementioned pests during the months of highest rainfall. This makes it an ideal case to identify the maximum levels of risk that characterize an index-based insurance, and where there is a loss of productivity in the fruit export process. For the analysis and validation of the proposed model, the first step was to collect and characterize the random variables for climate risk and phytosanitary risks. At this point, the data are expected to have a significance (<5%) according to the quadratic error and the sample size. Subsequently, we proceed with the fuzzy modeling of the frequency and severity random variables as linguistic random variables. Here it is expected that the aggregate distribution of losses will present positive skewness coefficients, similar to those obtained by Peña et al. (2020) in the characterization of this type of distributions. Subsequently, we proceeded to establish the correlation between the losses of the aggregate loss distribution and precipitation according to the case study. Based on the structure of these variables, a modified Monte Carlo method will be used to model the aggregate loss distribution, taking into account the fuzzy representation of random variables [24, 25].

3.2 Study area

The research will be carried out in an agricultural production unit dedicated to the avocado production system. For the characterization of agro-climatic and phytosanitary events, an area of 2 hectares of Hass avocado crop will be taken as a reference, with a total density of 450 trees of 4 years of age. A sample of thirty trees was selected to analyze their behavior over time.

3.3 Climate parameters

The meteorological station was installed in May 2022 and, starting from June of the same year, it has been generating daily data seven days a week, recorded in 15-minute intervals throughout the day. For the study case, data from the station have been used from June 2022 up to the current date, calculating a monthly average of these data. However, it is important to note that this research has a limitation in the amount of data obtained.

To overcome this limitation, an estimation of additional data was conducted, taking into account previous years, from 2018 to projecting until the year 2025. The additional data was collected with the same frequency as the meteorological station located in the study area. The aim of this estimation was to obtain a larger amount of data and reduce the mean squared error that may arise due to a low frequency in statistical measurements.

For the analysis, priority has been given to the precipitation variable, due to its recognized influence on crop productivity results and the incidence of the mentioned pest insects. This choice is supported by relevant bibliographical references [26, 27, 28], which back the importance of considering precipitation as a determining factor in crop development and pest incidence. These bibliographical references provide solid foundations to support the selection of the variable and the approach adopted in the research.

3.4 Characterization of phytosanitary events

To characterize phytosanitary events, periodic visits are made to the production unit to identify the agronomic risks associated with the insect pests in the study.

3.5 Fuzzy Characterization of Losses on Agricultural Crops.

The Aggregate Loss Distribution in avocado cultivation is a model used to analyze and quantify the economic losses associated with adverse events that affect crop productivity in the study area. This model takes into account different factors, such as the frequency and intensity of weather events and the incidence of pests, which are the main factors that can affect the quality and yield of avocado trees. In this model, data is collected on relevant variables such as precipitation, temperature, relative humidity,and other climatic factors, as well as the presence and severity of pests. These data areused to construct a probability distribution that represents the possible economic lossesthat can occur in the crop.

The development of the LDA model requires having an appropriate database to characterize the random variables, including those of linguistic nature. It is essential to perform an analysis of the loss distribution considering two fundamental elements of the model: frequency, which represents the number of crop units affected by risk events in a given period, and severity, which indicates the average loss suffered by each crop unit affected by a risk event.

The specific aggregate loss distribution for avocado cultivation is obtained through a convolution with Monte Carlo simulations. This convolution is the resulting process of combining the discrete frequency distribution with the continuous severity distribution. By using this method, a more comprehensive and realistic view of the potential losses that could occur in the avocado cultivation system is achieved. Furthermore, to assess losses from events, the OPVaR percentile (Operational Value at Risk) is used.

This value is estimated based on established parameters and represents a statistical measure indicating the level of expected and unexpected losses. It is a valuable tool for calculating potential losses associated with events, allowing for better planning and risk management for the agricultural producer.

It is important to highlight that this model is based on historical data and assumptions about the relationships between different factors that influence losses. Moreover, its accuracy and reliability depend on the quality and quantity of available data, as well as the suitability of the probability distribution used.

3.5.1 Characterization of Quantitative and Qualitative Risks. Risk Map.

In this process, the K-Means method is used to group data into categories, classifying objects into groups according to their characteristics. The classification algorithm aims to minimize the sum of distances between each object and the centroid of its group or cluster, commonly by using the quadratic distance.

The K-Means method consists of several steps. First, the number of clusters is selected and the centroids are set in the data space, which can be randomized. Second, the objects are assigned to the centroids, assigning each object to the nearest centroid. Finally, the centroid position of each group is updated, taking as the new centroid the average position of the objects belonging to that group. This approach is based on relevant literature references [29, 30, 31] and is widely used in various clustering and data analysis applications. It allows the identification of patterns and structures within the data, which facilitates the understanding and analysis of complex data sets.

4 Results

In this case study, information collected by the meteorological and hydrological station in the study area was used. However, there was a limitation in the frequency of the available data, since the station began to record information in June 2022. At the beginning of the investigation, a quadratic error of more than 12% was detected in the calculations performed. Despite this drawback, it was possible to significantly reduce this error by incorporating additional data estimates from 2018 and projecting up to 2025. This made it possible to obtain a greater amount of data and reduce the quadratic error to 4.94%.

The distribution obtained follows a normal pattern, based on a correlation of 0.86 between rainfall and the aggregate distribution of losses. This distribution shows a long tail, indicating that catastrophic losses are less likely due to the asymptotic shape of the distribution. In the sample of thirty (30) crop units selected, a total of 42 losses are expected in both crops, and farmers should consider this in their economic estimates. It is important to note that the distributions analyzed should have a long tail. If this is not the case, there may be a crop problem or a phytosanitary event that is affecting the crop units. This is confirmed by the co-efficient of skewness, which must be positive to indicate a long-tailed distribution. In this particular case, the coefficient is 1.59, which means that catastrophic losses are less frequent due to the asymptotic shape of the distribution.

The mean helps us identify the upper limit of expected losses, meaning those that fall below this limit are considered as expected losses.In the specific case we are analyzing, thirty-nine (39) expected losses have been identified, with an estimated value of COP $ 1,625,725. It is important to note that, in the avocado crop studied, only one case has been identified that could generate a catastrophic loss. To complement this analysis of expected losses, it is essential to take into account the phytosanitary management practices that the farmer must follow in order to achieve adequate pest control and optimal crop management (Table 1).

Table 1. Characterization of Losses.

Data measures analyzed	Value	Quantity
Medium	$ 1.625.725	39
Percentile 99.99%(Opvar)	$ 7.869.317	1
Expected losses	$ 2.606.727	38

This analysis shows that there are 7 crop units that could be affected, which indicates a low frequency. However, if this figure increases to 39 affected crop units (Table 2), the frequency becomes very high and the event can cause significant losses for farmers. For this reason, it is necessary to carry out an exhaustive analysis of the events affecting the crop, with the aim of developing plans and actions to help mitigate losses in those crop units that fail to reach the expected forty (40) kilograms of production per month. We will now proceed to model the risks associated with severity, using the same method used previously (Table 3).

Table 2. Frequency Characterization Cluster.

Cluster		Frequency			Events	Expert	Oscillation
Min	**LI**	**1**	**LS**	5		**Minimum**	
1	$ 3.16	39712.626	171.572798	0	7	Low	170.572798
2	39712.626	171.572798	191992.38	0	6	Medium	152279.754
3	171.572798	191992.38	97097.2261	0	26	High	96925.6533
4	191992.38	97097.2261	564885.417	0	39	Very High	-191978.38
Max		14			78	**Maximum**	

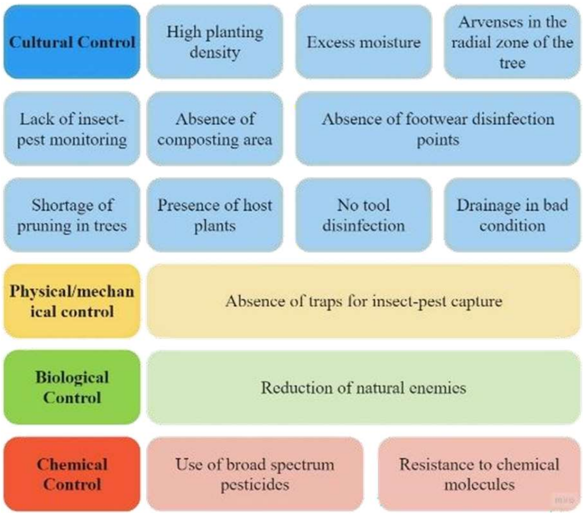
Table 3. Severity Characterization Cluster.

Labels	Min	Clusters		$ 2,000.00	# Data	Labels
1	$ 3.16060	$ 39,255.63	$ 0	0	8	Slight
2	$ 39,255.63	$ -	$ -	$ -	0	Moderate
3	$ -	$ -	$ -	$ -	0	Severe
4	$ -	$ -	$ 564,885.42	$ 1.00	0	Catastrophic
			Max			

During the identification of the risks associated with the crop, a total of 26 types of risk were identified, including operational, financial and phytosanitary risks. It is important to note that phytosanitary risks are those that entail the greatest economic loss. In addition, the current risks associated with the presence of insect pests, specifically the marceño cockroach and the monalonion, were monitored.

Within the framework of the Integrated Pest Management Plan (IPM), four key strategies were established: cultural, physical/mechanical, biological and chemical. These strategies are fundamental to efficiently manage crops and prevent the spread of pests. Agronomic risks were divided according to each IPM strategy mentioned above. So far, 14 risks related to the presence of insect pests have been identified, some of which significantly affect the increase of economically important insect populations (Figure 1).

Figure 1. Risks associated with increased incidence of pest insects.



The effects are the result of agro-climatic events caused by precipitation, as well as the presence of phytosanitary events within the crop. In the characterization of the risks identified, the following are highlighted (Figure 2):

•High Frequency and Severe Impact: - Excessive atmospheric precipitation: causes yield reduction, plant detrimento, loss of flowers, decrease of oxygen in the soil and creates a favorable environment for the marceño beetle during rainy seasons. In addition, it can cause plant death; -Interest rate risk: This risk is generated by fluctuations in interest rates, which affects the sale of fruit for export; -Operational- Phytosanitary Risk: the lack of adequate integrated management of pests and of the plant in general results in the production of fruit that does not meet the qualities required for export, which lowers its value. During the harvest, the farm was able to market only 2.9 tons, which represents a yield of less than 40%.

• Very High Frequency and Moderate Impact: - Biological contamination during the pruning and harvesting process: adequate decontamination of cutting tools is not performed between each unit of treated crop. Pruning that is not carried out can lead to excessive vegetative growth of the plants and a decrease in fruit size, creating favorable conditions for an increase in the population of the pest insect pests marceño beetle and chinch bug;- Contamination of the cultivated land: Adequate control of entry to the crop is omitted, including disinfection of footwear and weed or pruning residues at the tree planting site;- Lack of integrated pest management: There is no adequate control of pest control action thresholds or early identification of pests. In addition, there is no monitoring or prevention programs (planting of trap plants) and no traps (light and chromatic) are implemented in the crop.

Physical-mechanical damage to the fruit(1), biological contamination in the fruit cutting process(2), contamination of cultivated land(3), excess atmospheric precipitation(4), deficit of atmospheric precipitation(5), low temperatures(6), high temperatures(7), failure to develop a crop fertilization plan(8), failure to carry out proper pruning(9), failure to properly execute IPM (Integrated Pest Management)(10), high planting densities(11), lack of tree grafting(12), lack of crop drainage(13), public risk(14), public risk(15), legal risk(16), fire risk(17), worker safety and welfare(18), high winds(19), floods(20), landslides(21), market risk(22), exchange rate risk(23), interest rate risk(24), inflation risk (25)and operational - phytosanitary risk(26)(Figure 2).

Figure 2. Risk Matrix

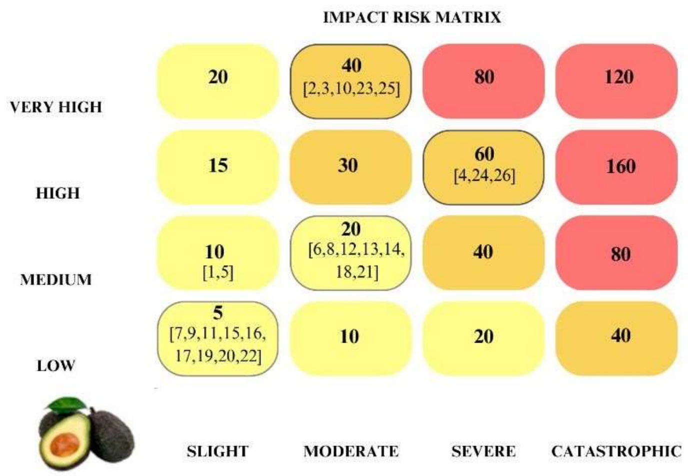
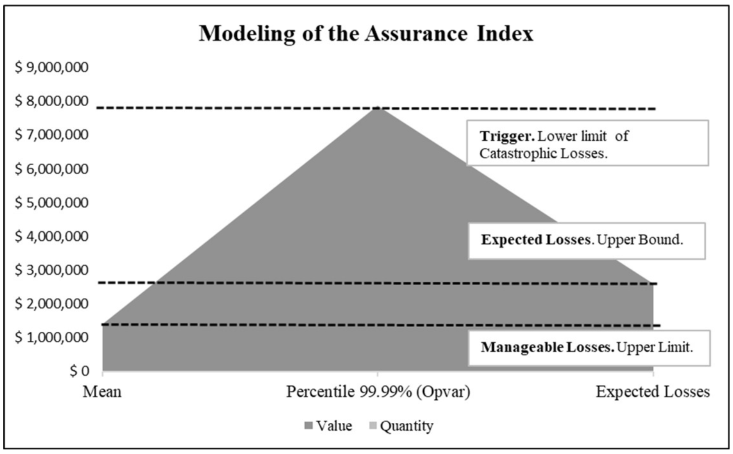


Figure 3. Modeling of the Assurance Index.



On the other hand, the results have identified the possibility of a single catastrophic event, with an estimated lower limit of COP $7,869,317 (Opvar). From there, the insurance index defined by the insurer in the policy constitución is defined (Figure 3).

5 Conclusions

This study allowed the quantification of agroclimatic data and variables for an adequate risk management in the Hass avocado crop, contributing to the digitization of the agricultural sector in Colombia. It was possible to identify that the variable that most affects crop yield is rainfall, finding a correlation between rainfall and the aggregate distribution of crop losses. This has made it possible to obtain the expected losses that are not insurable in the insurance sector, the manageable losses that are between the average and the Opvar, and that can be transferred through index insurance in the event that the farmer is unable to manage his risks or his management costs are high. Catastrophic losses, located at the 99.9% percentile of the normal distribution, were also identified.

Based on this, the lower limit of the trigger of the index insurance is established, which seeks to transfer the risk in manageable losses, thus providing an economic alternative to the agricultural sector, especially to the avocado crop, in case of experiencing economic losses that cannot be assumed.

This research opens new lines of research related to the modeling of digital agriculture in Colombia, applicable to various crops. These lines of research aim to implement best practices in planting, pest control, production processes and the use of drones for the development of intelligent systems that allow the generation of networked information and the development of predictive models in the agricultural sector. These improvements are not only limited to avocado cultivation, but can also be applied to other crops such as coffee, cocoa, citrus and other agricultural products in Colombia.

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