Optimization and Predictive Analysis in Food Production in the Face of Climate Change

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I. Introduction

Climate change has profoundly transformed agricultural production dynamics around the world, creating unannounced challenges that threaten global food security. Fluctuating rainfall patterns, rising temperatures, and the increasing frequency of extreme weather events are just some of the most significant impacts facing farmers today. These adverse conditions have not only reduced agricultural yields, but have also put at risk the sustainability of a sector vital to human life and the well-being of millions of people [1]. In addition, crop quality is affected, increasing production costs and limiting access to food in already vulnerable regions [2]. In particular, smallholder farmers, who rely on subsistence crops for their livelihood, are in a critical situation, facing even greater risks due to their limited capacity to adapt to these climatic changes [3].

In the face of these challenges, optimizing agricultural processes has become an essential strategy to mitigate the effects of climate change. This optimization not only seeks to improve the efficiency of agricultural practices, but also to ensure that these are sustainable in the long term [4]. In this context, predictive analysis has emerged as a powerful tool. By processing large volumes of data, it is possible to more accurately predict agricultural yields and propose targeted interventions that optimize the use of critical resources, such as water, fertilizers, and energy [5], [6]. For example, the use of IoT (Internet of Things) sensors that collect real-time data on environmental and agricultural variables has allowed farmers to make more informed decisions, thus maximizing productivity and reducing losses [7], [11], [14].

The objective of this work is to develop a comprehensive approach that combines predictive models, based on logistic and linear regression techniques, with a mathematical optimization model specifically designed to maximize agricultural production in various scenarios [8]. Regression models will be used to analyze historical data covering climatic factors, soil characteristics, and agricultural management practices. The mathematical model, on the other hand, will focus on maximizing yields under resource constraints such as water availability, nutrients, and operating costs [9]. This approach will allow identifying key patterns in the data and proposing customized strategies that adapt to the specific conditions of each agricultural context [10],[12].

The proposed approach offers a double advantage. First, predictive models can identify essential relationships between climate variables and agricultural yields, providing crucial information that can guide decision-making [13]. Second, the optimization model allows designing practical strategies that make the most of available resources, aligning with sustainability and productivity goals [15],[16]. This combined approach not only has the potential to mitigate the negative effects of climate change on agriculture, but can also transform the way crops are planned and managed, promoting a more resilient future for agriculture.

Previous studies have shown that the integration of mathematical models and predictive analytics can significantly improve agricultural yields [14]. Recent research has used various modeling techniques to predict the impact of climate variables on crops and design effective interventions that respond to these challenges [1]. These initiatives have contributed to increasing the resilience of agricultural systems to adverse climate events, which is essential in a world where climate uncertainty is increasingly pronounced [4],[8]. In this context, this work seeks to expand these advances, proposing a comprehensive framework that allows farmers, researchers and decision makers to implement data-driven and results-oriented solutions [3],[7]. In this way, it is expected to contribute significantly to ensuring global food security in a world marked by increasing climatic uncertainties [10],[15],[17].

II. Methodology

A. Type of Study

A predictive analysis study was conducted to identify climatic and agricultural management factors that influence the success of agricultural production, as well as to optimize available resources to maximize yield. This approach combined statistics, through logistic regression, and the formulation of a mathematical optimization model.

B. Techniques and Tools

The data used in this analysis were carefully extracted from various public databases, including the Food and Agriculture Organization of the United Nations (FAO), as well as from local records that provide valuable and up-to-date information on the agricultural and food situation. These sources are essential for obtaining accurate and reliable data, as they allow for a deeper and more contextualized analysis of trends and patterns in food production and distribution.

1) Logistic Regression: Logistic regression was used to predict the probability of success in agricultural production based on climatic variables and management practices. The model was trained using 70% of the data as training set and the remaining 30% for testing. The models were trained with a historical data set using the scikit-learn library in Python. The quality of the model was assessed using metrics such as ROC curve and confusion matrix, which were generated in *SPSS* to validate the predictive power and reliability of the model.

2) Mathematical Optimization Model: A mathematical optimization model was designed whose objective was to maximize agricultural yield considering restrictions:

- Objective Function:
  Maximize:
  $$Z = \sum_{i=1}^{n} (R_i - C_i)$$
  where R_i are the expected returns and C_i the costs associated with the inputs.
- Constraints:
  $\sum_{i=1}^{n} A_i \cdot X_i \leq A_{\text{total}}$ (Total water availability) $\sum_{i=1}^{n} F_i \cdot X_i \leq F_{\text{total}}$ (Fertilizer availability) $X_i \geq 0$ (Non-negativity in the planted area)

The optimization model was solved using the *Pyomo* library in Python, using the *GLPK* solver. This model allowed evaluating multiple scenarios simulating variations in climatic conditions and resource availability.

C. Literature Search Procedure

The literature search was conducted in academic databases such as *Google Scholar*, *Scopus*s, and *Web of Science*, using keywords related to agricultural production, climate change, logistic regression, and mathematical optimization. Peer-reviewed articles and previous studies relevant to the study design were selected, with the aim of understanding previous approaches in predictive analytics and optimization in agriculture. The literature review allowed identifying methodologies used in previous studies, which contributed to the formulation of the optimization model and the application of logistic regression.

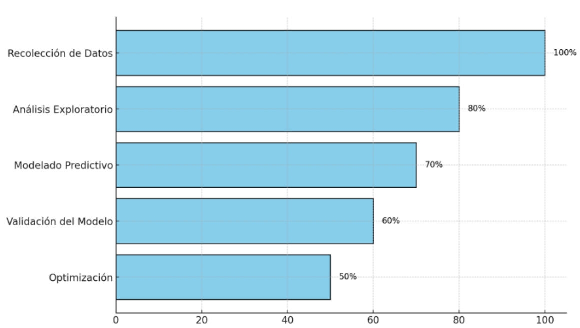

Fig. 1. Structure of a predictive model based on typical stages

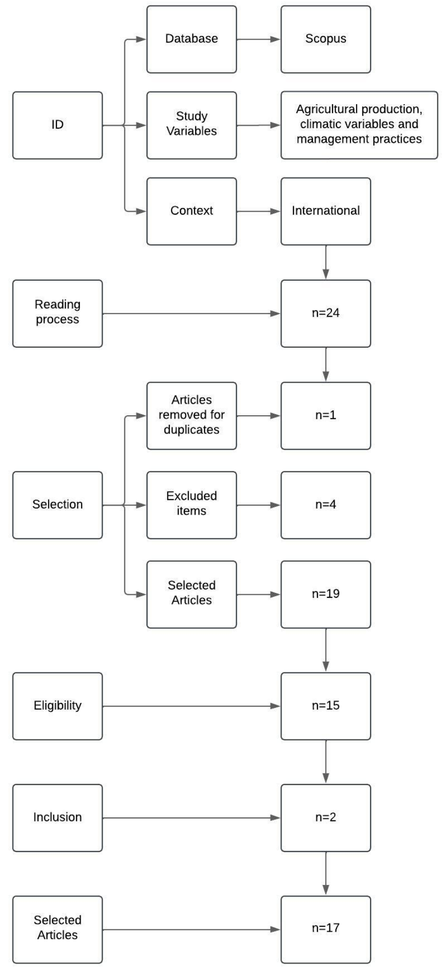

Fig. 2. PRISMA flowchart for article systematization

D. Analysis of Studies

The analysis of the reviewed studies focused on evaluating the methodologies applied in the existing literature on agricultural yield prediction and resource optimization in a climate change context. Different logistic regression and mathematical optimization approaches used by other researchers were identified, which were considered to improve the quality of the model proposed in this study. In addition, the results obtained in previous studies were compared with the expected results to validate the model in terms of its effectiveness under similar conditions.

The sheets used in this study contextualized key aspects of the previous studies. The demographic variables sheet detailed the characteristics of the participants, such as age, sex, and socioeconomic background. The techniques and instruments sheet described the methodologies and tools used in the predictive analysis of food production. Finally, the validity and reliability of the instruments sheet evaluated the precision and consistency of the tools used, ensuring the reliability of the results.

No.	Author(s)	Year	Country	Type of Study	Sample Size	Institution of Participants	Socioeconomic Condition
1	Jian Yin, and Danqi Wei	2023	China	Modeling and optimization study of crop distribution using the MaxEnt model.	Not specified	Guizhou University of Finance and Economics and Northeast Agricultural University.	Not detailed
2	Deepak K. Ray, James S. Gerber, Graham K. MacDonald, and Paul C. West	2015	United States	Analysis of global data on crop yield variability and its relationship with climate variability.	13,500 political units	Institute on the Environment (IonE), University of Minnesota	Not detailed
3	Harishmaika N, Shilpa N, and S A Ahmed	2023	India	Quantitative study on climate variability.	Not specified	Environ Monit Assess 195	Not detailed
4	Isidro J. Mirón	2023	Spain	Bibliographic review on food safety and security in the face of climate change, focusing on adaptation and mitigation.	Not specified	District of Public Health, Diagnosis, and Treatment of SESCAM.	Not detailed
5	Hui Chen, Meng-Xuan Lin, Li-Ping Wang, Yin-Xiang Huang, Yao Feng, Li-Qun Fang, Lei Wang, Hong-Bin Song, and Li-Gui Wang	2023	China	Study on human brucellosis in China, using predictive analysis based on machine learning.	327,456 cases of brucellosis.	Not specified	Not detailed
6	J. S. Kimuyu	2021	Kenya	Original research using ecological niche modeling (ENM).	Not specified	Technical University of Kenya.	Addresses the vulnerability of communities in malaria-endemic areas.
7	Arlitt Amy Lozano Povis, Carlos E. Álvarez-Montalván, Nabil H. Mogollón.	2021	Peru	Systematic review on the impact of climate change on agriculture in the Andes.	Not specified	Continental University, Huancayo Campus, Peru.	Not detailed
8	Wan Nurnazati Wan Ab. Rahman, Wan Nurfatihah Wan Zulkifli, Nur Nabilah Zainuri, Hanis Amira Khairul Anwar.	2024	Malaysia	Research model proposal.	Not specified	Faculty of Computer Science and Information Technology, Universiti Putra Malaysia.	Highlights the importance of addressing food insecurity, which affects various socioeconomic classes, especially low-income communities.

TABLE I

SHEET TO CONTEXTUALIZE THE DEMOGRAPHIC VARIABLES THAT CHARACTERIZE THE STUDIES

No.	Author(s)	Year	Country	Type of Study	Sample Size	Techniques	Instruments
1	Yueyang Symus Say, Mark Wong Kei-Fong, Eddie Ng Yin-Kwee	2022	Singapore	Research study on agricultural yield prediction using machine learning models.	Not specified	Generative machine learning models	Machine Vision, Adversarial Autoencoder (AAE)
2	Julius Olatunji Okesola, Olaniyi Ifeoluwa, Sunday Adeola Ajagbe, Olubunmi Okesola, Adeyinka O. Abiodun, Francis Bukie Osang, Olakunle O. Solanke	2024	Nigeria	Research study on crop yield prediction analysis using supervised learning techniques.	Based on historical data.	Random Forest, Stochastic Gradient Descent, Extra Tree Regressor, AdaBoost Regressor, and Linear Regression	Python, Web interface, and Performance metrics
3	Michael J Roberts, Noah O Braun, Thomas R Sinclair, David B Lobell, Wolfram Schlenker	2017	United States	Comparative research study on process-based crop models and statistical models.	1,121,601 observations	Comparison and combination of process-based crop simulation models and statistical models.	Crop simulation models, Statistical regression models, and Climate and meteorological data
4	Ying Mei Leong; Ean Heng Lim; Nor Fatiha Binti Subri; Norazira Binti A Jalil	2023	Malaysia	Review on applications of Artificial Intelligence of Things (AIoT) in agriculture.	Not specified	Literature review on AIoT applications, including real-time data analysis, automation, and resource optimization.	Artificial Intelligence (AI) technologies, Internet of Things (IoT), Decision support systems, and Advanced AI algorithms.
5	T. Sathies Kumar, S. Arunprasad, A. Eniyan, P.Abdul Azeez, S. Bharath	2023	India	Research on the use of Machine Learning (ML) in crop selection and cultivation.	These are the data sets used to train Machine Learning algorithms.	Machine Learning algorithms (neural networks, decision trees, ensemble models) for crop selection.	Machine Learning algorithms, IoT sensors for real-time data acquisition, Satellite images for agricultural landscape analysis, Datasets.
6	Citlali Yulyana ROJO ÁVILA, Cipatli Yurydia ROJO ÁVILA, Blanca Paulette ROJO ÁVILA	2024	Mexico	Review/Analysis on the use of artificial intelligence in the context of climate change.	Not specified	Data analysis, literature review on artificial intelligence and climate change	References to artificial intelligence technologies, climate data analysis, focus on policies and strategies related to the Paris Agreement.
7	Fausto Vizcaíno Naranjo, Fredy Cañizares Galarza, Edmundo Jalón Arias	2023	Ecuador	Study on the integration of IoT and machine learning techniques for crop yield prediction.	Not specified	Integration of IoT sensors and machine learning techniques, specifically gradient boosting regression models.	IoT sensors for environmental data collection, pest conditions, and specific crop attributes.
8	Keh-Jian Shou, Chung-Che Wu, Jia-Fei Lin	2018	Taiwan	Predictive analysis of landslide susceptibility using typhoon event data.	Use of typhoon event data	Rainfall frequency analysis, logistic regression modeling, satellite image analysis (NDVI), landslide control factors analysis.	General Atmospheric Circulation Models (AGCM), SPOT satellite images, rainfall station data, Geographic Information Systems (GIS).

TABLE II

SHEET TO CONTEXTUALIZE THE TECHNIQUES AND INSTRUMENTS THAT HAVE BEEN USED IN THE STUDIES.

No.	Author(s)	Year	Country	Type of Study	Sample Size	Instruments	Validity	Reliability
1	Eissa Alreshidi	2019	Saudi Arabia	Research study on SSA	Not specified	IoT/AI technologies in agriculture	Validity of IoT/AI technologies in SSA is reviewed	The need for validation of IoT/AI applications is mentioned.
2	Mustapha El-Maayar, Manfred A. Lange	2013	Egypt, Greece, Morocco	Study on the impact of climate change on crop yield	Not specified	Regression models and statistical analysis	Statistical validity of the models used is mentioned	Statistical methods are used to assess the reliability of the results.
3	Hamzah Abdul Hamid, Yap Bee Wah, Khatijahhusna Abdul Rani, Xian Jin Xie	2024	Malaysia	Study on multinomial logistic regression	100 and 400	Clustering techniques (DIANA and Ward)	Validity of the goodness-of-fit test is analyzed	Type I error control and test power are mentioned.
4	D. Pushpa Gowri, Anitha Ramachander	2024	India	Review on digital agriculture	Not specified	Digital technologies in agriculture	Validated through the evaluation of technologies and their impact on agriculture	Review of technologies and practices suggests consistency in findings.
5	Daniel Sánchez Garcia, Carlos Rubio Bellido, Madelyn Marrero Melendez, Francisco Javier Guevara Garcia, Jacinto Canivell	2017	Spain	Study on energy savings in buildings	Not specified	Office building in Seville, DesignBuilder software, thermal comfort surveys.	The simulation model is validated with real data.	Acceptable error metrics (MBE and CV(RMSE)) are used.
6	Pascal Muam Mah, Iwona Skalna, Tomasz Pełech-Pilichowski, John Muzam, Eric Munyeshuri, Promise Offiong Uwakmfon, Polycap Mudoh	2022	Poland	Study on integration of sensors and machine learning for climate change	412 diesel, 636 gasoline, 157 LPG	Vehicle emission data in Zabrze-Krakow	Validated through the collection and comparative analysis of emission data.	Emission statistics and prediction analysis are used to ensure reliability.
7	Andrew Lewis, James Montgomery, Max Lewis, Marcus Randall, Karin Schiller	2023	Australia	Predictive model for irrigated agriculture	Not specified	Simulation models, RTO (Robust Temporal Optimization)	The predictive model is validated with climate and agricultural data	Error metrics and cross-validation are used to ensure reliability.
8	Keh-Jian Shou, Chung-Che Wu, Jia-Fei Lin	2018	Slovakia, Croatia, Germany, Ukraine	Study on river water temperatures of the Danube	Water temperature data (1990-2020)	SARIMA models, nonlinear regression models	Validated through time series analysis and climate scenario comparison	Stability and effectiveness of the SARIMA model suggest consistent results in simulations.

TABLE III
SHEET TO CONTEXTUALIZE THE VALIDITY AND RELIABILITY OF INSTRUMENTS USED IN THE STUDIES.

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