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# AI in Colombian Food Markets: Using Machine Learning to Address Price Crisis

# IA en Mercados de Alimentos en Colombia: Usando Machine Learning para Enfrentar Crisis de Precios

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## *Abstract*

Price shocks have long been a challenge for farmers in developing countries, posing a substantial threat to their investments and livelihoods when they encounter low prices at the time of harvest, often pushing them towards poverty. Local governments' crisis responses often use inefficient, indiscriminate aid distribution. While local and regional governments can apply many tools to prevent sudden changes in crop prices, those tools tend to be expensive and difficult to implement in local communities. The principal objective of this study is to illustrate the feasibility of a cost-effective machine learning tool that predicts the most likely affected municipalities by a price shock, enabling local governments to effectively target assistance where it is needed. Two models were used in the article, a random forest and a decision tree algorithm. The findings suggest that, despite using a simple structure in both algorithms, the models were able to predict up to 79% of the municipalities affected by prices shocks. Furthermore, this article highlights that this relatively uncomplicated model structure can equip governments with accurate data, which could be employed in price crisis responses at a lower cost, thereby enhancing the efficiency of aid distribution.
*Keywords:* Machine learning; crops price crises; policy targeting.

## *Resumen*

Los choques de precios han sido por largo tiempo uno de los principales problemas que los agricultores se enfrentan en países en desarrollo. Este problema crea un riesgo a su inversión y estilo de vida cuando se encuentran con precios bajos al momento de la cosecha, llevándolos a situación de pobreza. Gobiernos regionales generalmente responden a las crisis de manera ineficiente, repartiendo ayudas indiscriminadamente. A pesar de que gobiernos locales pueden aplicar muchas herramientas para prevenir los cambios drásticos en los precios agrícolas, esas herramientas tienden a ser muy costosas y difíciles de implementar. El principal objetivo de esta investigación es mostrar la posibilidad de usar una herramienta de machine learning que sea costo efectivo que predice las municipalidades más propensas a ser afectadas por un shock de precios, permitiendo a los gobiernos locales dirigir eficazmente la asistencia donde más se necesita. Dos modelos son usados en este articulo, random forest y arboles de decisión. Los hallazgos sugieren que usando estructuras simples de árbol de decisión y Random Forest, se logra predecir hasta un 79% de los municipios afectados por el choque. Este articulo muestra que esta estructura simple de machine learning puede equipar a los gobiernos con datos confiables para ser usados en crisis de precios a un costo bajo de focalización.
*Palabras Clave:* Aprendizaje automático; crisis precios alimentos; políticas focalización.

# INTRODUCTION

Price volatility has been one of the major problems in the agriculture sector for developing countries. The lack of financial markets, high dependency on weather resources, and global markets create a risky environment for farmers who produce seasonal crops (Magrini et al., 2019; Haile et al., 2016; Nakelse et al., 2018; D'Souza and Jolli, 2013). The main challenge that farmers face in highly volatile markets is the uncertainty of future prices. This uncertainty leads to the "sell low-buy high" problem (Burke et al., 2019), where farmers increase their production when they see the price increasing, but at the time of selling the crop, the price is lower than expected due to the aggregated increase in supply from all the farmers. This situation disrupts the profits of the farmers and affects their welfare.

The primary solutions to this problem require significant investment in financial markets, storage infrastructure, or cash transfer policies (Caruanas, 2016). However, these solutions are not affordable for low- and middle-income countries. This paper proposes a new way to overcome this problem by using the new trend of artificial intelligence and machine learning (ML) (Jordan and Mitchell, 2015; Ruiz-Real et al., 2021). As an illustration of the advantages offered by the new technical framework developed in recent decades, this research primarily goal is to demonstrate the viability of employing machine learning models for the identification of municipalities most susceptible to crises. The key goal of these models is to produce reliable data that local authorities can leverage to concentrate subsidies and policies in the areas most severely impacted, thus enhancing the efficiency of government spending and the effectiveness of policies while reducing costs.

Two crop price crises were selected as case studies to demonstrate the efficacy of the models, focusing on the onion and potato price crises of 2017. This study harnesses the power of two straightforward machine learning (ML) algorithms: the Random Forest and Decision Tree. The findings highlight the Random Forest model with 500 trees as the most accurate predictor for potato and onion affected areas by the price shocks. Additionally, the article shows that the proposed ML models are effective in predicting true negative values in municipality production, particularly in onion production.

The rest of the paper is organized as follows: a section that specifies the literature review and the context of the problem, a segment that defines the research question, an explanation of the theory behind the models used, a section that explains the data used in the article and the definition of the variables, an explanation of the methodology, an analysis that showcases the results, testing, and validation process, and finally, a segment that presents the conclusions.

# LITERATURE REVIEW

## *Context of the Crisis*

In late 2016 and early 2017, the agricultural sector in Colombia experienced a crisis characterized by sustained low prices for potatoes and onions, which severely affected farmers in the central region of the country (DANE, 2018). Figures 1 and 2 illustrate the time series of potato and onion prices, respectively, with a smoothed trend. These markets are known for their high volatility, but the crisis led to even greater variation in prices. As shown in Figure 1, potato prices had been steadily increasing from 2013 to 2016, but experienced a sharp decline in January 2017. Similarly, Figure 2 shows a comparable pattern for onion prices during the same time period. Both figures highlight that in 2017 food price crisis resulted in the lowest historical prices for both potato and onion crops.

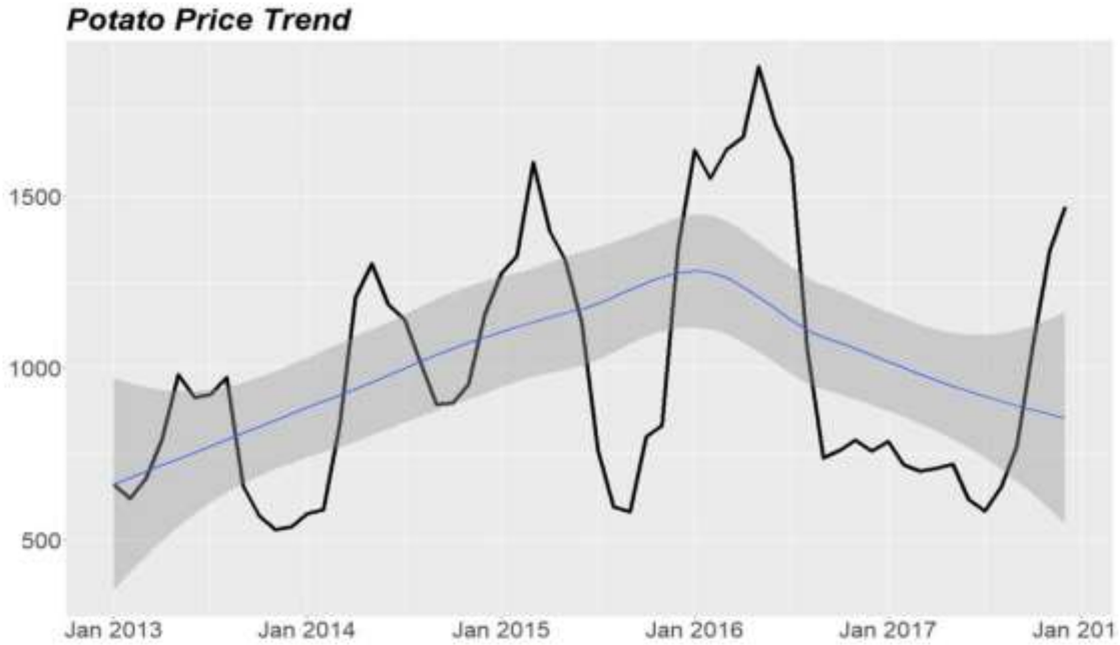


**Figura 1.** Potato Price (Pesos per Kg)

Source: Own elaboration using data from Corabastos reported prices

Data: Weekly Kg Prices of Potato in Corabastos wholesale-Bogotá

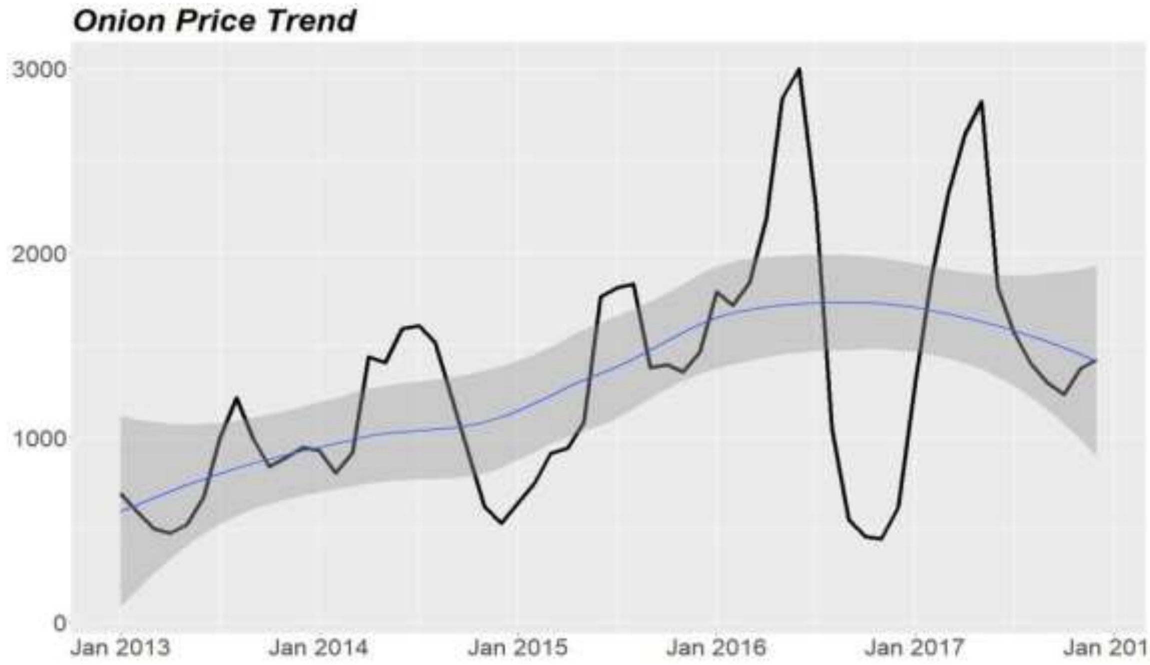


**Figura 2.** Onion Price (Pesos per Kg)

Source: Own elaboration using data from Corabastos reported prices

Data: Weekly Kg Prices of Potato in Corabastos wholesale-Bogotá

Additionally, Figures 3 and 4 provide insight into the production intensity of the central region of Colombia. The graphics use a color scale to indicate production intensity, ranging from white to red, with red representing the highest concentration of production. Figure 3 illustrates that the maximum value of potato production diminished from 37,840 tons per year in 2013 to 10,751 tons per year in 2017, indicating a decline in average potato production. Additionally, the graph shows that fewer municipalities produced potatoes in 2017 compared to 2013.

This trend in production can be attributed to the price drop that affected many municipalities in the central region of Colombia. The price crisis lasted for 8 months in 2017, which had a significant impact on production decisions that year. Similarly, onion production also experienced a decline in maximum production, changing from 40,797 to 9,179, and multiple municipalities also experienced a production shrink. These graphs demonstrate that during a period of price crisis, many regions continue to produce despite facing an unprofitable price due to excess supply. While it may appear that farmers adapted to the price volatility, many still faced financial difficulties due to the shock.

2013 2017

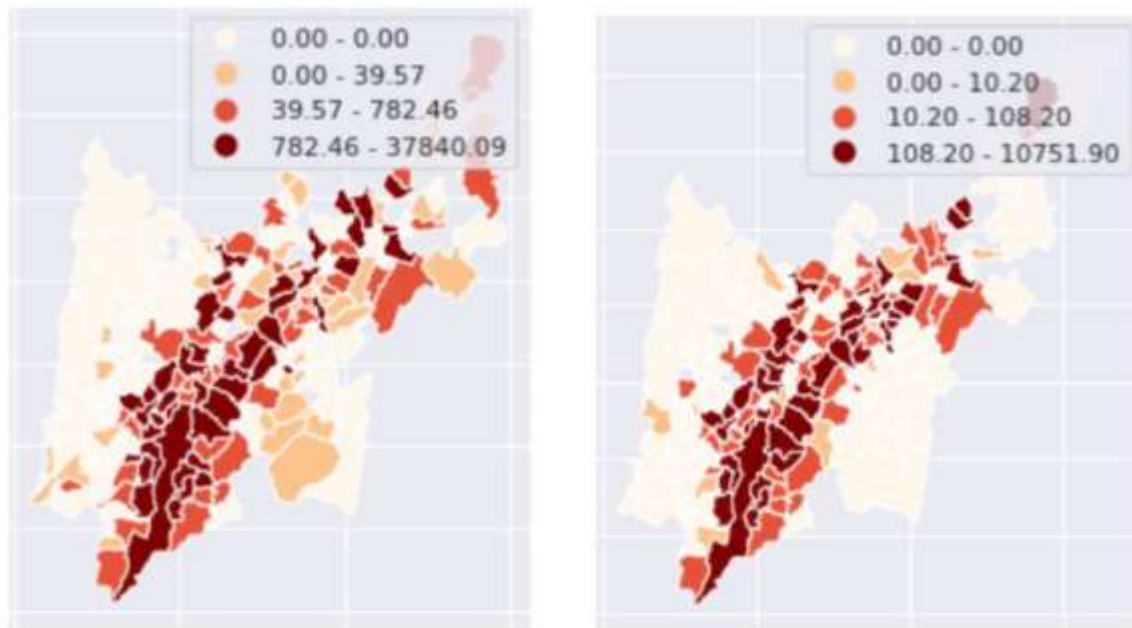


**Figura 3.** Potato Production by Municipality in Cundinamarca and Boyacá
Source: Own elaboration using municipality data of production by crop from DANE
Data: Annual Production of Potato by Municipality in the Central Region of Colombia.

2013 2017

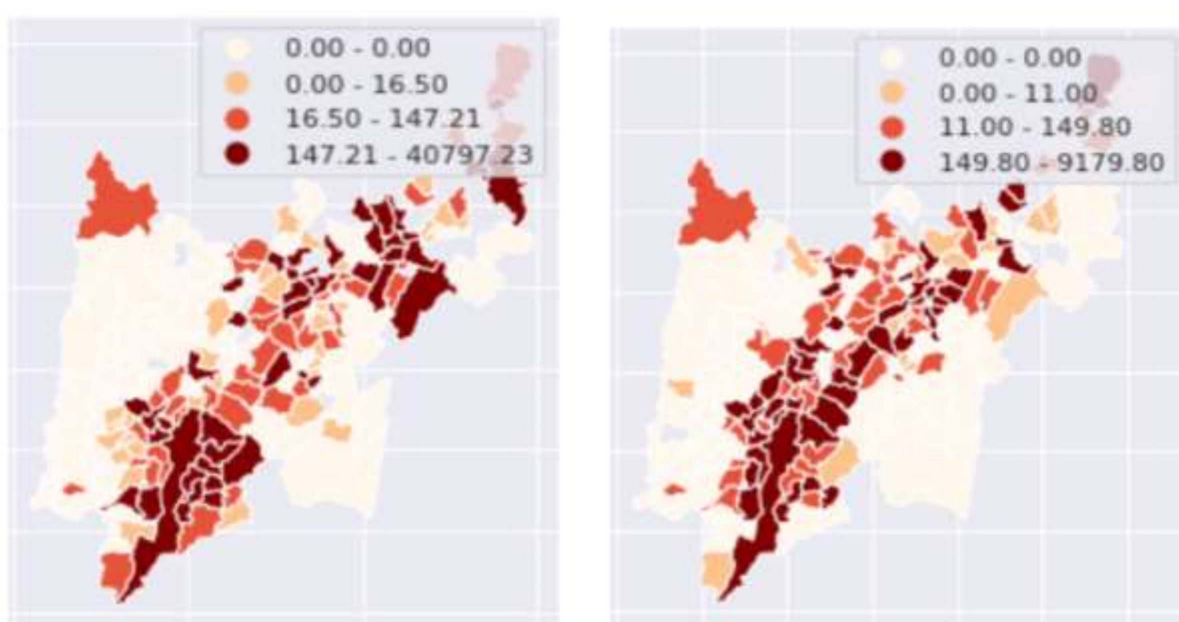


**Figura 4.** Onion Production by Municipality in Cundinamarca and Boyacá
Source: Own elaboration using municipality data of production by crop from DANE
Data: Annual Production of Onion by Municipality in the Central Region of Colombia.

Low- and middle-income countries often experience price crises due to the lack of market mechanisms that promote stability (Magrini et al., 2019; Haile et al., 2016; Nakelse et al., 2018; D'Souza and Jolliffe, 2013). These crises can cause long-term problems for farmers, including reduced welfare and food insecurity due to the inability to smooth consumption with irregular income (Christian and Dillon, 2018; Sahn, 1989). In addition, large price fluctuations can lead to poor investment decisions, such as selling low and buying high, which prevent farmers from taking advantage of arbitrage opportunities (Caruanas, 2016).

### *Past vs New Solutions*

The occurrence of price crises in volatile markets has been widely studied (Haile et al., 2016; Nakelse et al., 2018). These crises can be caused by various factors, such as weather shocks, international political shocks, or a poor understanding of market signals such as price and production seasons. To address this issue, three key solutions have been proposed in the literature: response solutions involving cash transfers or safety nets; preparedness and planning solutions; and market solutions with financial instruments.

The first solution focuses on providing cash transfers to support farmers during times of crisis. This requires a robust budget from the government or high social capital that enables the community to gather resources in prosperous times and use them during crises (Wagener and Zenker, 2020). However, these conditions can be difficult to find in developing countries with limited budgets or weak institutions.

The second solution involves investing in storage infrastructures that enable farmers to store and dry harvested products for use after the season is over (Caruanas, 2016). This is commonly used for products such as wheat and soybeans, but it requires expensive infrastructure and coordination between the public and private sectors, which may be difficult to achieve in developing countries.

The third solution is to incorporate financial instruments such as futures and options, which provide stakeholders with more information to make better decisions, and insurance, which is useful during times of crisis (Caruana et al., 2005; Crockett, 1996). These financial tools can align the incentives of the market and create a more stable environment, but they are often private initiatives that take time to establish.

New solutions are now emerging thanks to the availability of large datasets and new machine learning techniques. For example, Wagener and Zenker (2020) use machine learning techniques to predict interest rates, while Yasir et al. (2020) use neural network models to predict the price of wheat in Senegal based on production levels. This article proposes an innovative solution that uses machine learning forecasting to identify the regions that are most likely to be affected by a price crisis. This could be a valuable tool for policymakers who want to focus their budget on the regions that are most affected by a price crisis. One advantage of this strategy is that it is relatively low-cost and can provide a faster response than previous attempts.

## RESEARCH QUESTION

The research aims to demonstrate the effectiveness of a simple machine learning algorithm in identifying municipalities that are most likely to be affected by a crisis. This objective highlights the practicality of a machine learning tool that empowers policymakers to precisely direct support during price-related crises.

## DATA

This research uses two primary sources of data. Firstly, it relies on municipal production data sourced from the National Bureau Department of Statistics in Colombia (known as DANE in Spanish), comprising a comprehensive dataset of 9,931,207 observations spanning five years across 1,000 districts, 22 markets, and 164 products.

For the specific scope of this study, the data has been restricted to municipalities in the Cundinamarca and Boyacá departments during the period from 2013 to 2017. The research places particular emphasis on the production levels of four key crops: potato, tomato, lettuce, and onion.

The second source of data encompasses monthly average price reports from Corabastos, Bogota, spanning the years 2013 to 2017. In a similar manner, this dataset has been limited to the four principal products: potato, tomato, lettuce, and onion.

## METHODOLOGY

This research is a quantitative study that emphasizes a methodological approach which policymakers and local governments can employ effectively to provide assistance during price crises, especially in situations where alternative solutions may be unavailable or costly.

### *Data Processing*

From the total data set the model uses as main outcomes or dependent variables, two constructed variables that follow this equation:

$$D_i = 1[Q_i > Q_{75}]$$

Where $D_i$ is a dummy variable that takes the value of 1 if the production of the municipality is greater than the 75$^{th}$ percentile of the distribution of production of all municipalities in that period for onion and potato crops. The research uses this approach because defining oversupply is challenging, but categorizing municipalities in the upper segment of the distribution provides the most precise means of identifying those municipalities that primarily focus on crop production. The document used this binary variable to identify the riskier municipalities in crisis.

As inputs of the model our analysis employs 37 variables, including four different week lags: 16, 18, 20 and 22 periods of price and total production of tomato, lettuce, potato and onion.

In the end, the dataset encompasses two dummy dependent variables for both potato and onion crops, in addition to the 37 input variables. This results in a dataset containing a total of 39 variables.

### *Machine Learning Models*

This study evaluates two tree-based machine learning models: a decision tree model and a Random Forest model (Pal, 2005). A decision tree model is a widely used machine learning algorithm. It resembles an inverted tree, where each internal node represents a decision based on a specific feature, and each leaf node represents an outcome or prediction. In this research, the decision tree is used for classification. They work by recursively partitioning the data into subsets, making decisions at each branching point based on the most informative features (Edwards, 1988). The tree's structure and nodes are determined through algorithms like ID3, C4.5, or CART, which evaluate features' importance to optimize the tree's predictive accuracy (Ranganathan, 2022). This algorithm must find the best parameters that will minimize the cross-entropy function:

$$L(\widehat{D}, D) = -\sum D(x) \log \widehat{D}(x)$$

Where $D(x)$ is the probability distribution of the defined outcome in the previous section and $\widehat{D}(x)$ is the probability distribution estimated by the algorithm.

Random Forest on the other hand combines the power of decision trees to create a robust and accurate predictive model. It works by constructing a multitude of decision trees during the training phase, each based on a random subset of the data and a random subset of the features. These trees operate independently, and when making predictions, their results are aggregated to produce a final output. This ensemble approach helps Random Forest to mitigate overfitting and improve generalization, making it highly effective for classification and regression tasks (Rigatti, 2017). The Random forest algorithm also uses as its main objective the cross-entropy function.

### *Model Refinement and Calculation Process*

The variables used in these models were described in the data processing section. Following standard machine learning practices, 80% of the dataset is allocated for training the models, with the remaining 20% reserved for model testing to assess prediction accuracy. The primary goal of these models is to predict districts most susceptible to crises, and to validate their accuracy, the study employs data from the 2017 price crisis as the testing period. Production data is divided into training and testing sets, with the former containing data before 2017 and the latter encompassing data in 2017 crisis.

Models were fine-tuned using the sci-kit-learn package in Python and allowed the software to select the best parameters for both models following the algorithm process explained in the Machine learning models. The specifications presented in this article represent the best tuning parameters that were generated from a generic optimization of the algorithm. This research did not use cross-validation for tuning the parameters, for two reasons. First, we wanted to demonstrate the accessibility of these techniques as an easy-to-use tool that can be leveraged by policymakers. Incorporating cross-validation tuning would complicate the use of the algorithm. Second, we achieved good results without using extra tuning, so we did not consider it necessary.

## RESULTS

This section shows the result of a random forest model and the decision tree model prediction in the districts that are likely to have oversupply. The outcome is the dummy described in the data segment. Results are reported using the common accuracy formula in the literature:

$$Accuracy = \frac{\#\ of\ correct\ predictions}{Total\ predictions}$$

Table 1 summarizes the results obtained from applying both methodologies to potato and onion crops. Our findings indicate that the training scores for all models are quite similar, ranging between 0.95 and 0.99. However, when testing the models on the crisis period(testing sample), the scores decrease to 71% and 62% for random forest and decision tree models, respectively, in the case of potato production. A similar trend is observed in the case of onion production, with testing scores of 79% and 65%, respectively. These results are noteworthy, as they are comparable to or exceed the prediction rates reported in existing literature on crisis forecasting, such as Babenko et al. (2017) and Jean et al. (2016), where prediction rates range from 60% to 75%.

To demonstrate the accuracy of our model, Figures 5 and 6 compare the municipalities at risk with those predicted by the model. Figure 5 depicts a comparison of the districts in high risk with the prediction of the random forest model. Although the model correctly predicts regions without crises, it struggles to accurately predict regions that are at risk, especially in the central part of the map. In contrast, Figure 6 shows the prediction in districts with onion production, which demonstrates better accuracy and is consistent with the results presented in Table 1

**Table 1:** Accuracy of the Machine Learning Models

| | Potato Production | | Onion Production | |
|---|---|---|---|---|
| | Train Score | Test Score | Train Score | Test Score |
| Random Forest | 0.98 | 0.71 | 0.99 | 0.79 |
| Decision Tree | 0.95 | 0.62 | 0.95 | 0.65 |

Notes: Comparison of the different models calculated by the authors
Source: Own elaboration using the constructed data set and the predicted values from the models.

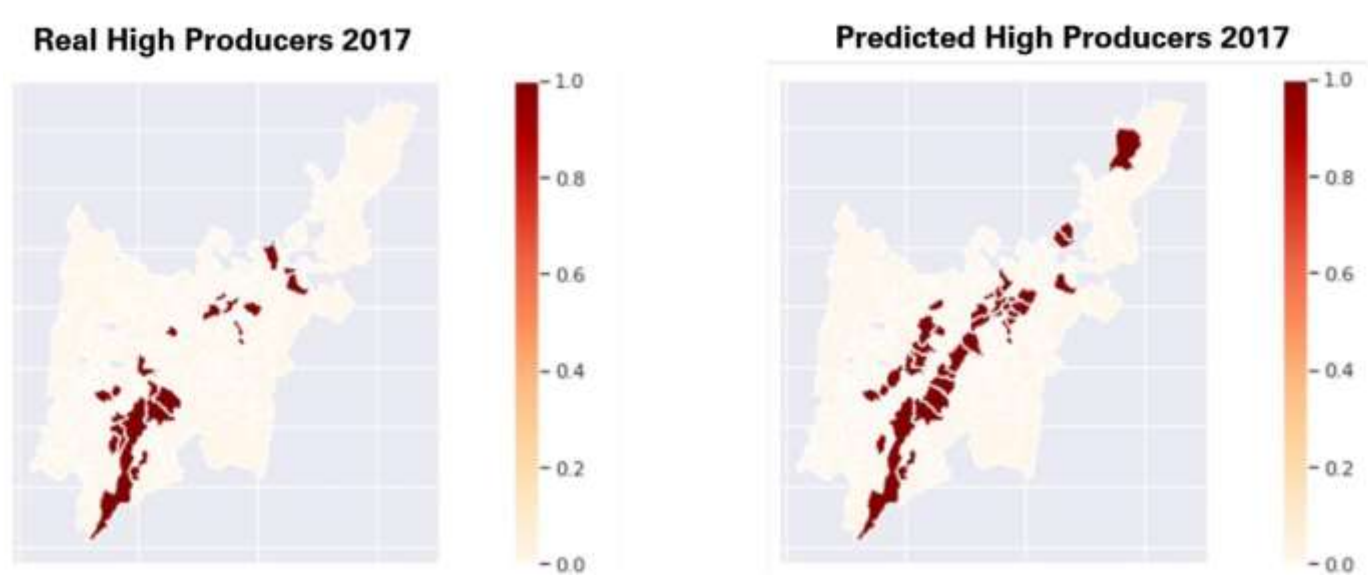


**Figura 5.** Prediction of Districts with High Risk During Price Crisis of Potato
Source: Own elaboration using the constructed data set and the predicted values from the models
Notes: Comparison of real data with forecasted data of the municipalities affected by the price shock in 2017. Cundinamarca and Boyacá Included.

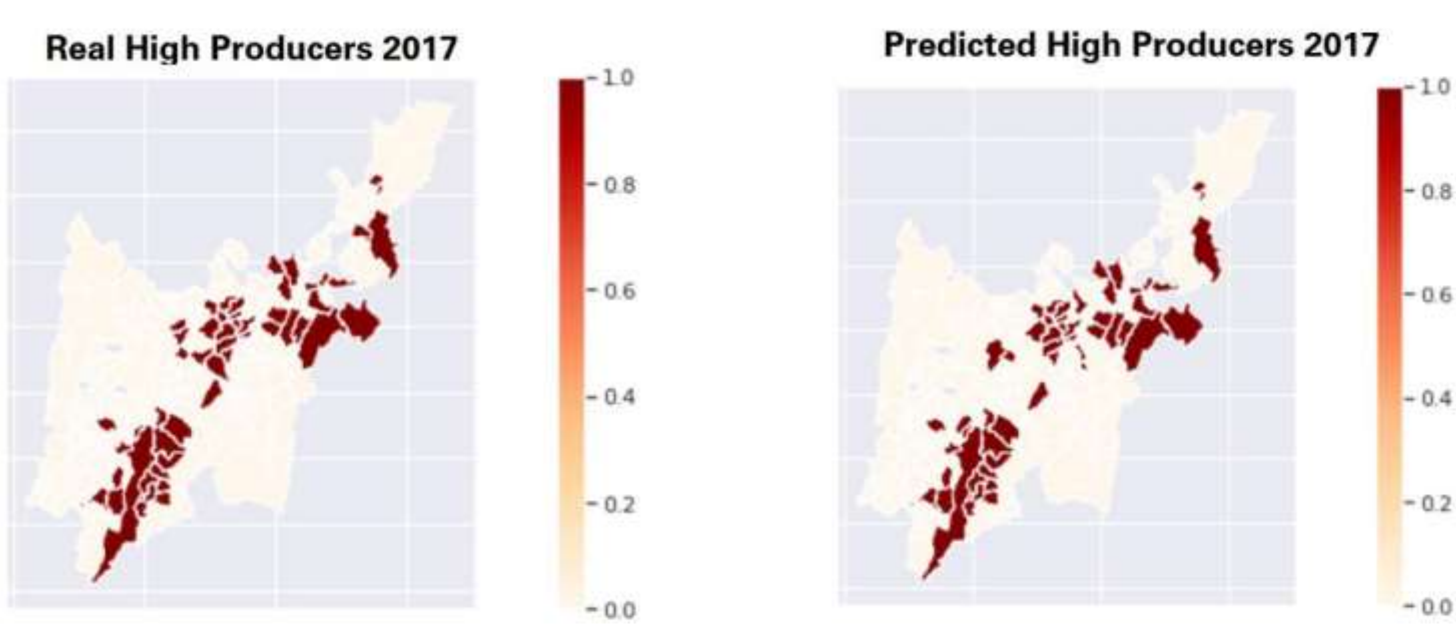


**Figura 6.** Prediction of Districts with High Risk During Price Crisis of Onion
Source: Own elaboration using the constructed data set and the predicted values from the models

Notes: Comparison of real data with forecasted data of the municipalities a ected by the price shock in 2017. Cundinamarca and Boyacá Included.

## Validation

To gain a better understanding of our predictions, we created receiver operating characteristic (ROC) curves to visualize the relationship between the true positive rate and false positive rate. Figure 7 displays the ROC curves for our forecasting models, revealing that our models accurately predict the places with a crisis, with 71% and 74% accuracy for potato and onion, respectively. The graphs demonstrate that our models perform well in predicting true negatives, but not as well with true positives. Nevertheless, our models' performance is impressive compared to previous studies, and they can be valuable tools for policymakers seeking to direct subsidies or support to farmers after a price crisis.

Potato Production Forecasting

Onion Production Forecasting

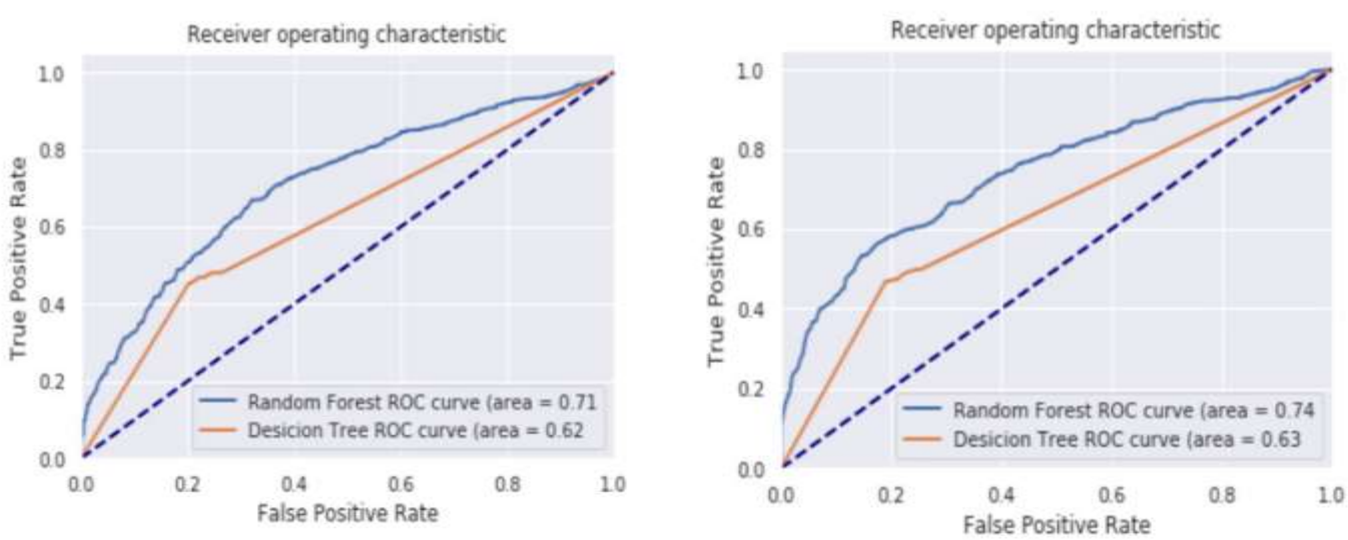


**Figura 7.** ROC Curve for Potato and Onion Production Forecasting
Source: Own elaboration using the results of the models.
Notes: ROC curve comparison of the two models developed by the authors in the municipalities with risk in the central region of Colombia.

## CONCLUDING REMARKS

The primary objective of this research is to showcase the feasibility of utilizing machine learning models to identify municipalities that are highly prone to crises. By establishing the feasibility of using these models, local governments can efficiently direct assistance during price crisis shocks using available public data and straightforward calculation methods. Many potential users are hesitant to adopt these techniques due to the complexity of processing neural networks and the difficulty in understanding the process. This article shows that two simple models, Random Forest and Decision Tree, can be reliable tools that policymakers can use without much difficulty. The findings indicate that these parsimonious models accurately capture the trends of the most important events and can thus serve as effective policy tools.

Although the accuracy of the potato production prediction is lower, our model accurately predicts the districts with crises in onion production. Furthermore, the ROC curves demonstrate that the models excel at predicting true negatives.

This research demonstrates the power of machine learning to provide accurate and accessible tools for policymakers, which can lead to more effective decision-making in the agricultural sector. We hope that this article inspires local authorities to incorporate advanced techniques with simple implementations into agricultural frameworks.

## STATEMENT OF AUTHORS

**Niño Chaparro G.**: Coding, results presentation and writing. **Niño Chaparro A.:** Data collection, methodology definition and writing **Chaparro Pesca:** Literature review and writing.

## DECLARATION OF CONFLICT OF INTEREST

The present research does not represent any conflict of interest with them, the journal, the publishing entity, and the funding entities.

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