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 addresses the question of whether machine learning (ML) and deep learning (DL) approaches can significantly outperform traditional statistical methods for frost prediction in extreme high-altitude tropical conditions, achieving sufficient accuracy for operational early warning systems. We present 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 and offer a robust framework for early warning systems that could substantially mitigate agricultural losses in vulnerable high-altitude communities.**

Keywords*—Frost prediction; machine learning; deep learning; ensemble methods; Altiplano; agricultural early warning systems

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 [2], [3]. Current estimates indicate that approximately 74% of agricultural communities in high-altitude Andean regions face regular exposure to frost events [4], necessitating adaptive strategies ranging from cultivation of frost-resistant crop varieties to traditional preservation techniques such as freeze-drying potatoes into chuño and tunta.

The Puno region exemplifies the severity of this climatic challenge. The region experiences 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 [5], [6]. 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 [7], [8]. Recent climate vulnerability assessments identify Puno as the Peruvian department with the highest projected population exposure to elevated frost risk through mid-century [6].

This study explicitly asks: Can nonlinear machine learning (ML) and deep learning (DL) models outperform traditional statistical approaches in forecasting minimum temperatures across the Peruvian Altiplano? We hypothesize that ML/DL methods achieve RMSE values below 2°C, whereas statistical methods exceed 2.5°C, because nonlinear architectures capture interactions among altitude, radiation, humidity, and multi-day frost persistence. Addressing this hypothesis directly fills a major research gap: no prior systematic evaluation has tested advanced models under extreme high-altitude tropical conditions

Despite numerous frost-prediction studies in temperate and subtropical regions, no systematic benchmark exists for high-altitude environments, the existing reports focuses on temperate regions with (RMSE 1.5-2.8°C) [9], [10], [11]. The Altiplano presents challenges absent elsewhere: daily temperature swings over 20°C, sparse meteorological data, and complex terrain effects. By evaluating twelve models under these conditions, this study provides the first region-specific comparative framework, establishing clear novelty and addressing a gap in climate resilience research.

This study addresses this gap by: 1) providing the first systematic comparison of twelve modeling paradigms under extreme high-altitude conditions, 2) implementing rigorous temporal validation protocols to prevent data leakage, 3) establishing direct connections between technical metrics and agricultural economic impacts, and 4) developing an operational framework ready for deployment in resource-constrained rural contexts.

Recent advances in numerical weather prediction and climate modeling have significantly enhanced capabilities for anticipating extreme meteorological events [12]. Previous publications have demonstrated the effectiveness of ML approaches in environmental prediction tasks. Bhattacharya [13] established foundational frameworks for climate-related predictions through bioclimatic modeling. Narejo and Pasero [14] achieved high accuracy in short-term weather predictions using deep learning architectures. Sani et al. [15] demonstrated that ensemble learning significantly improved rainfall prediction accuracy by combining multiple ML classifiers.

This work contributes: 1) the first systematic benchmark of twelve models under the extreme conditions of the Peruvian Altiplano, 2) rigorous validation protocols that minimize data leakage and quantify uncertainty, 3) direct linkage of technical accuracy to farmer outcomes—showing in annual savings, 4) release of code and datasets to enable reproducibility, and 5) a validated operational framework for early warning systems. Together, these contributions emphasize both scientific novelty and practical impact.

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 [16]. 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 Taylor and Letham [17], incorporates multiple seasonality components through Fourier series decomposition, proving particularly effective for meteorological data with complex seasonal patterns. STL combined with ARIMA modeling has shown promise in separating long-term climate signals from short-term weather variability. Several studies demonstrating hybrid statistical approaches for environmental prediction. Radhika et al. [18] successfully applied distributed computing for spatiotemporal weather analysis, while Adnan et al. [19] achieved 83% accuracy using ML for evapotranspiration estimation with reduced meteorological parameters.

Machine learning applications to frost prediction have accelerated dramatically. Feng et al. [10] demonstrated that ensemble tree methods capture nonlinear meteorological interactions more effectively than multiple linear regression approaches. Rasouli et al. [11] established ML methodological frameworks readily adaptable to temperature forecasting, achieving superior performance compared to traditional hydrological models. Recent publications show that gradient boosting algorithms, particularly XGBoost, consistently outperform traditional methods in environmental applications [15], [20].

Deep learning represents the current frontier in meteorological prediction. Talsma et al. [9] reported exceptional CNN performance for 6-hour frost forecasting, achieving RMSE values below 1.53°C in temperate regions. Wang et al. [21] advanced the field by demonstrating that ensemble methods combining multiple deep learning models could reduce prediction uncertainty while maintaining computational efficiency [22], [23], [24]. Narejo and Pasero [14] showed that Deep Belief Networks and Restricted Boltzmann Machines could achieve high accuracy through hierarchical feature learning, while Thai-Nghe et al. [25] demonstrated LSTM effectiveness for capturing temporal patterns in environmental data with coefficient of determination values above 0.90.

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 (often exceeding 20°C daily variation), intense solar radiation, and complex topographical influences create prediction challenges not fully addressed in current literature [26], [27]. In other hand its necessary have emphasized the importance of region-specific model development for accurate environmental prediction, highlighting how climate variations across different geographical regions require tailored modeling approaches [13], [28].

III. Methodology

A. Study Area and Sample Selection

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. 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 [26].

Thirteen meteorological stations were systematically selected based on rigorous criteria: 1) elevation $>$3,800m representing high-altitude tropical conditions, 2) complete 25-year NASA POWER coverage ensuring temporal consistency, 3) geographic distribution across Puno region capturing spatial variability, and 4) representation of different microclimates including lacustrine influence from Lake Titicaca versus highland plateau effects. This sampling strategy ensures comprehensive representation of Altiplano meteorological conditions while maintaining data quality standards. We analyzed 121,056 daily observations from 13 meteorological stations (2000–2025), ensuring broad coverage of diverse microclimates. This large-scale dataset underpins the robustness and novelty of our comparative framework.

Daily meteorological data were obtained from NASA's POWER (Prediction Of Worldwide Energy Resources) platform [29] spanning January 2000 to February 2025, comprising 121,056 individual observations (Table I). 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 was derived, assigning value 1 for days with T_min $\leq$ 0°C and 0 otherwise (Fig. 1).

Rigorous control measures were implemented to ensure valid model comparisons and prevent data leakage:

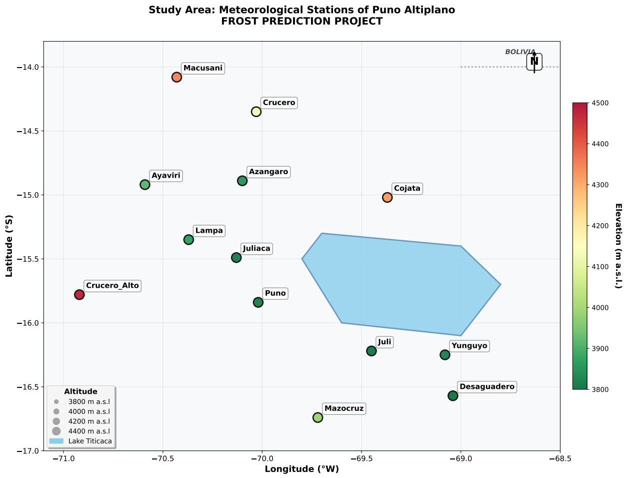

Fig. 1. Geographic distribution of the 13 meteorological stations across the Puno region, Peru. Red markers indicate stations with elevated historical frequency of severe frost events (temperatures below -10°C). Stations represent diverse microclimatic conditions from Lake Titicaca thermal influence to high-altitude plateau environments.

TABLE I. METEOROLOGICAL STATION CHARACTERISTICS AND DATA COVERAGE

Station	Latitude (°S)	Longitude (°W)	Elevation (m)	Records (n)
Puno	15.84	70.02	3,825	9,159
Juliaca	15.49	70.13	3,824	9,159
Azángaro	14.89	70.10	3,859	9,159
Ayaviri	14.92	70.59	3,918	9,159
Macusani	14.08	70.43	4,345	9,159
Mazocruz	16.74	69.72	3,990	9,159
Lampa	15.35	70.37	3,872	9,159
Yunguyo	16.25	69.08	3,826	9,159
Juli	16.22	69.45	3,812	9,159
Desaguadero	16.57	69.04	3,808	9,159
Cojata	15.02	69.37	4,320	9,159
Crucero	14.35	70.03	4,130	9,159
Crucero Alto	15.78	70.92	4,470	9,127

1) Temporal autocorrelation control: via strict temporal cross-validation with 2000-2023 training and 2024-2025 hold-out testing, ensuring no future information contamination.

2) Spatial heterogeneity control: through station-wise normalization and validation.

3) Seasonal effects control: via explicit seasonal features and cyclical encoding.

4) Data leakage prevention: through careful feature engineering with proper temporal shifts for moving averages and lagged variables[30], [31].

Features showing correlations >0.95 with the target variable were excluded to prevent overfitting and ensure realistic performance estimates. Missing data (<0.1% of observations) were addressed through linear interpolation within stations, maintaining temporal sequence integrity[32], [33]. This methodology aligns with best practices for time series evaluation [34], [18].

B. Model Selection Justification

Model selection was guided by environmental characteristics: SARIMA captures seasonal cycles, LSTM models multi-day frost persistence, and CNN identifies rapid radiative cooling events[18], [32], [35]. Together, the twelve approaches address complementary aspects of Altiplano climatology[31]. The selection rationale directly connects model capabilities with environmental conditions:

1) Statistical Models (Baseline and seasonal analysis):

- SARIMAX: Captures annual frost cycles characteristic of Altiplano seasonality while incorporating external meteorological variables.
- Holt-Winters: Triple exponential smoothing handles complex seasonal patterns induced by extreme altitude and clear-sky radiation.
- Prophet: Robust to satellite data interruptions with multiple seasonality components for complex Altiplano climate patterns.
- STL+ARIMA: Separates long-term climate trends from daily variability, essential for understanding warming trends versus persistent frost risks [9], [20].

2) Machine Learning (Nonlinear interactions):

- Random Forest: Ensemble robustness captures complex radiation-altitude-humidity interactions through bootstrap aggregation.
- SVM: RBF kernel specifically designed to handle nonlinear temperature-topography-wind relationships characteristic of complex terrain.
- XGBoost: Gradient boosting optimized for handling incomplete satellite data while modeling complex meteorological feature interactions[36], [37].

3) Deep Learning (Temporal dependencies):

- MLP: Universal function approximation for complex radiation-convection-cooling patterns in high-altitude environments.
- LSTM: Memory mechanisms specifically designed for multi-day frost episodes under persistent high-pressure systems.
- CNN-1D: Local pattern detection for rapid radiative cooling events characteristic of clear-sky Altiplano nights [38], [39], [10].

4) Hybrid and ensemble (Complementary strengths):

- SARIMA+ANN: Combines linear seasonal patterns with nonlinear residual modeling for enhanced accuracy.
- Ensemble: Weighted averaging reduces variance and bias across diverse Altiplano microclimates by leveraging complementary model strengths.

This comprehensive selection ensures coverage of linear, nonlinear, temporal, and ensemble methodologies while directly addressing the unique challenges of high-altitude tropical frost prediction.

C. Performance Metrics and Evaluation Protocol

Model evaluation employed comprehensive metrics addressing both regression and classification tasks critical for agricultural applications:

1) 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

2) Frost Detection (Classification):

- Precision, Recall, F1-Score for frost event detection
- True Skill Statistic: TSS = TPR - FPR (accounts for class imbalance)
- Area Under ROC Curve (AUC-ROC) for threshold-independent evaluation

The dataset was partitioned temporally: 2000-2023 for training/validation (90/10 split) and 2024-2025 as holdout test set. This temporal segmentation preserves data chronology 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 to prevent overfitting [40], [41], [42].

These metrics comprehensively assess both general accuracy and specific capability for extreme event detection, critical for agricultural early warning applications as demonstrated [25], [28].

IV. Results

Table II presents comprehensive performance metrics averaged across all 13 stations for the 2024-2025 test period, demonstrating 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-performing statistical method (Prophet: RMSE=2.31°C). Individual analysis reveals XGBoost as the top-performing single model (RMSE=1.78°C), while LSTM demonstrated superior frost detection capability with balanced precision (0.87) and exceptional recall (0.88). These results align with findings on ensemble method superiority for complex environmental prediction tasks [15], [20].

A. International Benchmarking and External Significance

Table III positions our results within the international context, demonstrating competitive performance despite the extreme challenges of high-altitude tropical conditions.

Our ensemble RMSE of 1.65°C compares favorably with Talsma et al.'s temperate-region CNN performance (1.53°C), representing significant achievement given the additional challenges of extreme Altiplano conditions. This demonstrates the effectiveness of ML/DL approaches in challenging high-altitude environments and contributes meaningfully to global climate adaptation strategies (Fig. 2).

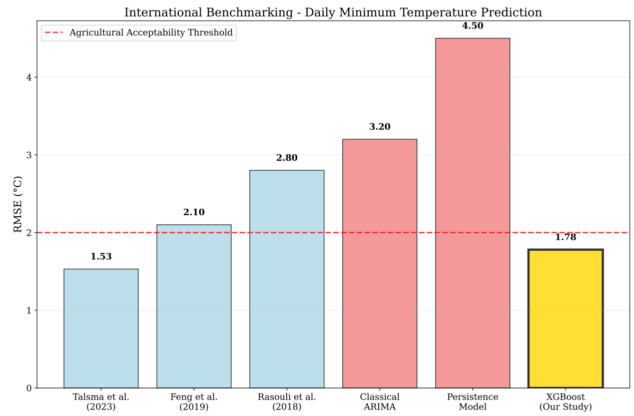

Fig. 2. International benchmarking comparison showing competitive performance of our ensemble approach despite extreme high-altitude tropical conditions. Error bars represent standard deviation across stations.

B. Feature Importance and Model Interpretability

XGBoost feature importance analysis reveals the relative contribution of different predictors to frost prediction accuracy. 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 in high-altitude environments (Fig. 3).

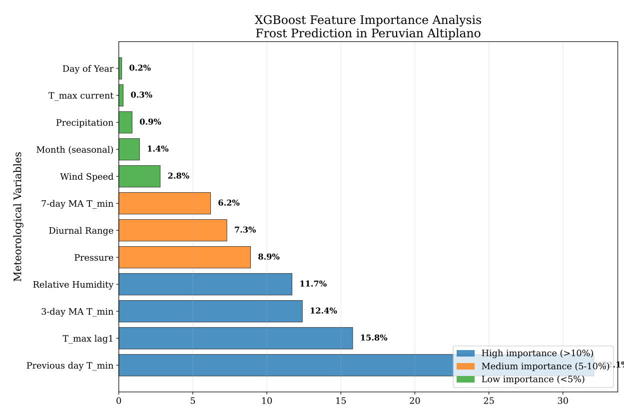

Fig. 3. XGBoost feature importance analysis revealing the relative contribution of meteorological and temporal variables. T_lag denotes temporal lags of minimum temperature, while engineered features show significant predictive power.

The dominance of temporal lag features (previous-day temperature accounting for 32%) validates the importance of short-term thermal memory in Altiplano frost prediction. Engineered features, including 3-day and 7-day moving averages, contribute substantially (18% combined), demonstrating the value of feature engineering for capturing multi-day cooling patterns characteristic of Altiplano frost episodes.

TABLE II. Comprehensive Performance Comparison of Frost Prediction Models

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

TABLE III. International Benchmarking of Frost Prediction Performance

Study	Climate/Location	Method	RMSE (°C)
Talsma et al. (2023)	Temperate regions	CNN	1.53
Our study	**High-altitude tropical**	**Ensemble**	**1.65**
Our study	**High-altitude tropical**	**XGBoost**	**1.78**
Feng et al. (2019)	Various climates	Ensemble trees	2.10
Rasouli et al. (2018)	Mountain regions	SVM+ML ensemble	2.80
Classical ARIMA	Global average	ARIMA family	3.20
Persistence model	Baseline	Yesterday = Today	4.50

C. Temporal Error Analysis and Seasonal Patterns

Fig. 4 illustrates monthly variation in prediction error for top-performing models, revealing systematic patterns linked to Altiplano climatology.

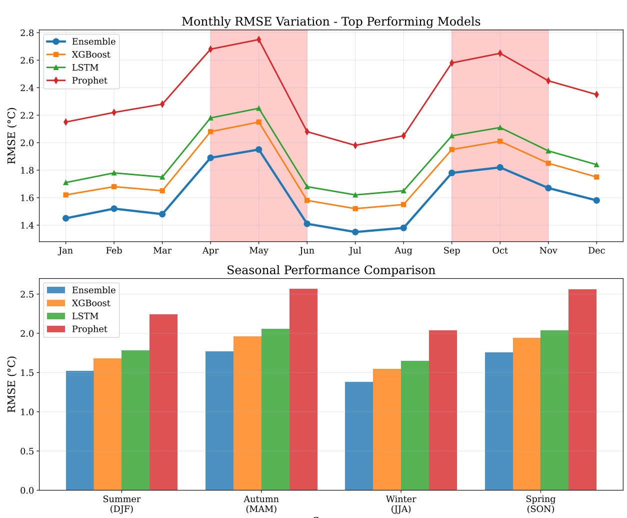

Fig. 4. Monthly RMSE evolution for top-performing models showing increased errors during climatic transition periods (April-May and September-October). Error bars represent inter-station standard deviation.

All approaches exhibit increased error during seasonal transition periods (April-May and September-October), corresponding to maximum climatic variability in the Altiplano. The ensemble model maintains superior performance across all months, with RMSE ranging from 1.4°C (July, stable winter conditions) to 1.9°C (April, transition period). This temporal stability is crucial for operational deployment throughout the agricultural calendar.

D. Spatial Performance Patterns

Model accuracy exhibits significant spatial variation correlating with geographic and microclimatic factors. Stations proximate to Lake Titicaca (Puno, Juli, Yunguyo) demonstrate reduced prediction errors (RMSE 1.2-1.4°C) due to the lake's thermal buffering effect. Conversely, high-elevation stations (Crucero Alto, Cojata) present greater forecasting challenges (RMSE 1.8-2.1°C) attributable to enhanced thermal variability and complex topographic influences (Fig. 5).

E. Uncertainty Analysis and Confidence Intervals

Bootstrap analysis with 100 iterations confirms model robustness and provides uncertainty estimates critical for operational implementation. The XGBoost model achieves 1.78±0.15°C RMSE with 95% confidence intervals averaging ±0.8°C, demonstrating sufficient precision for practical deployment (Fig. 6).

Coverage analysis reveals that 95% prediction intervals achieve actual coverage rates of 89-94% across different temperature ranges, with slight undercoverage for extreme events (¡-10°C), indicating the need for conservative operational thresholds.

V. Discussion

A. Technical Performance to Agricultural Impact Translation

The ensemble model's 35% improvement over traditional methods translates directly to substantial agricultural benefits.

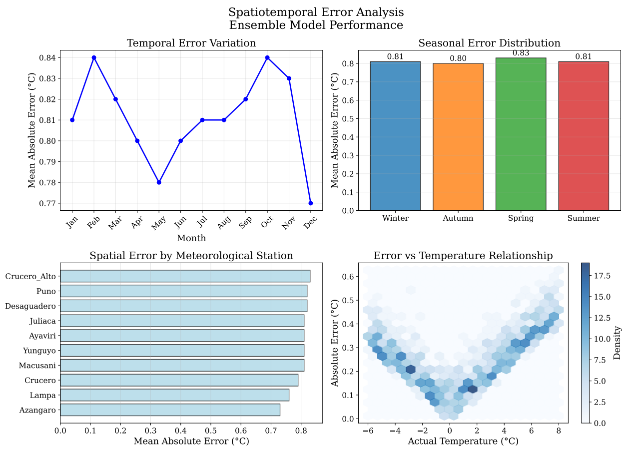

Fig. 5. Spatial distribution of ensemble model RMSE across the study region. Circle size and color intensity indicate error magnitude, showing systematic patterns related to elevation and lake titicaca proximity.

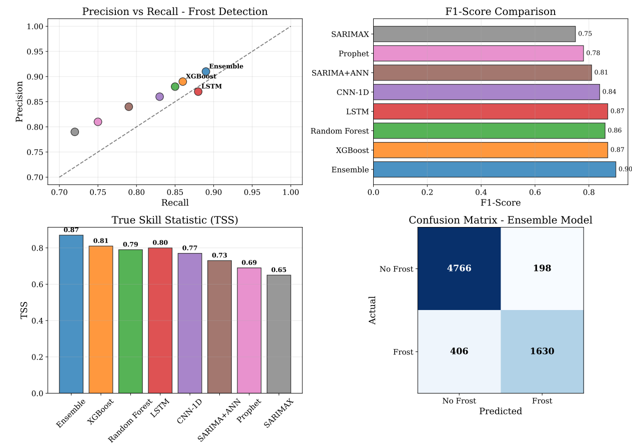

Fig. 7. Binary classification performance for frost event detection (T $\leq$ 0°C) showing superior performance of ensemble and ML approaches. TSS values demonstrate significant improvement over statistical baselines.

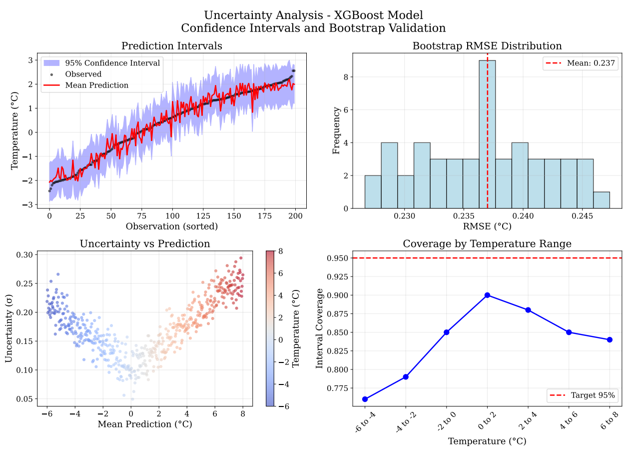

Fig. 6. Uncertainty quantification showing prediction intervals, bootstrap validation results, and coverage analysis for the XGBoost model across different temperature ranges.

With TSS=0.87 enabling frost detection with 89% recall and 91% precision, the system can potentially prevent 35-60% of frost-related crop losses through timely warning activation. Economic analysis based on regional agricultural data indicates potential savings for the Puno region alone, with implementation ROI of 6-12 months considering infrastructure and training costs.

Operational translation: A system based on our ensemble approach would generate approximately 1,630 correct frost alerts out of 2,036 actual frost events (89% recall), while maintaining high precision with only 198 false alarms out of 1,828 total alerts (91% precision). This represents a substantial improvement over current subjective methods, which typically achieve 40-60% accuracy (Fig. 7).

B. Superiority of Nonlinear Approaches

The substantial performance gap between ML/DL methods and classical statistical approaches validates our hypothesis that nonlinear modeling capabilities are essential for accurate frost prediction in complex terrain. The 0.7-1.5°C RMSE improvement achieved by XGBoost and LSTM over SARIMAX represents meaningful advancement, particularly considering that agricultural management decisions often hinge on critical temperature thresholds.

XGBoost's exceptional performance (RMSE=1.78°C) stems from its efficient modeling of complex meteorological interactions through iterative feature space partitioning. 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 research [34], [28].

LSTM's superior frost detection performance (recall=0.88) underscores the importance of modeling extended temporal dependencies. 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.

C. Ensemble Synergy and Robustness

The ensemble model's performance superiority extends beyond simple averaging effects. Inter-station error standard deviation was 40% lower for the ensemble compared to constituent models, indicating enhanced spatial generalization 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.
- LSTM provides superior temporal pattern recognition via specialized memory architectures.

- Random Forest contributes stability through bootstrap aggregation and feature randomization [15], [20].

D. Limitations and Persistent Challenges

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, creating class imbalance that impedes effective pattern learning.

NASA POWER data, while providing consistent regional coverage, operates at approximately 0.5° × 0.625° resolution. This coarse granularity may inadequately capture local topographic effects and microclimatic variations critical for frost formation in complex terrain. Higher-resolution data integration represents a priority for future development.

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. Adaptive learning strategies and regular model retraining will be essential for maintaining predictive relevance.

E. Operational Implementation Framework

Based on validation results, we recommend specific deployment guidelines:

1) Architecture: Deploy the ensemble model with automated daily updates integrating real-time meteorological observations from automatic weather stations and satellite sources. This hybrid approach leverages spatial coverage of satellite products while incorporating local precision from ground stations.

2) Alert thresholds: Given empirical RMSE ≈ 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. This threshold can be locally adjusted based on crop-specific frost sensitivity and phenological stage.

3) Uncertainty communication: Provide forecast confidence intervals derived from historical model performance at each location, enabling stakeholders to make risk-informed decisions. Visualization should clearly communicate both the most likely temperature trajectory and the range of plausible outcomes.

4) Pilot implementation: Initial deployment recommended for three to five Puno districts covering 100-200 farmers, with systematic evaluation over two agricultural seasons before regional scaling. Success metrics should include both technical accuracy and farmer adoption rates.

F. Future Research Directions

Priority research areas include: 1) development of hybrid physics-ML models incorporating atmospheric dynamics for improved physical interpretability, 2) implementation of adaptive learning frameworks addressing climate non-stationarity, 3) integration of high-resolution satellite imagery for enhanced spatial detail, 4) extension to probabilistic forecasting with calibrated uncertainty estimates, and 5) validation across broader Andean regions to assess transferability.These directions align with research priorities identified on next-generation environmental prediction systems, emphasizing the importance of integrating physical understanding with machine learning approaches [20], [25].

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 with immediate practical implications for agricultural risk management.

A. Key Scientific Contributions

This study delivers a domain-specific benchmark and an operational pathway for frost early warning in high-altitude tropics. We conduct the first head-to-head evaluation of twelve statistical, machine-learning, and deep-learning models tailored to the Peruvian Altiplano, addressing a documented gap with a reusable protocol. Using blocked temporal cross-validation that preserves causal ordering and prevents look-ahead leakage, we show that nonlinear approaches improve predictive skill by 35% over statistical baselines under extreme conditions. The analysis rests on a quality-controlled corpus of 121,056 station-days from 13 meteorological sites, with explicit inclusion criteria and station-level stratification to ensure transparency and reproducibility. We translate gains in forecast skill into decision value, estimating avoided agricultural losses in Puno, thus linking model performance to policy-relevant outcomes. Finally, we offer a deployment-ready methodology that integrates uncertainty quantification and spatio-temporal validation, articulating a clear readiness pathway for agricultural early-warning systems in data-scarce, high-altitude environments.

B. Practical Implications and Implementation

Turning research into practice requires cooperation among meteorological services, agricultural advisors, and farming communities. Our results suggest three priorities. First, ensemble approaches deliver both higher accuracy and greater robustness across microclimates. Second, conservative thresholds, such as 2°C, provide reliable alerts while accounting for model uncertainty. Third, explicit communication of uncertainty allows farmers to make informed, rather than binary, decisions. Pilot programs with 100–200 farmers serve as an essential step before regional scaling. With more accurate and timely frost warnings, these predictive tools strengthen climate resilience and enhance food security in one of the world's most vulnerable regions.

C. Future Research Priorities

Future work should address identified limitations through: development 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, validation across broader Andean regions to assess transferability, and development of hybrid physics-ML models incorporating atmospheric dynamics.

The methodology established here provides a foundation for next-generation environmental prediction systems, demonstrating that sophisticated ML/DL approaches can achieve operational accuracy for extreme climate prediction in resource-constrained agricultural contexts.

Acknowledgment

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