

A Predictive Framework for Crop Health Assessment Using Time-Series Models and Machine Learning Under Climate Variability

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Abstract

Climate variability has posed increasingly large-scale threats that have a significant impact on all agricultural systems worldwide, such as climate change, various uncontrollable variables, shifting precipitation patterns, and extreme temperatures combined with the degradation of fertile soil jeopardize food security in major cities. For this reason, steps have been taken to develop predictive models based on artificial intelligence technology as a sustainable alternative for agricultural management in times of change, through the early detection of agricultural stress conditions before they affect the harvest and to reduce yield losses. This paper proposes a hybrid predictive framework for assessing crop health that integrates time series forecasting models, including Prophet and ARIMA, with machine learning algorithms such as Random Forest and support vector machines. The objective of this framework is to process two main data streams: climatological variables such as temperature, precipitation, and humidity, along with soil indicators including pH, nutrient levels, and soil moisture, by combining the temporal decomposition capabilities of time-series models with the ability of ensemble- and kernel-based classifiers to recognize nonlinear patterns. The proposal's primary aim is to provide highly robust, multi-horizon predictions of the current crop health status across various agricultural contexts. The method employed is based on a systems thinking approach, which treats the crop-climate-soil system as an interconnected whole, rather than conceptualizing it as isolated components. A conceptual architecture is presented, including an analysis of data requirements, various integration challenges, and indicators of expected yields. The results are expected to prove the complementary strengths of both model families when applied to heterogeneous agricultural datasets. Contributing to sustainable and climate-resilient agriculture by offering a scalable, data-driven decision-support tool that can be replicated across multiple crop types and geographic regions, future work will focus on model validation using open agricultural and meteorological datasets.

Keywords

Artificial Intelligence, Time-series forecasting, Agricultural resilience, Food safety and Climate change adaptation.

1. Introduction

Over the past decade, climate variability has emerged as one of the most complex challenges facing agriculture, due to the simultaneous and increasing occurrence of atypical precipitation patterns, extreme temperature changes, and shifts in soil fertility on a global scale. Saleem et al. (2024) note that recent projections estimate that drought-affected regions could expand from 15.4% to 44% by 2100; moreover, the yield reduction may exceed 50% by 2050 and

approach 90% at the end of the 21st century. Based on these scenarios, regions with the most vulnerable agricultural systems will suffer significant reductions in yields, putting food supply and availability for large cities at high risk (Garajeh et al., 2023). Given this scenario, it is essential to deploy technologies that enable monitoring and highly accurate prediction of climate impacts on agroecosystems, through the integration of emerging technologies such as artificial intelligence and remote sensing with adaptive management strategies that facilitate the transition toward climate-smart agriculture (Mmbando, 2025).

Given this context, early detection of agricultural stress before risks materializes and result in irreversible yield losses should be a strategic objective for agricultural producers. Advances in computational sciences such as hyperspectral imaging, thermal infrared sensing, and fluorescence detection combined with the growing availability of unmanned aerial platforms and ground-based sensor networks, have made it possible to generate large volumes of data with high spatial and temporal resolution on the physiological status of crops. The synergy between non-destructive technologies and machine learning algorithms has enabled the automation, intelligent detection, classification, and prediction of plant stress, identifying droughts, nutritional deficiencies, and pathogenic infections and even anticipating their development before visible symptoms manifest (Muhammad et al., 2025). Enhancing machine learning approaches has demonstrated strong and growing potential for monitoring agricultural crops, with the goal of anticipating plants' physiological responses to both biotic and abiotic stress conditions (Zarbakhsh et al., 2025).

To capture the temporal dimension inherent in these signals and interpret it, that is, to translate it into operational forecasts classical time-series models have been used. In the agricultural sector, Meta's Prophet model has been successfully implemented to predict wheat yield, achieving low prediction errors a MAPE of 10.03% and an RMSE of 0.39 when modeling annual seasonality (Desai and Shingala, 2023). Specific comparisons focused on rainfall forecasting have shown that variants based on Prophet specifically Neural Prophet can improve accuracy and precision compared to the original Facebook Prophet version, with RMSEs of 2.25 versus 2.85, respectively (Anuradha et al., 2023). At the same time, the ARIMA model has proven to be a versatile tool in agricultural engineering, with documented applications in yield forecasting, weather forecasting, water management, pest outbreak prediction, livestock production forecasting, and soil health monitoring. Furthermore, hybrid combinations can be established with techniques such as LSTM and ANN to capture nonlinearities that ARIMA cannot capture on their own (Venu and Namitha, 2025).

When it comes to non-linear pattern recognition and crop health classification, classical machine learning algorithms still play a vital role. Recent comparative studies have evaluated the performance of KNN, decision trees, Random Forest, SVM and Naive Bayes for predicting soil nutrient status and found that Random Forest has 99% accuracy and outperforms alternative methods, demonstrating its ability to support informed decisions about crop selection, soil preparation and fertilization (Sadasivan et al., 2025) leads to hybrid systems that combine both algorithms for intelligent crop selection based on soil health and environmental factors such as temperature, humidity, 20, 20.

The implementation of these methods depends on the availability of reliable data streams on climate variables and soil indicators. To support precision agriculture, low-cost open-source hydrometeorological measurement systems that can record air and soil temperature, soil moisture, and photon flux density with high temporal resolution have been proposed, thereby expanding monitoring coverage in resource-limited regions (Tatsumi et al., 2021).

This study proposes a hybrid forecasting framework to assess crop health under complex climate variability based on systems thinking, which views crops, climate and soil as a single system rather than as isolated components. The proposal integrates Prophet and ARIMA time series forecasting models with the classic machine learning algorithms Random Forest and SVM to process two main data streams: on the one hand, climatic variables such as temperature, precipitation and humidity; and, on the other hand, soil indicators such as pH, nutrient levels and moisture. By combining temporal partitioning features of time series models with nonlinear pattern recognition of ensemble and kernel classifiers, this system aims to provide highly robust multi-horizon predictions of crop health in a variety of agricultural contexts. The conceptual architecture described here aims to provide a scalable, data-driven decision support tool that can be replicated across multiple crop types and geographic regions under a sustainable and climate-resilient agriculture agenda under complex conditions. As part of our future work, we will focus on validating the system using open agricultural and meteorological datasets to demonstrate the complementary strengths of the two model families.

1.1 Objectives

To design a proposed framework with hybrid predictive capabilities for assessing soil health in monocultures, integrating time-series models to generate forecasts, and combining this with machine learning algorithms based on climate and soil variables, with the aim of using it as a decision-support tool for agricultural decision-making in the face of complex climate variability scenarios.

- **Conceptual framework:** systematically identify and integrate climate and soil variables that best explain crop health, based on a review of the specialized literature on agricultural predictive modeling.
- **Framework Architecture:** Propose a conceptual architecture for a hybrid model with capabilities that allow for the integration of time-series forecasting methods such as Prophet and ARIMA with machine learning classifiers such as Random Forest and SVM to name a few for the multi-horizon prediction of crop health indicators.
- **Theoretical feasibility assessment:** Analyze methodological complementarity among the model families to define expected performance metrics and establish integration criteria applicable to agricultural datasets.

2. Literature Review

Over time, open datasets have been published that comprise various meteorological, moisture, and soil indicators from national agricultural monitoring networks (LI et al., 2024), as well as open repositories of soil sensors and weather stations deployed on active farms (Mousoulis et al., 2023). When these data are integrated into a single collection and subjected to geospatial analysis, it becomes possible to link crop dynamics and the uniform distribution of nutrients, and to view hydrological processes as an interconnected whole, thereby laying the groundwork for ensuring productivity, sustainability, and resilience in agricultural systems (Akanbi et al., 2024). Under this systemic approach, precision agriculture enabled by IoT technology has reported significant improvements 45% in water efficiency, 30% reduction in pesticide use, 22% increase in productivity, and 35% improvement in soil health through the analytical processing of data captured by sensor networks (Kaur et al., 2025), while AIoT platforms with edge computing have reported R^2 values of 0.985 and 50% reductions in error for early warning tasks regarding climate impacts, operating even in fully autonomous mode without an internet connection (Naeem et al., 2026). At the decision-making level, these capabilities take the form of prototyped tools to support data-driven decision-making in agricultural settings (Vanezi et al., 2023).

The synergistic integration of timeseries models and machine learning algorithms offers decisive advantages for agricultural forecasting (Yan et al., 2025). Scientific and technological advances have enabled hybrid frameworks focused on predicting crop yield time series to combine machine learning techniques with climatic factors, improving accuracy and precision compared to unimodal approaches. In particular, by establishing a framework that integrates the S-GSTAR model for forecasting climate variables temperature, precipitation, and humidity with Prophet to project the productivity of food crops, MAPE values below 1.40% for temperature, 1.13%-1.92% for humidity, and 16.11%-54.21% for precipitation were achieved, while Prophet achieved MAPE values of 0.00% - 4.65% for rice and 1.29%-8.21% for peanuts, with less favorable results for beans (MAPE 4.89%-85.09%) (Pratama et al., 2025). Additionally, stacked models that fuse temporal and spatial patterns using LSTM and CNN, along with Linear Regression, Random Forest, and Gradient Boosting as a meta-learner, have reported an RMSE of 16.92 t/ha, an MAE of 13.12 t/ha, and an R^2 of 0.89, outperforming recent baselines in regional yield prediction (Gowda et al., 2025).

Given this situation, remote sensing has come to play an important role in characterizing the biophysical state of vegetation. Practical applications have been documented, such as monitoring NDVI and surface temperature using Landsat and MODIS to detect climate change-induced plant stress, integrating a wide range of variables including evapotranspiration, precipitation, sunny days, cloud cover, soil salinity, soil moisture, groundwater quality, soil types, digital elevation models, slope, and aspect (Saleem et al., 2024). A minority have fully integrated remote sensing, deep convolutional neural networks, and platforms such as Google Earth Engine to assess the impacts of climate change on food security (Garajeh et al., 2023). This gap warrants the adoption of comprehensive analytical systems, where climate-smart agriculture is envisioned as a combined approach that integrates artificial intelligence, predictive analytics, crop modeling and precision agriculture with remote sensing, climate forecasting, land management and continuous monitoring to improve resilience, resilience and stability.

Automation of plant stress detection is a strategic goal in modern agriculture using non-destructive techniques such as hyperspectral imaging, thermal infrared sensing and fluorescence detection. Combined with the increasing availability of drones, unmanned aerial vehicles, satellites, and ground sensor networks, these technologies have

enabled the generation of large amounts of data with high spatial and temporal resolution on the physiological state of crops. Integration with machine learning algorithms has enabled the automation of the detection, classification, and prediction of plant stress, drought, nutritional deficiencies, and pathogen infections, and even the anticipation of their development before visible symptoms appears (Muhammad et al., 2025).

In the field of time series modeling, the development of open-source algorithms applicable to the agribusiness sector. The Prophet library developed by Meta has yielded extraordinary results in predicting wheat yields, achieving competitive error metrics: a MAPE of 10.03% and an MSE of 0.39 in the summer, when seasonality is modeled at the annual level (Desai and Shingala, 2022).

The convergence of the models analyzed in the literature review demonstrates the maturity of the components, as well as the persistent gaps that justify this proposal. First and foremost, the Prophet and ARIMA families have demonstrated competitive and often superior performance compared to neural network models for forecasting agricultural and climate variables, with documented metrics including MAPEs below 1.40% for temperature (Pratama et al., 2025), an RMSE of 0.39 for summer forecasts (Desai and Shingala, 2022), and an R^2 of 0.89 in integrated LSTM+CNN+RF+GB models (Gowda et al., 2025). Furthermore, the integration of both model families, in conjunction with open hydrometeorological data (LI et al., 2024; Mousoulis et al., 2023) which can be captured using low-cost systems and multiscale geospatial analysis (Akanbi et al., 2024), forms a robust technical model for building a predictive tool, analogous in spirit to the climate-smart agriculture proposed in comprehensive reviews (Mmbando, 2025; Nandeha et al., 2025).

3. Methods

Phase 1: Setting Up the Computing Environment: Only open-source libraries for Python 3.0 were used to develop the models, avoiding dependencies, subscriptions, or registrations, as well as access to external APIs. Libraries used for model development were Prophet for time series with complex seasonal variations, Statistical Models for developing classic ARIMA models, scikit-learn for building machine learning classifiers and matplotlib/seaborn for generating visualizations. In addition, the global seed (SEED = 42) was set to ensure that all results are reproducible in any run.

Phase 2: Data generation and calibration: We chose to use a strategy involving calibrated synthetic data. Climate data were generated with annual seasonality using a sinusoidal function modeling temperature change throughout the year, parameterized by the actual temperature range in each area: $\pm 4^\circ\text{C}$ in Veracruz, $\pm 8^\circ\text{C}$ in Puebla, and $\pm 6^\circ\text{C}$ in Mexico City. The rainy season was modeled using a multiplier that increases rainfall from May to October, replicating the Mexican monsoon pattern documented by SMN-CONAGUA. Finally, a humidity–precipitation correlation was established, where relative humidity is calculated as a function of daily precipitation and Gaussian noise, which represents the actual physical relationship between the variables.

Phase 3: Treatment and labeling: mean imputation was used for missing values; this strategy is robust to the skewed distributions inherent in meteorological variables. Health labels of healthy, threatened and critical crops were created using a multi-criteria scoring function that assesses six simultaneous conditions: three climatic and three edaphic. This feature serves as a proxy for expert knowledge and will be replaced by actual field marks during the empirical validation phase.

Phase 4: Layer 1: Time Series Forecasting: Two complementary models were used for different purposes: Prophet was used to model the daily average temperature; furthermore, this library has native capabilities for seasonal decomposition without requiring the series to be stationary, as well as robustness to outliers and automatic handling of trend changes. ARIMA, on the other hand, was used to model cumulative monthly precipitation. Before fitting the model, the augmented Dickey-Fuller (ADF) test was applied to verify stationarity.

Phase 5, Layer 2: Crop Health Classification: The feature space integrates the ten variables from the preprocessed dataset. Min-Max normalization was applied prior to training, which is essential for the proper functioning of the SVM and also improves the convergence of the Random Forest when dealing with variables on vastly different scales such as pH, which ranges from 5 to 8, as opposed to potassium, which ranges from 120 to 320 mg/kg. For the Random Forest model, 200 trees were constructed with a maximum depth of 10 levels (corresponding to the 10 variables). This model was chosen due to its extensive ability to capture nonlinear interactions between climatic and edaphic variables

without requiring distribution assumptions. It also directly produces an interpretable measure of variable importance. Furthermore, the SVM with an RBF kernel was selected as the model because it allows for the establishment of contrasts due to its high effectiveness in high-dimensional spaces with nonlinear decision boundaries. The data partition follows an 80/20 Pareto ratio with stratification by class, ensuring a proportional representation of the three health categories in both datasets.

4. Data Collection

The data used for this experiment were synthetically generated using a calibration protocol based on historical records from the National Metrological Service and the National Water Commission, which provide daily temperature, precipitation, and relative humidity time series for monitoring stations throughout Mexico.

- **Annual seasonality:** modeled using a sinusoidal function parameterized by annual mean temperature and temperature range reported for each region: Veracruz, Puebla, and Mexico City.
- **Precipitation regime:** structured around the Mexican monsoon pattern during the rainy season, which occurs between May and October, consistent with the Köppen-García climate classification for each study area.
- **Humidity-precipitation covariance:** which reflects the physical dependence between the two variables documented in the records from the National Meteorological Service stations.

For soil data, ranges for edaphic variables were derived from two complementary institutional sources: the National Institute of Statistics and Geography (INEGI), through its National Geostatistical Framework, which includes georeferenced soil characterization profiles with information on texture, pH, and edaphic classification by state; In conjunction with the Agri-Food and Fisheries Information Service (SIAP) of the Ministry of Agriculture and Rural Development (SADER), which maintains records of agricultural soil conditions by production zone, including levels of macronutrients (nitrogen, phosphorus, and potassium) and soil moisture by agricultural cycle. Based on information from both institutions, representative ranges were established by zone for the model's five edaphic variables (Table 1):

Table 1. Variables by entity

Variable	Veracruz	Puebla	Mexico City
pH	5.5 – 6.5	6.0 – 7.2	6.5 – 7.5
Nitrogen (%)	0.10 – 0.25	0.08 – 0.18	0.12 – 0.22
Phosphorus (mg/kg)	8 – 20	5 – 15	10 – 25
Potassium (mg/kg)	150 – 300	120 – 250	180 – 320
Soil moisture (v/v)	0.30 – 0.55	0.20 – 0.40	0.25 – 0.45

5. Results and Discussion

5.1 Numerical Results

The simulation covers the period from 2000 to 2026 at daily resolution and generates a total of 9,862 records per zone and 29,586 records in the integrated dataset. This 26-year time period was deliberately chosen to capture annual variations associated with climate change, including years of extreme precipitation and temperature anomalies documented by SMN in the three study areas (Figure 1- Figure 4).

5.2 Graphical Results

When comparing the confusion matrix, it is notable that the Random Forest is much more robust than the SVM, as the difference in predictions is 26 incorrect predictions compared to 600 for the SVM.

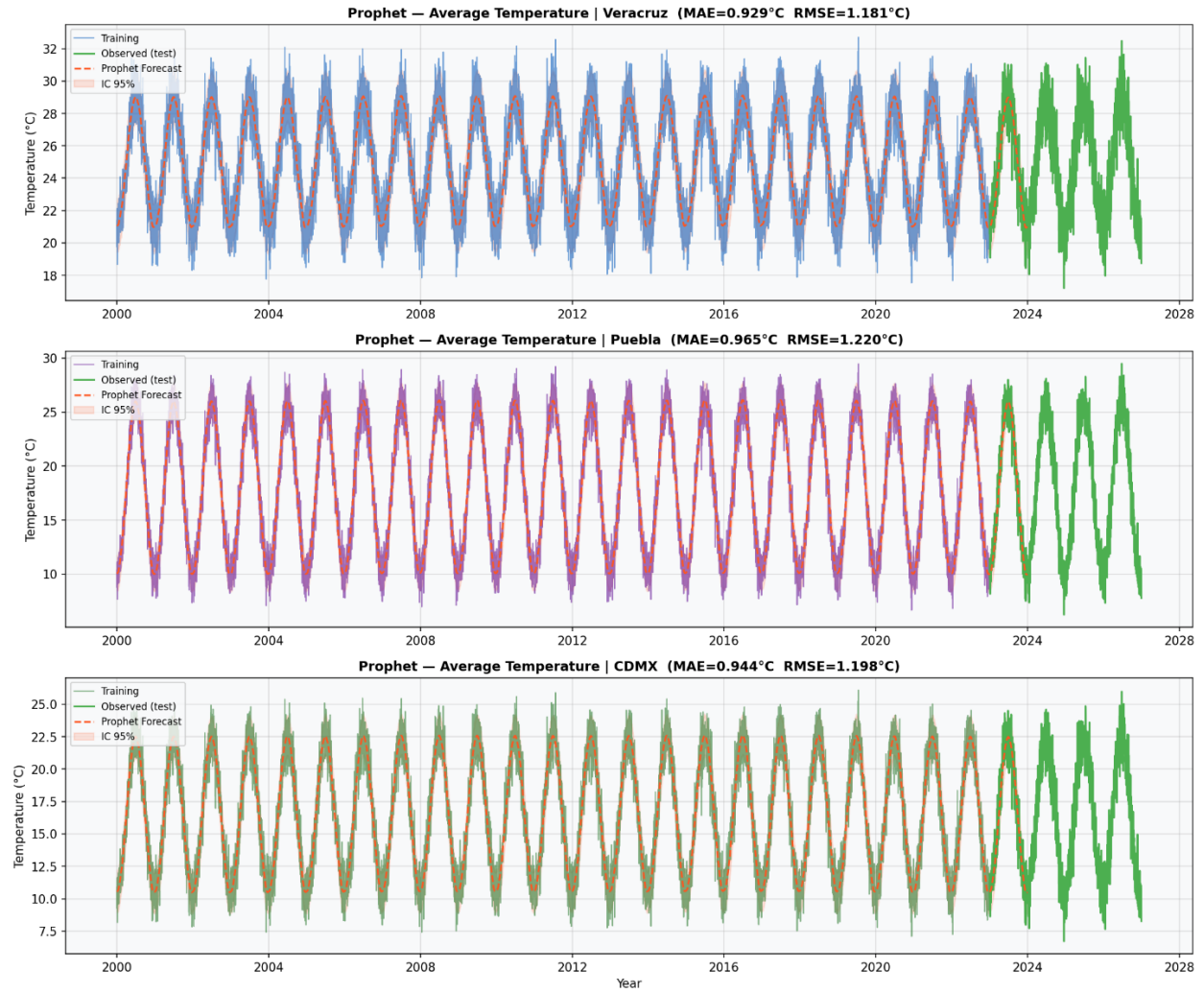


Figure 1. Average Temperature Forecast by Geographic Region

Table 2. Prophet Metrics by Region

Zona	MAE (°C)	RMSE (°C)
Veracruz	0.929	1.181
Puebla	0.965	1.220
Mexico City (CDMX)	0.944	1.198

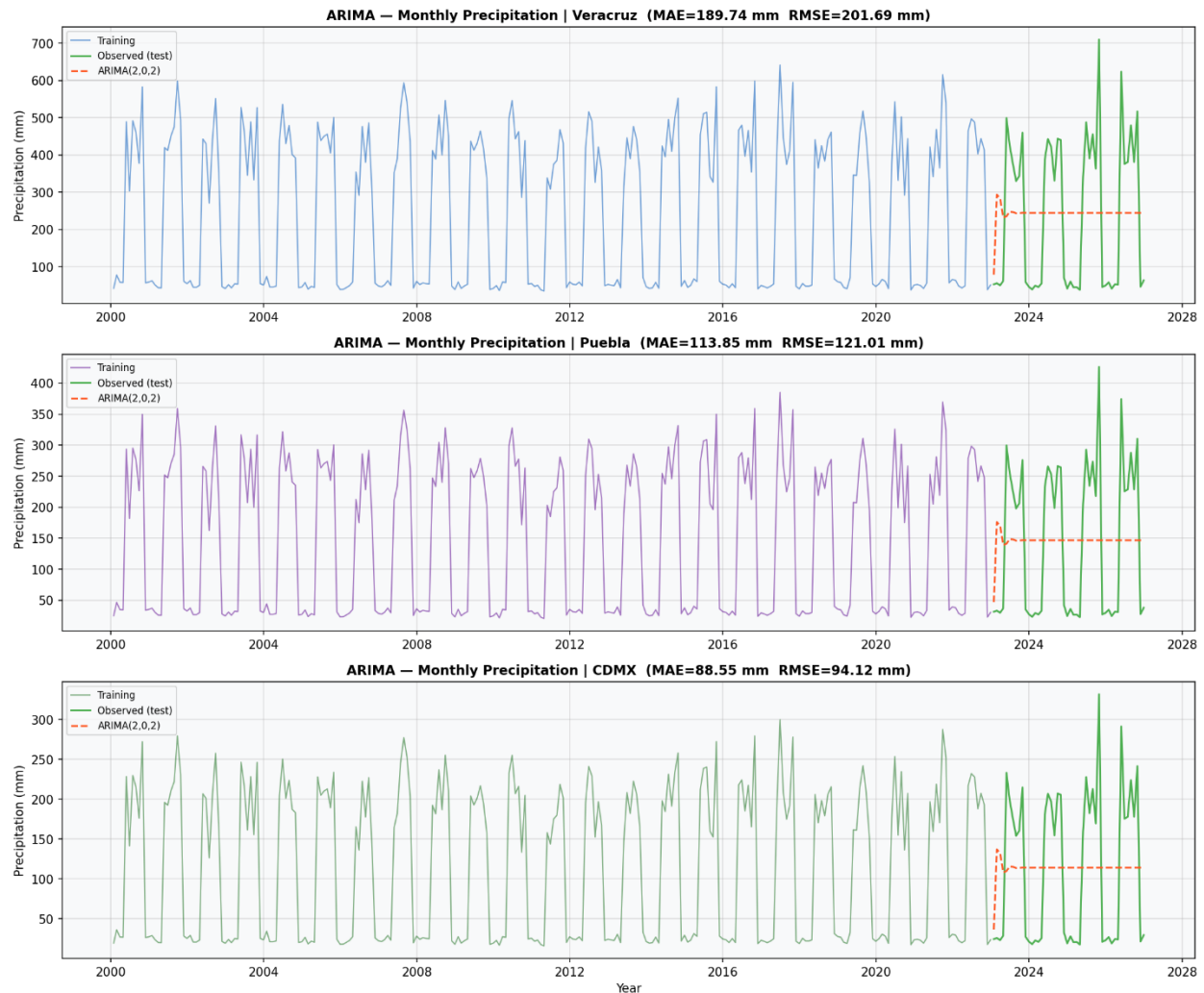


Figure 2. Monthly Precipitation Forecast by Geographic Area

Table 3. ARIMA Metrics by Region

Zona	p-value	MAE (mm)	RMSE (mm)
Veracruz	0.0001	189.74	201.69
Puebla	0.0001	113.85	121.01
Mexico City (CDMX)	0.0001	88.55	94.12

5.3 Proposed Improvements

In Figure 4, it is notable that precipitation and average temperature together account for approximately 31.5% of the model's total predictive power, confirming that climatic variables are the predominant predictors. On the other hand, soil moisture and nitrogen are significant; that is, precipitation determines that soil moisture influences nitrogen availability. Finally, phosphorus and potassium are not statistically significant within this dataset; it should be noted that this is not because they are irrelevant from an agronomic standpoint, but because their ranges of variation across zones are insufficient to distinguish between health classes. This points to a significant area of opportunity and/or improvement for the empirical validation phase, through the incorporation of field measurements to increase predictive power

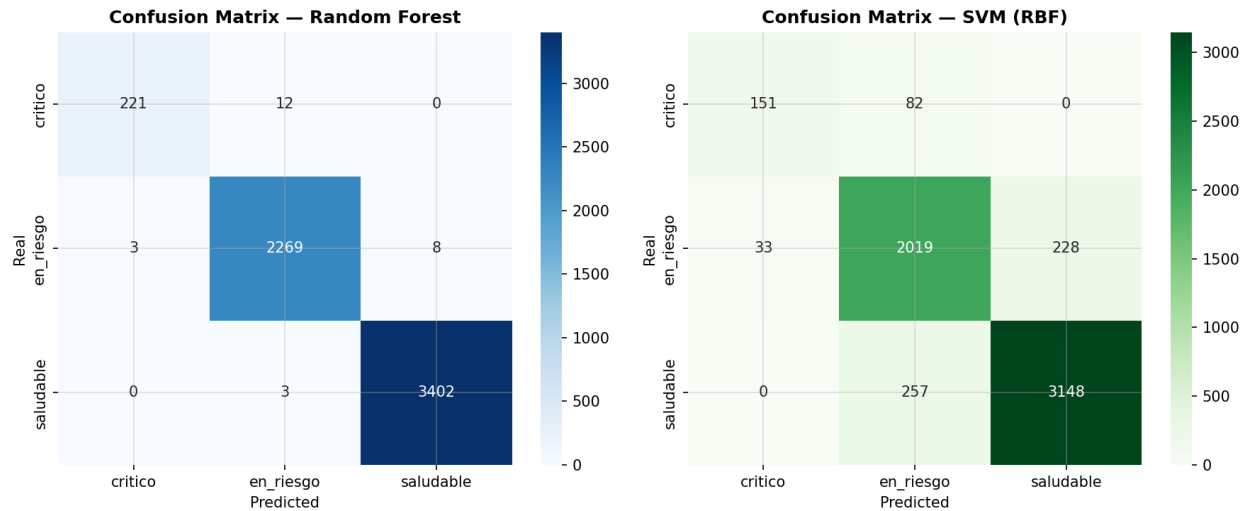


Figure 3. Confusion Matrix

5.4 Validation

Figure 5 shows a significant gap in agricultural resilience among the three regions. It is noteworthy that Veracruz operates under very favorable conditions most of the time, whereas Mexico City (CDMX) and Puebla experience more than 50% of their days under risk conditions, underscoring the urgent need for a predictive system that issues early warnings to prevent the risk from materializing.

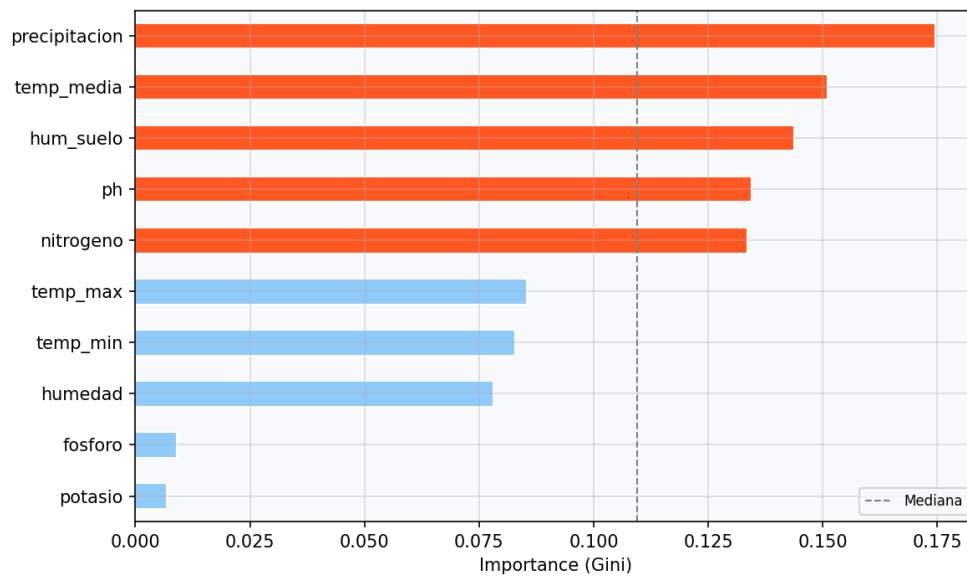


Figure 4. Importance of Variables

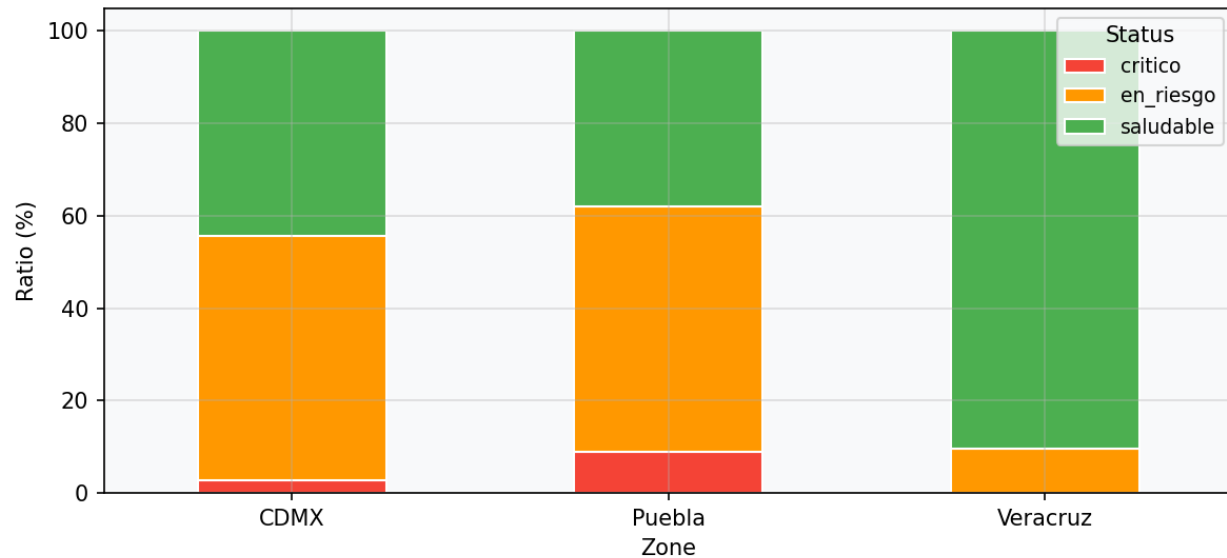


Figure 5. Distribution of health status by zone

6. Conclusion

The overall objective of designing, documenting, and theoretically evaluating a hybrid predictive framework for assessing crop health under conditions of climate variability was successfully achieved. The justified selection of ten variables distributed across two fluxes: a climatological stream comprising mean temperature, cumulative precipitation, and relative humidity; and a soil stream comprising pH, nitrogen (%), phosphorus (mg/kg), potassium (mg/kg), and soil moisture (v/v), with ranges calibrated by region based on profiles from INEGI's National Geostatistical Framework and SIAP-SADER records. The selection was not arbitrary: it was based on prior evidence reporting accuracies of up to 99% for Random Forest in predicting soil nutrient status (Mathew et al., 2024), in hybrid frameworks that combine soil health with environmental factors (Dey, 2026), and on the feasibility of deploying low-cost sensor networks to sustain hydrometeorological data streams in resource-constrained regions (Tatsumi et al., 2021). Empirical confirmation came from the variable importance analysis (Section 5.4), in which precipitation and temperature together accounted for approximately 31.5% of the total predictive power, while soil moisture and nitrogen completed the causal chain: precipitation → moisture → nitrogen. The marginal variation in phosphorus and potassium was not interpreted as agronomically irrelevant, but rather as insufficient variation among zones in the synthetic dataset, which points to a specific area for improvement in the empirical validation phase.

Tables 2 and 3 showed that the framework had many layers. The Prophet's predictions for daily mean temperature had similar sub-unit errors across all three zones (MAE 0.929 °C/RMSE 1.181 °C in Veracruz; MAE 0.965 °C/RMSE 1.220 °C in Puebla; MAE 0.944 °C/RMSE 1.198 °C in Mexico City). These values are like those reported in the literature for Prophet in wheat yield (MAPE 10.03%, RMSE 0.39) and for Neural Prophet in precipitation (RMSE 2.25 vs. 2.85) (Anuradha et al., 2023). ARIMA also checked that the data was stationary (p-value = 0.0001 in all three zones) and produced MSE/RMSE values that were different in each zone for the total monthly rain (Veracruz 189.74/201.69 mm; Puebla 113.85/121.01 mm; Mexico City 88.55/94.12 mm). This confirmed the model's ability to be used as an input for the downstream classifier. The way it is set up is like other hybrid frameworks that have been used before in the literature for agricultural yield prediction (Gowda et al., 2025; Pratama et al., 2025) and with the logic of using AI to help with climate-smart agriculture (Mmbando, 2025).

The confusion matrix, which shows the number of correct and incorrect predictions made by the two classifiers, showed that Random Forest made 26 incorrect predictions compared to 600 for the SVM. This is a big difference, and it is like the results of other studies that have compared Random Forest and SVM. These studies have said that Random Forest is the best at classifying things in agriculture (Mathew et al., 2024). This difference does not mean the SVM is wrong, but it does show that there is a clear order of things: Random Forest is still the main classifier, and SVM is used as a basic example for future studies.

The simulation covered the time period from 2000 to 2026 with daily records and generated 9862 records per year. zone and a total of 29,586 records in the total data set. The 26-year time horizon was chosen to reflect changes occurring every few years due to climate change, based on historical records from the National Meteorological Service and CONAGUA. One of the most important insights was the difference in how well farmers can grow crops in different regions. While conditions are generally good in Veracruz, crops are threatened more than 50% of days in Mexico City and Puebla. This suggests that they need a system that can predict this and warn farmers before the risk arises and they lose their crops.

This proposal is a tool that can be used to support agricultural decision-making. It is designed to be used in a way that can be adapted to different situations. It is in line with the climate-smart agriculture agenda, which focuses on increasing productivity, adapting to change, and making sure that agriculture can continue to function well in the face of climate change (Mmbando, 2025). It has already been shown to reduce errors by 50% and has an R^2 of 0.985 in early warning systems for climate impacts when used with AIoT edge computing architectures.

For future work, the focus will be on testing this using open data on farming and the weather. There are three specific areas where we can make things better: (i) Replace the multi-criteria labelling function with actual field labels. (ii) Expand the spatial variation of phosphorus and potassium to increase the predictive power of the macronutrients. (iii) Compare the multi-zone performance of the framework with unimodal baselines to isolate the minimum contribution of each family. This practical phase will make the framework move from a theoretical prototype, based on calibrated simulation, to a system that has been checked to work in real situations.

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Biographies

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Dra. Gabriela Guadalupe Escobedo Guerrero. She has a degree in Industrial Administration from UPIICSA-IPN; graduated with a Master's Degree in Politics and Management in Technological Change at CIECAS-IPN and has a Ph.D. degree in Administrative Sciences obtained from the ESCA UST-IPN; He has a Member of the National Research System (SNI) CONACyT with the distinction: Researcher Candidate. Since 2007 he has been at the ESCA-UST, where he has taught undergraduate classes in both modalities (face-to-face and distance). She is currently a researcher and teacher in the Postgraduate Studies Section of the ESCA UST-IPN; He has taught at the Master's degrees in Business Administration (MAN) and in the MAES.