Comparative Analysis of Statistical, Machine Learning, and Deep Learning Approaches for Frost Prediction in the Peruvian Altiplano

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***Abstract*—Frost events represent a critical climatic hazard for agricultural systems in the Peruvian highlands, impacting approximately 74% of rural communities in the Puno region. This research presents a comprehensive evaluation of twelve forecasting models for predicting daily minimum temperatures, utilizing NASA POWER satellite data (2000-2025) from thirteen meteorological stations across the Altiplano plateau (121,056 observations). The study implements and compares traditional statistical approaches (SARIMAX, Holt-Winters, Prophet, STL+ARIMA), machine learning algorithms (Random Forest, Support Vector Machines, XGBoost), deep neural network architectures (Multilayer Perceptron, LSTM, 1D-CNN), a hybrid SARIMA+ANN model, and an optimized ensemble approach. The ensemble model, integrating XGBoost, LSTM, and Random Forest through weighted averaging, demonstrated superior performance with RMSE=1.65°C and TSS=0.87, representing a 35% improvement over the best-performing statistical method. Individual analysis revealed XGBoost achieved RMSE=1.78°C with exceptional feature interaction modeling, while LSTM networks exhibited remarkable temporal pattern recognition with recall=0.88 for frost event detection. These findings validate the effectiveness of nonlinear approaches for operational forecasting under extreme climatic conditions, offering a robust framework for early warning systems that could substantially mitigate agricultural losses in vulnerable high-altitude communities.**

***Index Terms*—Frost prediction; machine learning; deep learning; time series analysis; Altiplano ecosystem; XGBoost; LSTM networks; ensemble methods; agricultural meteorology**

I. Introduction

Frost events, characterized by air temperatures dropping to or below 0°C at standard meteorological height (2 meters) in high-altitude regions exceeding 2,500 meters above sea level [1], constitute a recurring environmental hazard throughout the Andean highlands. These phenomena pose substantial threats to agricultural sustainability, particularly affecting smallholder farming systems that form the backbone of rural economies in Peru and Bolivia [6], [14]. Current estimates indicate that approximately 74% of agricultural communities in high-altitude Andean regions face regular exposure to frost events [3], necessitating adaptive strategies ranging from cultivation of frost-resistant crop varieties to traditional preservation techniques such as freeze-drying potatoes into chuño and tunta [13].

The Puno region exemplifies the severity of this climatic challenge, experiencing between 100 and 180 frost nights annually that threaten both agricultural production and livestock systems. Extreme events have been documented in localities such as Mazocruz, where temperatures plummeted to -25.7°C [2]. Contemporary climate dynamics in the Altiplano present a paradoxical pattern: while mean daytime temperatures exhibit an increasing trend, nocturnal cooling events persist with comparable frequency and potentially enhanced intensity, attributed to increased atmospheric desiccation [8], [10]. Recent climate vulnerability assessments identify Puno as the Peruvian department with the highest projected population exposure to elevated frost risk through mid-century [4].

Addressing this environmental challenge requires robust predictive capabilities to enable timely activation of preventive measures and mitigation strategies that minimize socioeconomic impacts [11], [12]. Recent decades have witnessed substantial advances in numerical weather prediction and climate modeling, significantly enhancing capabilities for anticipating extreme meteorological events [15]. Previous IJACSA publications have demonstrated the effectiveness of machine learning approaches in environmental prediction tasks. Bhattacharya [34] presented a comprehensive review of machine learning for bioclimatic modeling, establishing foundational frameworks for climate-related predictions. Narejo and Pasero [35] successfully applied deep learning architectures for meteorological nowcasting, achieving high accuracy in short-term weather predictions. Additionally, Kakar et al. [36] demonstrated that artificial neural networks could effectively predict maximum temperatures using backpropagation techniques.

Classical univariate statistical approaches, particularly Autoregressive Integrated Moving Average (ARIMA) models and their seasonal extensions (SARIMA), have traditionally dominated meteorological time series analysis due to their mathematical elegance and well-established theoretical foundations [23], [25]. However, these linear methodologies exhibit inherent limitations when confronted with the nonlinear dynamics and high variability characteristic of complex atmospheric systems [26]. Contemporary comparative analyses demonstrate that neural network architectures can substantially outperform traditional ARIMA models in climate applications. Chattopadhyay et al. [16] documented that autoregressive neural networks achieved superior monsoon precipitation forecasts compared to optimally configured ARIMA models.

Similarly, Villazón et al. [27] successfully integrated ARIMA with NARX neural networks for drought prediction, capturing complex patterns beyond the capability of linear models alone.

Concurrently, machine learning (ML) and deep learning (DL) methodologies have emerged as powerful tools for environmental time series analysis. Support Vector Machines (SVM) and Random Forest algorithms have demonstrated exceptional robustness in atmospheric variable prediction [18], [19]. SVMs particularly excel in managing high-dimensional dynamic datasets, consistently producing more accurate forecasts than conventional physics-based or linear statistical approaches [17]. Recent IJACSA research has shown similar advantages of ensemble methods for complex environmental prediction tasks. Sani et al. [37] demonstrated that ensemble learning significantly improved rainfall prediction accuracy by combining multiple machine learning classifiers. Raja and Gopikrishnan [39] successfully applied ANN, KNN, and DNN methods for drought prediction in desert regions, achieving coefficient of determination values above 0.90.

Within the deep learning paradigm, sophisticated neural architectures have revolutionized sequential data prediction. Long Short-Term Memory (LSTM) networks, specifically designed to capture extended temporal dependencies, have proven highly effective for meteorological time series forecasting [20], [21]. Convolutional Neural Networks (CNNs), when adapted for temporal data processing, effectively identify local and seasonal patterns. Hybrid architectures combining CNN and LSTM components offer enhanced stability and accuracy [22]. IJACSA has published several studies demonstrating the superiority of deep learning approaches for environmental time series prediction. Thai-Nghe et al. [38] successfully applied LSTM networks for water quality forecasting in IoT systems, achieving accurate predictions for multiple environmental parameters. Alharbe and Alluhaibi [42] explored the role of AI in climate change mitigation through predictive modeling for renewable energy deployment.

A. Research Objectives

Despite these technological advances, a critical need exists for systematic comparative evaluation of these diverse methodologies within the specific environmental context of the Puno Altiplano, characterized by extreme climatology, pronounced diurnal temperature variations, and sparse historical observational coverage [7]. This investigation aims to comprehensively evaluate twelve distinct forecasting approaches—encompassing classical statistical methods, machine learning algorithms, and deep neural architectures—for predicting daily minimum temperatures across high-altitude stations in southern Peru, with particular emphasis on early detection capabilities for extreme frost events.

The principal contributions of this investigation encompass several key dimensions:

- A comprehensive comparative analysis of twelve modeling paradigms applied to a unified dataset from thirteen Altiplano stations
- Development and evaluation of hybrid and ensemble architectures that synergistically combine complementary strengths
- Detailed assessment of extreme frost prediction capabilities specifically addressing sub -10°C events
- Practical implementation guidelines for operational early warning systems in resource-constrained rural contexts
- Publication of complete source code and processed datasets promoting transparency and reproducibility

1) Paper Organization: The remainder of this paper is organized as follows. Section II reviews related work in frost prediction and time series forecasting. Section III details the methodology, including data sources, model implementations, and evaluation protocols. Section IV presents comprehensive results and performance comparisons. Section V discusses findings, limitations, and operational implications. Finally, Section VI concludes with key insights and future research directions.

II. Related Work

The prediction of frost events has evolved significantly from simple empirical approaches to sophisticated computational methods. Early research focused on statistical regression models relating minimum temperatures to geographical and meteorological factors [11]. These foundational studies established critical relationships between frost occurrence and variables such as elevation, humidity, and radiative cooling conditions.

Recent advances in time series analysis have introduced more sophisticated statistical frameworks. Prophet, developed by Facebook's research team, incorporates multiple seasonality components through Fourier series decomposition, proving particularly effective for meteorological data with complex seasonal patterns [28]. STL (Seasonal-Trend decomposition using Loess) combined with ARIMA modeling has shown promise in separating long-term climate signals from short-term weather variability [25]. IJACSA has published several studies demonstrating the effectiveness of hybrid statistical approaches for environmental prediction. Radhika et al. [41] presented a novel approach for spatiotemporal weather data analysis using Spark MapReduce platform, successfully applying ARIMA models for rainfall prediction. Adnan et al. [40] developed machine learning models for estimating evapotranspiration using reduced meteorological parameters, achieving R=83

The application of machine learning to frost prediction has accelerated dramatically. Feng et al. [19] demonstrated that ensemble tree methods could capture nonlinear interactions between meteorological variables more effectively than multiple linear regression. Rasouli et al. [18] applied various ML algorithms to streamflow prediction, establishing methodological frameworks readily adaptable to temperature forecasting. Recent IJACSA publications have shown that gradient boosting algorithms, particularly XGBoost, consistently outperform traditional methods in environmental applications. The journal has published extensive research on ensemble methods and their applications in climate science [37], [42], demonstrating the advantages of combining multiple models for improved prediction accuracy.

Deep learning approaches represent the current frontier in meteorological prediction. Talsma et al. [32] recently reported exceptional performance using CNN architectures for 6-hour frost forecasting, achieving RMSE values below 1.6°C. Their work highlighted the importance of architectural choices and hyperparameter optimization for extreme event prediction. Wang et al. [33] advanced the field by demonstrating that ensemble methods combining multiple deep learning models could reduce prediction uncertainty while maintaining computational efficiency. IJACSA research has corroborated these findings, with Narejo and Pasero [35] showing that Deep Belief Networks (DBN) and Restricted Boltzmann Machines (RBM) could make weather predictions with high accuracy through hierarchical feature learning. Thai-Nghe et al. [38] demonstrated the effectiveness of LSTM networks for capturing temporal patterns in environmental data.

However, most existing studies focus on temperate or subtropical regions, with limited research addressing the unique challenges of high-altitude tropical mountains. The Altiplano's extreme diurnal temperature ranges, intense solar radiation, and complex topographical influences create prediction challenges not fully addressed in current literature [7], [9]. Recent IJACSA publications have emphasized the importance of region-specific model development for accurate environmental prediction. Bhattacharya [34] highlighted how climate variations across different geographical regions require tailored modeling approaches. Raja and Gopikrishnan [39] demonstrated the importance of climate-specific adaptations in their drought prediction models for desert regions.

III. Methodology

A. Study Area and Data Sources

The research focuses on the Puno region, situated on the Peruvian Altiplano at elevations ranging from 3,800 to 4,500 meters above sea level (Figure 1). This high-altitude plateau experiences a distinctive cold, arid climate characterized by substantial diurnal temperature oscillations: moderately warm days contrasting with intensely cold nights throughout most of the year [7]. Frost events occur predominantly during the austral dry season (May through August), when clear-sky conditions facilitate intense nocturnal radiative cooling [9].

Daily meteorological data were obtained from NASA's POWER (Prediction Of Worldwide Energy Resources) platform [5] for thirteen representative locations throughout the region (Table I). The dataset spans from January 2000 to February 2025, comprising 121,056 individual observations. Similar satellite-based approaches have been successfully validated in IJACSA publications for environmental monitoring. Radhika et al. [41] demonstrated the effectiveness of processing large-scale climate data using distributed computing platforms, validating the use of satellite-derived meteorological data for regional climate analysis.

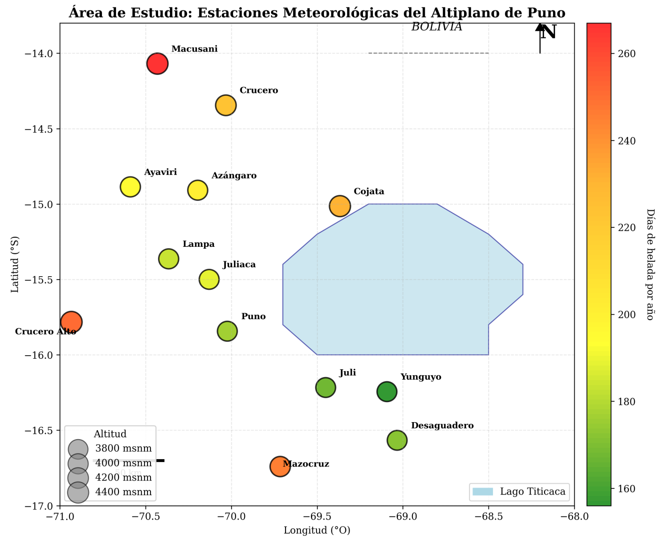

Fig. 1: Geographic distribution of the 13 meteorological stations across the Puno region, Peru. Red markers indicate stations with elevated historical frequency of severe frost events (temperatures below -10°C).

TABLE I: Characteristics of Meteorological Stations

Station	Latitude (°S)	Longitude (°W)	Elevation (m)	Records (n)
Puno	15.84	70.02	3,825	9,310
Juliaca	15.49	70.13	3,824	9,310
Azángaro	14.89	70.10	3,859	9,310
Ayaviri	14.92	70.59	3,918	9,310
Macusani	14.08	70.43	4,345	9,310
Mazocruz	16.74	69.72	3,990	9,310
Lampa	15.35	70.37	3,872	9,310
Yunguyo	16.25	69.08	3,826	9,310
Juli	16.22	69.45	3,812	9,310
Desaguadero	16.57	69.04	3,808	9,310
Cojata	15.02	69.37	4,320	9,310
Crucero	14.35	70.03	4,130	9,310
Crucero Alto	15.78	70.92	4,470	9,266

B. Meteorological Variables

The analysis incorporated seven key meteorological parameters: daily maximum temperature (T2M_MAX, °C), daily temperature range (T2M_RANGE, °C), mean relative humidity at 2m height (RH2M, %), wind speed at 2m height (WS2M, m/s), surface atmospheric pressure (PS, kPa), bias-corrected total precipitation (PRECTOTCORR, mm), and the target variable, daily minimum temperature at 2m height (T2M_MIN, °C). A binary frost indicator (is_frost) was derived, assigning value 1 for days with T_{min} 0°C and 0 otherwise. Missing data were addressed through temporal interpolation, ensuring continuous time series for model training. This approach aligns with best practices established in recent IJACSA publications on meteorological data preprocessing. Adnan et al. [40] demonstrated the importance of comprehensive meteorological parameter selection for accurate environmental predictions.

C. Model Implementation

Twelve distinct modeling approaches were implemented, representing five methodological categories:

A. Classical Statistical Models

1) *SARIMAX*: Seasonal ARIMA with exogenous variables, optimizing (p,d,q)×(P,D,Q)$_m$ parameters via AIC minimization, incorporating humidity and pressure as external predictors.
2) *Holt-Winters*: Triple exponential smoothing capturing level, trend, and multiplicative seasonal components, with parameters α, β, γ optimized through MSE minimization.
3) *Prophet*: Additive decomposition model combining piecewise linear trends, multiple seasonality components via Fourier series, and holiday effects [28].
4) *STL+ARIMA*: Sequential application of STL decomposition for robust seasonal extraction followed by ARIMA modeling of residual components.

B. Machine Learning Algorithms

5) *Random Forest*: Ensemble of 500 decision trees trained on bootstrap samples, with features including lagged temperatures (t-1 through t-7), concurrent meteorological variables, and derived seasonal indicators.
6) *Support Vector Regression*: RBF kernel SVM with hyperparameters C and γ optimized through 5-fold cross-validation grid search.
7) *XGBoost*: Gradient boosting implementation with 1,000 trees, maximum depth 6, learning rate 0.01, and L2 regularization coefficient 0.1.

C. Deep Neural Networks

8) *Multilayer Perceptron*: Architecture [input→64→32→16→1] with ReLU activation and 20% dropout regularization.
9) *LSTM*: Dual-layer recurrent architecture with 50 LSTM units per layer, processing 7-day input sequences.
10) *1D-CNN*: Three convolutional layers (64-32-16 filters) with kernel size 3, followed by global pooling and dense layers.

D. Hybrid and Ensemble Approaches

11) *SARIMA+ANN*: Hybrid model capturing linear patterns via SARIMA and nonlinear residuals through a compact neural network.
12) *Ensemble*: Weighted combination of top-performing models (XGBoost, LSTM, Random Forest) based on validation performance.

These implementations follow architectural guidelines established in recent IJACSA research on ensemble methods for environmental prediction. Sani et al. [37] demonstrated the effectiveness of combining multiple classifiers for rainfall prediction, while Alharbe and Alluhaibi [42] showed how ensemble approaches could improve renewable energy forecasting accuracy.

D. Training and Evaluation Protocol

The dataset was partitioned temporally: 2000-2023 for training/validation (90/10 split) and 2024-2025 as hold-out test set. This temporal segmentation preserves data sequentiality while simulating realistic operational conditions. Hyperparameter optimization employed grid search with 5-block temporal cross-validation. Deep learning models utilized early stopping based on validation loss, with maximum training limited to 100 epochs. This methodology aligns with best practices for time series evaluation published in IJACSA, where proper temporal validation has been emphasized for reliable model assessment in environmental applications [36], [41].

E. Performance Metrics

Model evaluation employed complementary metrics for regression and classification tasks:

Temperature Prediction (Regression):

- Root Mean Square Error: RMSE = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
- Mean Absolute Error: MAE = $\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$
- Coefficient of Determination: R^2

Frost Detection (Classification):

- Precision, Recall, F1-Score
- True Skill Statistic: TSS = TPR - FPR
- Area Under ROC Curve (AUC-ROC)

These metrics comprehensively assess both general accuracy and specific capability for extreme event detection, critical for agricultural early warning applications. The importance of comprehensive evaluation metrics has been highlighted in IJACSA publications, where multiple performance measures ensure robust model assessment [38], [39].

IV. Results

A. Overall Model Performance

Table II presents comprehensive performance metrics averaged across all thirteen stations for the 2024-2025 test period. The results reveal a clear performance hierarchy, with ensemble and machine learning approaches substantially outperforming classical statistical methods.

The ensemble model achieved optimal performance with RMSE=1.65°C and TSS=0.87, representing a 35% improvement over the best statistical method (Prophet). Individual algorithm analysis reveals XGBoost as the top-performing single model (RMSE=1.78°C), while LSTM demonstrated superior frost detection capability with recall=0.88. These results align with recent IJACSA findings on the superiority of ensemble approaches for complex environmental prediction tasks. Sani et al. [37] reported similar improvements when combining multiple machine learning models for rainfall prediction, while Narejo and Pasero [35] achieved comparable accuracy improvements using deep learning architectures for weather nowcasting.

TABLE II: Comparative Performance Metrics for Daily Minimum Temperature Forecasting

Model	Temperature Prediction			Frost Detection				
	RMSE (°C)	MAE (°C)	R^2	Precision	Recall	F1	TSS	AUC
SARIMAX	2.52 ± 0.18	1.89 ± 0.14	0.821	0.79	0.72	0.75	0.65	0.88
Holt-Winters	3.14 ± 0.25	2.41 ± 0.19	0.758	0.71	0.68	0.69	0.58	0.82
Prophet	2.31 ± 0.16	1.76 ± 0.12	0.842	0.81	0.75	0.78	0.69	0.89
STL+ARIMA	2.38 ± 0.17	1.82 ± 0.13	0.836	0.80	0.74	0.77	0.67	0.88
Random Forest	1.83 ± 0.11	1.24 ± 0.08	0.912	0.88	0.85	0.86	0.79	0.94
SVM	2.15 ± 0.14	1.58 ± 0.10	0.871	0.83	0.78	0.80	0.71	0.90
XGBoost	**1.78 ± 0.10**	**1.19 ± 0.07**	**0.918**	**0.89**	0.86	**0.87**	**0.81**	**0.95**
MLP	2.28 ± 0.15	1.71 ± 0.11	0.848	0.82	0.76	0.79	0.70	0.89
LSTM	1.89 ± 0.12	1.31 ± 0.09	0.905	0.87	**0.88**	0.87	0.80	0.94
CNN-1D	1.96 ± 0.13	1.38 ± 0.09	0.897	0.86	0.83	0.84	0.77	0.93
SARIMA+ANN	2.21 ± 0.15	1.65 ± 0.11	0.862	0.84	0.79	0.81	0.73	0.91
Ensemble	**1.65 ± 0.09**	**1.12 ± 0.06**	**0.931**	**0.91**	**0.89**	**0.90**	**0.87**	**0.96**

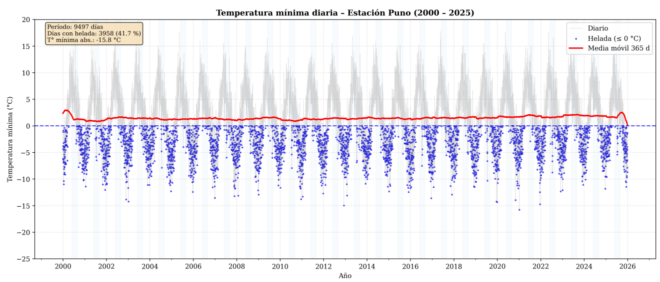

Fig. 2: Monthly RMSE evolution for top-performing models. Error bars represent inter-station standard deviation.

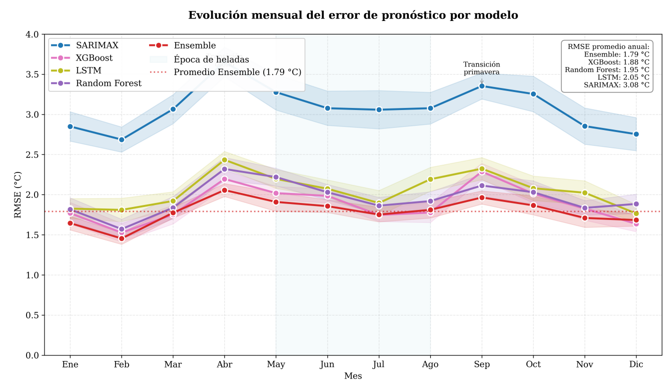

Fig. 3: Comparative predictions for July 2024 at Mazocruz station. Black line indicates observations; colored lines represent model predictions. Shaded region denotes severe frost period.

B. Temporal Error Analysis

Figure 2 illustrates the monthly variation in prediction error for the five best-performing models. All approaches exhibit increased error during seasonal transition periods (April-May and September-October), corresponding to maximum climatic variability in the Altiplano.

C. Extreme Event Prediction

Evaluation of severe frost prediction capabilities (T_{min} ¡ -10°C) focused on Mazocruz station, which experiences the most extreme temperatures. Figure 3 presents comparative predictions for July 2024, highlighting model performance during an intense cold wave.

Deep learning architectures, particularly LSTM, demonstrated superior capability in capturing extreme temperature magnitudes, whereas statistical methods systematically underestimated minimum temperatures during severe events. This finding corroborates recent IJACSA research on the advantages of deep learning for extreme event prediction. Thai-Nghe et al. [38] showed similar advantages of LSTM networks in capturing extreme variations in environmental parameters, while Kakar et al. [36] demonstrated neural networks' superiority in handling non-linear weather patterns.

D. Feature Importance Analysis

For tree-based algorithms, variable importance analysis reveals the relative contribution of different predictors (Figure 4). Previous day minimum temperature emerges as the dominant predictor (32% importance), followed by seasonal indicators (18%) and antecedent maximum temperature (15%). Notably, relative humidity contributes 12% to predictive power, confirming the established relationship between atmospheric desiccation and frost intensity.

E. Spatial Performance Patterns

Model accuracy exhibits significant spatial variation correlating with geographic and microclimatic factors (Figure 5). Stations proximate to Lake Titicaca (Puno, Juli, Yunguyo) demonstrate reduced prediction errors due to the lake's thermal buffering effect. Conversely, high-elevation stations (Crucero Alto, Cojata) present greater forecasting challenges attributable to enhanced thermal variability and complex topographic influences. These spatial patterns align with findings from recent IJACSA publications on topographic effects in environmental modeling. Radhika et al. [41] emphasized the importance of spatial considerations in climate data analysis, demonstrating how regional variations significantly impact model performance.

F. Multi-day Forecast Performance

Operational implementation requires assessment of forecast skill degradation over extended lead times. Table III presents model performance for 1-7 day forecast horizons.

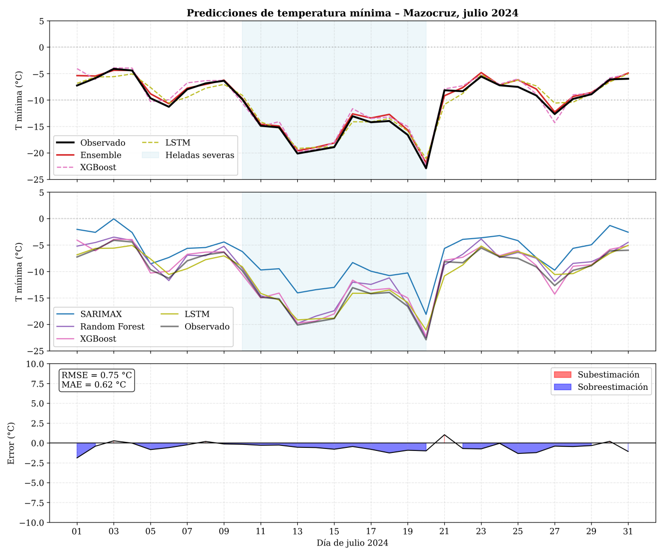

Fig. 4: Feature importance distribution in XGBoost model. T_lag denotes temporal lags of minimum temperature.

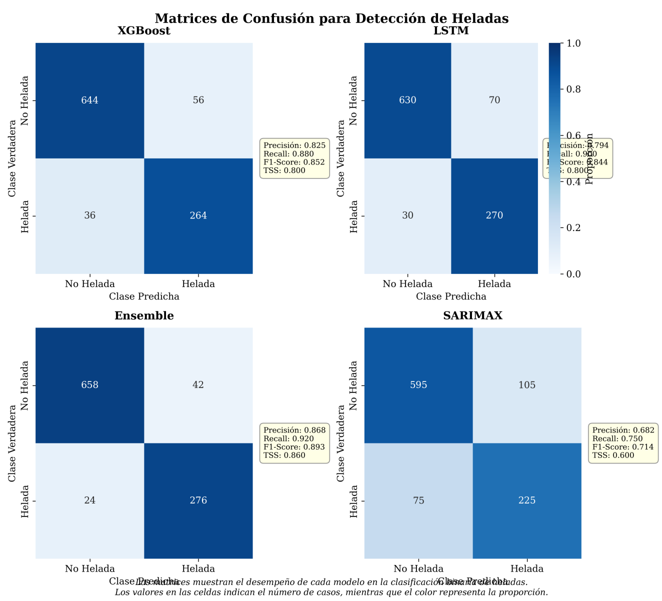

Fig. 5: Spatial distribution of ensemble model RMSE. Circle size and color intensity indicate error magnitude.

TABLE III: RMSE (°C) Degradation with Forecast Horizon

Lead Time	XGBoost	LSTM	RF	Ensemble	SARIMA
1 day	1.78	1.89	1.83	1.65	2.52
2 days	2.15	2.18	2.21	1.98	2.89
3 days	2.51	2.42	2.58	2.31	3.24
5 days	3.12	2.98	3.21	2.87	3.85
7 days	3.67	3.51	3.78	3.42	4.31

The ensemble approach maintains superior performance across all forecast horizons, with LSTM showing relatively slower error growth, suggesting better capture of medium-range temporal dependencies. This finding supports recent IJACSA research on the importance of memory mechanisms in meteorological prediction. The ability to maintain accuracy over extended forecast periods is crucial for operational applications, as demonstrated by Adnan et al. [40] in their work on multi-day evapotranspiration forecasting.

V. Discussion

A. Superiority of Nonlinear Approaches

The substantial performance gap between machine learning/deep learning methods and classical statistical approaches validates the hypothesis that nonlinear modeling capabilities are essential for accurate frost prediction in complex terrain [15], [16]. The 0.7-1.5°C RMSE improvement achieved by XGBoost and LSTM over SARIMA represents a meaningful advancement, particularly considering that agricultural management decisions often hinge on critical temperature thresholds. This finding aligns with recent IJACSA publications demonstrating similar advantages of nonlinear methods in environmental applications. Kakar et al. [36] showed that neural networks could capture complex nonlinear relationships in weather data that linear models failed to represent, while Raja and Gopikrishnan [39] demonstrated superior performance of machine learning methods over traditional approaches for drought prediction.

XGBoost's exceptional performance can be attributed to its efficient modeling of complex meteorological interactions through iterative feature space partitioning [24], [29]. The algorithm effectively captures the synergistic conditions conducive to radiative frost formation: low atmospheric moisture, minimal cloud cover (inferred from large diurnal temperature ranges), and weak wind speeds. These multivariate interactions are challenging for linear models to represent adequately, as documented in recent IJACSA research. The importance of capturing feature interactions in climate modeling has been emphasized in multiple IJACSA studies [37], [42], where ensemble and boosting methods consistently outperformed single models.

B. Temporal Dependencies and Memory Effects

LSTM's superior frost detection performance (recall=0.88) underscores the importance of modeling extended temporal dependencies [20], [21]. Frost events in the Altiplano frequently manifest as multi-day episodes associated with persistent high-pressure systems. Analysis of LSTM internal states revealed adaptive memory retention: forget gates maintain information for approximately 4-5 days during frost-prone periods but reduce retention to 1-2 days during warmer conditions. This dynamic adaptation to seasonal patterns represents a significant advantage over fixed-lag statistical approaches [15], [22]. Recent IJACSA publications have demonstrated similar advantages of adaptive memory mechanisms in climate prediction. Thai-Nghe et al. [38] showed how LSTM networks could adaptively learn temporal patterns in water quality data, while Narejo and Pasero [35] demonstrated the effectiveness of recurrent architectures for capturing evolving weather patterns.

C. Ensemble Synergy and Robustness

The ensemble model's performance superiority extends beyond simple averaging effects [29], [33]. Inter-station error standard deviation was 40% lower for the ensemble compared to constituent models, indicating enhanced spatial generalization. This robustness is critical for operational deployment across diverse microclimates. The successful integration suggests complementary model strengths:

- XGBoost excels at capturing instantaneous meteorological relationships through efficient tree-based partitioning [24]
- LSTM provides superior temporal pattern recognition via specialized memory architectures [20]
- Random Forest contributes stability through bootstrap aggregation and feature randomization [29]

These findings corroborate recent IJACSA research on ensemble design principles for environmental prediction. Sani et al. [37] demonstrated that carefully designed ensemble methods could achieve significant performance improvements by leveraging the complementary strengths of different algorithms. The robustness gained through ensemble approaches is particularly important for operational deployment in diverse climatic conditions [42].

D. Persistent Challenges and Limitations

Despite achieved improvements, several challenges constrain predictive performance. Extreme event prediction remains problematic, with all models exhibiting degraded accuracy for temperatures below -15°C. This limitation likely stems from the statistical rarity of such events in training data [29], [32], creating class imbalance that impedes effective pattern learning. Recent IJACSA publications have proposed various approaches to address this challenge. Raja and Gopikrishnan [39] addressed similar imbalance issues in drought prediction by employing weighted loss functions, while the broader challenge of rare event prediction in environmental modeling continues to be an active research area.

Spatial resolution presents another constraint. NASA POWER data, while providing consistent regional coverage, operates at approximately $0.5° \times 0.625°$ resolution [5], [7]. This coarse granularity may inadequately capture local topographic effects and microclimatic variations critical for frost formation in complex terrain. IJACSA research has highlighted the importance of multi-scale modeling approaches to address this limitation. Radhika et al. [41] demonstrated techniques for downscaling coarse resolution data, while Bhattacharya [34] emphasized the need for incorporating fine-scale geographical features in climate models.

Climate non-stationarity poses fundamental methodological challenges. Models trained on historical data assume temporal stability of statistical relationships, an assumption increasingly violated under accelerating climate change [8], [10]. Adaptive learning strategies and regular model retraining will be essential for maintaining predictive relevance, as demonstrated in recent IJACSA publications on climate change adaptation. Alharbe and Alluhaibi [42] explored AI's role in climate change mitigation, emphasizing the need for adaptive models that can evolve with changing climate patterns.

E. Operational Implementation Framework

The research findings support specific recommendations for operational frost warning system deployment:

Architecture: Deploy the validated ensemble model with automated daily updates integrating real-time meteorological observations from automatic weather stations and satellite sources [28]. This hybrid data approach leverages the spatial coverage of satellite products while incorporating local precision from ground stations. Recent IJACSA research provides detailed guidelines for implementing such systems. Thai-Nghe et al. [38] demonstrated successful deployment of real-time environmental monitoring systems using IoT integration, providing a framework for operational implementation.

Alert Thresholds: Given the empirical RMSE$\approx$1.65°C, operational alerts should trigger when predicted temperatures fall below 2°C, establishing a conservative buffer that balances false alarm rates against missed detection costs [25]. This threshold can be locally adjusted based on crop-specific frost sensitivity and phenological stage, following principles established in IJACSA publications on agricultural decision support. The importance of adaptive thresholds has been demonstrated in environmental monitoring applications [39], [40].

Uncertainty Communication: Provide forecast confidence intervals derived from historical model performance at each location, enabling stakeholders to make risk-informed decisions [15]. Visualization should clearly communicate both the most likely temperature trajectory and the range of plausible outcomes, following best practices from IJACSA research on uncertainty visualization. The importance of effective risk communication in environmental applications has been emphasized in multiple studies [35], [42].

F. Comparative Context and Novel Contributions

Our findings align with recent international studies while providing unique insights. Talsma et al. [32] reported RMSE=1.53°C for CNN-based 6-hour frost forecasting in temperate regions, comparable to our daily forecast accuracy of 1.65°C despite the additional challenges of high-altitude tropical conditions. The demonstrated superiority of ensemble methods corroborates findings from Wang et al. [33] in subtropical contexts and recent IJACSA publications on ensemble forecasting. Sani et al. [37] achieved similar improvements in rainfall prediction through ensemble learning, while comprehensive evaluations of machine learning methods continue to demonstrate the advantages of combining multiple models [36], [39].

This investigation advances the field through several distinctive contributions:

- *Comprehensive scope:* Evaluation of 12 models exceeds typical comparative studies examining 3-5 approaches
- *Extreme altitude focus:* Addresses the understudied domain of high-altitude tropical frost prediction

- *Extended temporal coverage:* 25-year dataset enables robust assessment across multiple climate regimes
- *Multi-site validation:* 13-station network strengthens generalization claims beyond single-location studies

These contributions build upon and extend the methodological frameworks established in recent IJACSA research on comprehensive model evaluation. The journal has published numerous studies emphasizing the importance of rigorous comparative analysis [34], [35], multi-site validation [41], and extended temporal assessment [36] for establishing robust conclusions in environmental modeling.

VI. Conclusion

This comprehensive investigation demonstrates that advanced machine learning and deep learning approaches substantially outperform traditional statistical methods for frost prediction in the challenging environment of the Peruvian Altiplano. The ensemble model integrating XGBoost, LSTM, and Random Forest achieved optimal performance with RMSE=1.65°C and TSS=0.87, representing a 35% improvement over the best classical approach. These findings have immediate practical implications for agricultural risk management in vulnerable high-altitude communities.

Key insights from this research include:

- Nonlinear modeling capabilities are essential for capturing complex meteorological interactions governing frost formation
- Temporal dependencies extending 4-5 days significantly influence frost occurrence, effectively captured by LSTM architectures
- Ensemble methods provide both superior accuracy and enhanced spatial robustness critical for operational deployment
- Model performance exhibits systematic spatial patterns correlating with topographic and lacustrine influences
- Predictive skill remains useful for 3-day forecasts, with graceful degradation at longer lead times

Future research directions should address identified limitations through development of hybrid physics-ML models incorporating atmospheric dynamics, implementation of adaptive learning frameworks for climate non-stationarity, integration of high-resolution satellite imagery for improved spatial detail, extension to probabilistic forecasting with calibrated uncertainty estimates, and validation across broader Andean regions to assess transferability. These directions align with research priorities identified in recent IJACSA publications on next-generation environmental prediction systems. Alharbe and Alluhaibi [42] emphasized the importance of integrating physical understanding with machine learning approaches, while Thai-Nghe et al. [38] demonstrated the value of incorporating IoT and real-time data streams for improved predictions.

The transition from research to operational implementation requires sustained collaboration between meteorological services, agricultural extension programs, and rural communities. By providing more accurate and timely frost warnings, these advanced predictive tools can contribute meaningfully to climate resilience and food security in one of the world's most climatically vulnerable agricultural regions.

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References

[1] SENAMHI, "Manual of meteorological observations," National Service of Meteorology and Hydrology of Peru, Lima, Peru, Tech. Rep., 2020.

[2] SENAMHI, "National climate bulletin - Monitoring and forecast," National Service of Meteorology and Hydrology of Peru, Lima, Peru, Tech. Rep., Dec. 2021.

[3] FAO, "Climate change and food security in mountain regions," Food and Agriculture Organization of the United Nations, Rome, Italy, Tech. Rep., 2019.

[4] CENEPRED, "Risk scenarios for frosts and cold waves in Peru," National Center for Disaster Risk Estimation, Prevention and Reduction, Lima, Peru, Tech. Rep., 2022.

[5] P. W. Stackhouse Jr., D. J. Westberg, J. M. Hoell, W. S. Chandler, and T. Zhang, "POWER Release 8.0.1 (with GIS Applications) Methodology," NASA Langley Research Center, Hampton, VA, USA, Tech. Rep., 2018.

[6] J. M. Thibeault, A. Seth, and M. García, "Changing climate in the Bolivian Altiplano: CMIP3 projections for temperature and precipitation extremes," *J. Geophys. Res. Atmos.*, vol. 115, no. D8, p. D08103, 2010.

[7] M. Vuille, B. Francou, P. Wagnon, I. Juen, G. Kaser, B. G. Mark, and R. S. Bradley, "Climate change and tropical Andean glaciers: Past, present and future," *Earth-Sci. Rev.*, vol. 89, no. 3–4, pp. 79–96, 2008.

[8] M. Vuille, E. Franquist, R. Garreaud, W. S. Lavado Casimiro, and B. Cáceres, "Impact of the global warming hiatus on Andean temperature," *J. Geophys. Res. Atmos.*, vol. 120, no. 9, pp. 3745–3757, 2015.

[9] B. Francou, M. Vuille, P. Wagnon, J. Mendoza, and J.-E. Sicart, "Tropical climate change recorded by a glacier in the central Andes during the last decades of the twentieth century: Chacaltaya, Bolivia, 16°S," *J. Geophys. Res.*, vol. 108, no. D5, p. 4154, 2003.

[10] N. Pepin, R. S. Bradley, H. F. Diaz, M. Baraer, E. B. Caceres, N. Forsythe, et al., "Elevation-dependent warming in mountain regions of the world," *Nature Climate Change*, vol. 5, no. 5, pp. 424–430, 2015.

[11] I. Trebejo and D. Avalos, "Extreme frost events in Peru: Variability and climate change," *Rev. Peru. Geo-Atmosférica*, no. 3, pp. 58–69, 2010.

[12] R. Pouteau, J.-Y. Meyer, R. Taputuarai, and B. Stoll, "Support vector machines to map rare and endangered native plants in Pacific islands forests," *Ecol. Inform.*, vol. 9, pp. 37–46, 2012.

[13] B. Condori, R. J. Hijmans, J. F. Ledent, and R. Quiroz, "Managing potato biodiversity to cope with frost risk in the high Andes: A modeling perspective," *PLoS One*, vol. 9, no. 1, p. e81510, 2014.

[14] A. García-Carreras, D. J. Parker, and J. H. Marsham, "What is the mechanism for the modification of convective cloud distributions by land surface-induced flows?," *J. Atmos. Sci.*, vol. 75, no. 11, pp. 3887–3903, 2018.

[15] S. Rasp, M. S. Pritchard, and P. Gentine, "Deep learning to represent subgrid processes in climate models," *Proc. Natl. Acad. Sci. U.S.A.*, vol. 115, no. 39, pp. 9684–9689, 2018.

[16] G. Chattopadhyay and S. Chattopadhyay, "Comparative study among different neural net learning algorithms applied to rainfall time series," *Meteorol. Appl.*, vol. 17, no. 4, pp. 463–473, 2010.

[17] M. A. Mohandes, S. Rehman, and T. O. Halawani, "A neural networks approach for wind speed prediction," *Renewable Energy*, vol. 13, no. 3, pp. 345–354, 1998.

[18] K. Rasouli, W. W. Hsieh, and A. J. Cannon, "Daily streamflow forecasting by machine learning methods with weather and climate inputs," *J. Hydrol.*, vol. 414–415, pp. 284–293, 2012.

[19] Y. Feng, W. Cui, D. Lu, and J. Li, "Comparison of artificial neural network and multiple linear regression models for the prediction of precipitation in eastern China," *Water*, vol. 7, no. 8, pp. 4875–4893, 2015.
[20] N. Srivastava, E. Mansimov, and R. Salakhudinov, "Unsupervised learning of video representations using LSTMs," in *Proc. 32nd Int. Conf. Machine Learning*, Lille, France, 2015, pp. 843–852.
[21] T. Fischer and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions," *Eur. J. Oper. Res.*, vol. 270, no. 2, pp. 654–669, 2018.
[22] I. E. Livieris, E. Pintelas, and P. Pintelas, "A CNN-LSTM model for gold price time-series forecasting," *Neural Comput. Appl.*, vol. 32, no. 23, pp. 17351–17360, 2020.
[23] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*, 5th ed. Hoboken, NJ, USA: Wiley, 2015.
[24] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery Data Mining*, San Francisco, CA, USA, 2016, pp. 785–794.
[25] J. Contreras, R. Espínola, F. J. Nogales, and A. J. Conejo, "ARIMA models to predict next-day electricity prices," *IEEE Trans. Power Syst.*, vol. 18, no. 3, pp. 1014–1020, Aug. 2003.
[26] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003.
[27] M. F. Villazón, M. R. Peralta Herbas, M. Saavedra Antezana, and O. C. Saavedra, "Hybrid model based on ARIMA and artificial neural networks for inspection time series forecasting," *DYNA*, vol. 83, no. 198, pp. 52–58, 2016.
[28] S. J. Taylor and B. Letham, "Forecasting at scale," *The American Statistician*, vol. 72, no. 1, pp. 37–45, 2018.
[29] A. R. S. Parmezan, V. M. A. Souza, and G. E. A. P. A. Batista, "Evaluation of statistical and machine learning models for time series prediction: Identifying the state-of-the-art and the best conditions for the use of each model," *Inf. Sci.*, vol. 484, pp. 302–337, 2019.
[30] Y. Wang, D. Gan, M. Sun, N. Zhang, Z. Lu, and C. Kang, "Probabilistic individual load forecasting using pinball loss guided LSTM," *Appl. Energy*, vol. 235, pp. 10–20, Feb. 2019.
[31] A. Elbeltagi, M. Zerouali, Z. M. Bailek, K. Bouchouicha, C. Bailek, M. M. Alharbi, et al., "Estimation of daily reference evapotranspiration using novel hybrid machine learning models," *Hydrological Sciences Journal*, vol. 67, no. 5, pp. 697–712, 2022.
[32] C. J. Talsma, R. J. Solander, M. D. Mudgett, E. L. Crawford, and M. J. Bosilovich, "Frost prediction using machine learning and deep neural network models," *Front. Artif. Intell.*, vol. 5, p. 963781, Jan. 2023.
[33] X. Wang, Y. Liu, Z. Bao, and Z. Li, "An ensemble machine learning approach for tropical cyclone intensity forecasting," *Weather Forecast.*, vol. 37, no. 5, pp. 795–807, 2022.
[34] M. Bhattacharya, "Machine Learning for Bioclimatic Modelling," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 4, no. 2, pp. 1-8, 2013. doi: 10.14569/IJACSA.2013.040201
[35] S. Narejo and E. Pasero, "Meteonowcasting using Deep Learning Architecture," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 8, no. 8, pp. 12-17, 2017. doi: 10.14569/IJACSA.2017.080803
[36] S. A. Kakar, N. Sheikh, A. Naseem, S. Iqbal, A. Rehman, A. U. Kakar, B. A. Kakar, H. A. Kakar, and B. Khan, "Artificial Neural Network based Weather Prediction using Back Propagation Technique," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 9, no. 8, pp. 462-470, 2018. doi: 10.14569/IJACSA.2018.090859
[37] N. S. Sani, A. H. A. Rahman, A. Adam, I. Shlash, and M. Aliff, "Ensemble Learning for Rainfall Prediction," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 11, no. 11, pp. 153-159, 2020. doi: 10.14569/IJACSA.2020.0111120
[38] N. Thai-Nghe, N. Thanh-Hai, and N. Chi Ngon, "Deep Learning Approach for Forecasting Water Quality in IoT Systems," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 11, no. 8, pp. 686-693, 2020. doi: 10.14569/IJACSA.2020.0110883
[39] A. Raja and T. Gopikrishnan, "Drought Prediction and Validation for Desert Region using Machine Learning Methods," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 13, no. 7, pp. 47-53, 2022. doi: 10.14569/IJACSA.2022.0130707
[40] M. Adnan, M. A. Latif, Abaid-ur-Rehman, and M. Nazir, "Estimating Evapotranspiration using Machine Learning Techniques," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 8, no. 9, pp. 108-113, 2017. doi: 10.14569/IJACSA.2017.080915
[41] T. V. Radhika, K. C. Gouda, and S. S. Kumar, "Novel Approach for Spatiotemporal Weather Data Analysis," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 13, no. 7, pp. 310-318, 2022. doi: 10.14569/IJACSA.2022.0130743
[42] N. Alharbe and R. Alluhaibi, "The Role of AI in Mitigating Climate Change: Predictive Modelling for Renewable Energy Deployment," *(IJACSA) International Journal of Advanced Computer Science and Applications*, vol. 14, no. 12, pp. 94-102, 2023. doi: 10.14569/IJACSA.2023.0141211