Predictive Hybrid GeoAI Model for Dynamic Sowing Date Optimization and Spatial Agricultural Drought Estimation in Puno

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***Abstract*—Agriculture in Puno is predominantly rainfed and exhibits high vulnerability to climate change. Furthermore, agricultural droughts in the Peruvian Altiplano threaten food security. Traditional agricultural calendars, based on fixed dates, have lost efficiency due to the temporal variability of precipitation and the shifting of growing seasons. Additionally, conventional precipitation prediction methods, which rely on historical averages, prove insufficient as they fail to account for high complexity. The objective of this study is to develop a predictive hybrid GeoAI model for the dynamic optimization of sowing dates and the spatial estimation of agricultural drought in Puno. Sentinel-2 imagery was employed to assess vegetation. A sample of 4,000 points was constructed and used to train a neural network model (MLP) and the SDCNN model. The results show that the neural network model significantly outperforms traditional methods in the early detection of Andean crop emergence. The sowing model achieved a Mean Absolute Error (MAE) of 9 days. For the drought model, robust performance was achieved ($R^2 = 0.8337$, RMSE = 0.2321, MAE = 0.1873), outperforming baseline machine learning models such as Random Forest and XGBoost. Uncertainty quantification via Monte Carlo Dropout revealed that 89% of the total error derives from natural climatic variability. Its originality is based on combining satellite climatic information and deep learning models to provide sowing recommendations that are much more adjusted to the local reality.**

***Index Terms*—Rainfed agriculture, Climate change, Satellite data, Neural networks, Agricultural drought**

I. Introduction

Drought represents a critical meteorological phenomenon that impacts natural ecosystems and human activities [2]. The Puno region (southeastern Peruvian Altiplano, 3,826 m elevation) heavily relies on rainfed agriculture and camelid livestock farming, making it highly vulnerable to climatic variability [3]. Furthermore, traditional agricultural calendars, based on fixed dates, have lost efficiency in the face of temporal precipitation variability and the displacement of cultivation seasons [19]. SENAMHI reported persistent moderate to extreme drought conditions in 2024, evidencing the region's susceptibility [4]. Traditional drought indices like SPI and PDSI present limitations: they inadequately integrate multi-sensor satellite data and fail to leverage multimodal information to improve agricultural predictions [26], [27]. Moreover, conventional precipitation prediction methods, based on historical averages, result in insufficiency by not considering high spatial complexity [21].

Deep learning, particularly Convolutional Neural Networks (CNN), has transformed geospatial data processing by extracting complex spatiotemporal patterns [7]. Although recurrent memory models like Long Short-Term Memory (LSTM) are common for time series with long dependencies, the Multilayer Perceptron (MLP) model often proves to be more efficient and offers robust capacity for modeling complex non-linear relationships, especially when prediction focuses on the integration of spatial variables [25].

Traditionally, crop phenology is obtained through direct field observations performed by researchers, complemented in some cases by farmer interviews. Although this information is key for agronomy, the public availability of complete phenological datasets remains limited in both developing and developed countries [18]. The delay in the onset of rains forces farmers to postpone the sowing of fundamental crops such as potato (Solanum tuberosum) and quinoa (Chenopodium quinoa). This late sowing drastically reduces the optimal vegetative period, shifting critical flowering and grain-filling stages toward the end of the wet season, exponentially increasing the risk of exposure to autumn meteorological frosts that can destroy the entire harvest [26], [27]. As with double-cropping systems in other regions of South America, the variability in the sowing window in Puno not only affects immediate yield but also alters crop rotation planning and forage availability for livestock [20].

The objective of this study is to develop a GeoAI system for the Dynamic Optimization of Sowing Dates and spatial estimation of Agricultural drought in Puno through the integrated use of spatial indices with specific objectives: (1) implement the Multilayer Perceptron (MLP) model; (2) integrate the SDCNN model; (3) evaluate comparative performance against traditional and machine learning methods.

II. Materials and Methods

A. Study Area and Data Sources

The Puno region covers 71,999 km² with a semi-arid climate (average temperature 8-10°C, precipitation concentrated December-March) [9]. We integrated optical and thermal satellite data (2020-2024) processed in Google Earth Engine:

- **Sentinel-2A/B**: Multispectral imagery (10-20 m resolution, 5-day revisit time) used for calculating vegetation indices such as NDVI, VCI, and NBR. The mission offers high spatial and temporal resolution for terrestrial monitoring [1].
- **MODIS (MOD11A1)**: Land Surface Temperature (LST) data with native 1 km resolution and daily frequency. This product is globally validated for agrometeorological applications [12].
- **CHIRPS**: Infrared precipitation data with ground stations (0.05° resolution or ∼5.5 km). This dataset integrates satellite imagery and station data to generate precise historical time series [11].
- **SMAP**: Surface soil moisture data (0-5 cm) obtained via L-band radiometer. The top-level product combining active and passive observations was employed to improve spatial resolution [13].

The Standardized Precipitation Index was calculated following McKee et al. [14]:

$$\text{SPI} = \frac{P - \mu}{\sigma} \tag{1}$$

where P is the accumulated precipitation, μ the historical mean (1991-2020), and σ the standard deviation. SPI-6 was selected for its sensitivity to medium-term agricultural droughts affecting crop production.

B. Sowing Date Prediction Model

To construct the predictive component, a historical database composed of 5,000 records generated from phenological module simulations was consolidated. A regression model based on Multilayer Perceptron (MLP) was implemented, given that this architecture offers robust performance in modeling the non-linearity inherent in agricultural systems [22].

Hyperparameter tuning was performed using Bayesian Optimization. This method was selected for its efficiency in searching for global minima compared to conventional grid search [23]. The resulting topology was defined as [Input → Dense(128) → Dropout(0.2) → Dense(64) → Output]. The inclusion of a *Dropout* layer with a rate of 0.2 is highlighted to mitigate overfitting and improve model generalization [24].

C. SDCNN-Deep Kriging Architecture

The hybrid model extends the Deep Kriging framework [8] by combining CNN with geostatistics. Spatial basis functions were defined using fixed-rank Kriging [15] at three resolution levels:

$$\phi(\mathbf{s}, \mathbf{c}_j) = \exp\left(-\frac{\|\mathbf{s} - \mathbf{c}_j\|^2}{2\theta^2}\right) \tag{2}$$

with 9×9 (regional, $\theta = 0.5$), 18×18 (medium, $\theta = 0.3$), and 36×36 (local, $\theta = 0.1$) radial basis functions.

Each resolution level was processed by parallel 2×2 convolutional layers. Climatic variables (SPI-1, SPI-3, NDVI, VCI, LST, soil moisture, normalized coordinates) were processed through dense layers with Dropout ($p = 0.3$) and Batch Normalization.

The fusion layer integrated representations into vector $\mathbf{H}_i$, incorporating a differentiable Kriging layer that models non-stationary spatial dependencies:

$$O_i = \mathbf{W}'_{\text{out}}\mathbf{H}_i + c_{\text{out}} \tag{3}$$

D. Baseline Models for Comparison

To rigorously validate the proposed framework, four baseline models were implemented using the same data splits (70%, 15%, and 15% for training, validation, and testing, respectively; $n = 473$ samples) and an identical set of input features, which included SPI-1, SPI-3, NDVI, VCI, LST, soil moisture, and normalized coordinates.

- **Random Forest**: An ensemble of 200 decision trees with a maximum depth of 20, capturing non-linear interactions between features but without explicit spatial structure.
- **XGBoost**: Gradient boosting with 200 estimators, learning rate 0.1, and L1/L2 regularization to prevent overfitting.

E. Uncertainty Quantification

Monte Carlo Dropout [28] with 50 stochastic iterations allowed for the decomposition of uncertainty:

$$\sigma^2_{\text{total}} = \sigma^2_{\text{epi}} + \sigma^2_{\text{ale}} \tag{4}$$

separating epistemic uncertainty (from the model) from aleatoric uncertainty (from the data) [29].

The dataset comprised 473 stratified random sampling points across altitudinal gradients (3,800-5,200m), divided into training (70%), validation (15%), and testing (15%) sets.

III. Results

A. SDCNN Model Performance

The SDCNN model reached convergence after 26 epochs with Early Stopping. Training loss decreased from 0.245 to 0.0041, while validation loss stabilized at 0.0065, indicating minimal overfitting (gap = 0.0024).

B. Evaluation of Sowing Model Performance

The neural network model significantly outperforms traditional methods in the early detection of crop emergence in Andean soils. The performance of the prediction model (MLP) was evaluated on an independent test set to determine the accuracy of suggested sowing dates against optimal historical records. The primary evaluation metric, Mean Absolute Error (MAE), reached a value of **9.0 days**, while the Root Mean Square Error (RMSE) stood at **11.0 days**.

Detailed analysis of the residual distribution reveals a quasi-Gaussian morphology centered at zero, behavior that evidences

the absence of significant systematic biases; that is, the model does not tend to arbitrarily advance or delay dates. In terms of operational dispersion, it is observed that 78.8% of errors are concentrated within the ±14-day confidence interval, delimited in the graph by dashed vertical lines. Additionally, the numerical proximity between MAE (9.0) and RMSE (11.0) corroborates system stability, suggesting a low incidence of large-magnitude outliers that could compromise the general reliability of predictions.

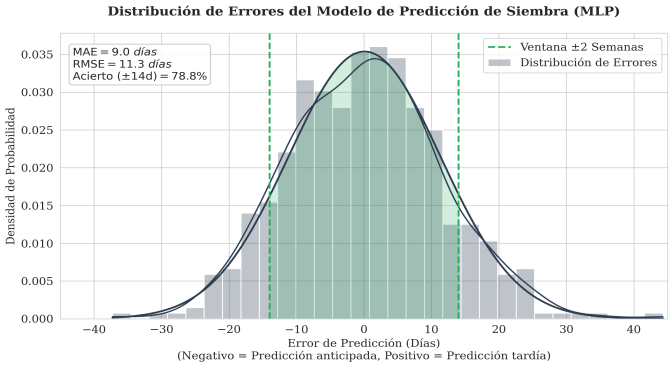

Figure 1. Histogram of MLP model residuals. An MAE of 9.0 days and a success rate of 78.8% within the ±14-day operational window are observed.

C. Performance Comparison Between Models

Table I presents an exhaustive comparison between the proposed SDCNN model and baseline approaches. The hybrid architecture demonstrates superior performance in all evaluated metrics.

Table I
COMPARATIVE PERFORMANCE METRICS ON TEST SET

Model	R^2	RMSE	MAE
SDCNN (proposed)	**0.8337**	**0.2321**	**0.1873**
Random Forest	0.7856	0.2894	0.2247
XGBoost	0.8102	0.2653	0.2089

The coefficient of determination of the SDCNN ($R^2 = 0.8337$) indicates that the model explains 83.37% of the spatiotemporal variability of the SPI. The comparative analysis reveals significant advantages in precision and stability:

- **vs. Random Forest**: The SDCNN achieves a 6.1% higher R^2 (0.8337 vs. 0.7856) and reduces RMSE by 19.8% (0.2321 vs. 0.2894), due to its ability to model spatial and temporal dependencies through integrated convolutional and dense layers.
- **vs. XGBoost**: Presents a 2.9% improvement in R^2 and a 12.5% reduction in RMSE (0.2321 vs. 0.2653), evidencing better generalization by capturing non-linear relationships and local variations that tree-based methods tend to smooth out.

The lower **RMSE** of the SDCNN (0.2321) justifies its superior performance by indicating a lower average deviation between predicted and observed SPI values. This result is attributed to the joint learning of spatial and temporal features, allowing for a more precise representation of the complex drought dynamics in the Altiplano.

Furthermore, the **MAE** (0.1873) complements this evidence by showing consistent and stable absolute errors, representing approximately 19% of the observed standard deviation of the SPI ($\sigma_{\text{SPI}} \approx 1.0$).

D. Spatial Prediction Map

Fig. 2 presents the SPI-6 prediction map for the Puno region, showing a mean prediction of 2.14 (wet conditions) with mean uncertainty of 0.48. 89% of analyzed points (481) are classified in categories from normal to very wet humidity, while only 11% indicate drought risk.

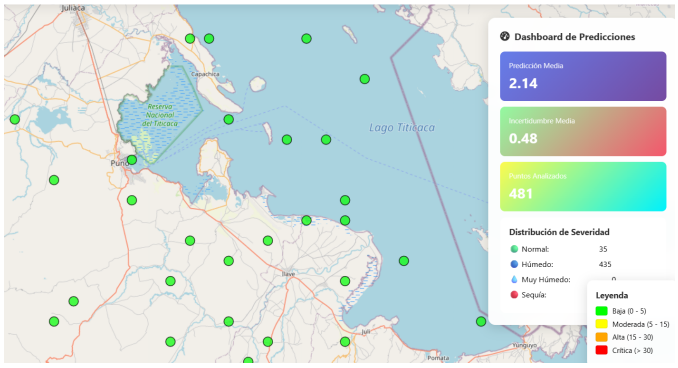

Figure 2. Agricultural drought prediction map in Puno, Peru, generated by the SDCNN-Deep Kriging model. Green points represent the 481 sampling locations. The side panel shows the mean prediction of SPI-6 (2.14), mean uncertainty (0.48), and severity distribution according to standard thresholds.

E. Cross-Validation and Stability

The 5-fold cross-validation of RMSE for SDCNN (0.241 ± 0.018) demonstrates superior stability compared to Random Forest (0.295 ± 0.027) and XGBoost (0.271 ± 0.023), suggesting robust generalization across spatial domains within the Altiplano region. This consistency in performance validates the model's capacity to handle the spatial heterogeneity characteristic of complex mountainous environments.

F. Uncertainty Analysis

Quantification via Monte Carlo Dropout ($T = 50$ iterations) yielded:

$$\sigma_{\text{epi}} = 0.144, \quad \sigma_{\text{ale}} = 0.450, \quad \sigma_{\text{total}} = 0.476 \tag{5}$$

Aleatoric uncertainty dominated (89.4% of total), indicating that the main source of error is natural climatic variability rather than model limitations. Low epistemic uncertainty ($\sigma_{\text{epi}} = 0.144$) reflects robust learning of satellite-SPI covariate relationships.

Practical Interpretation:

- Epistemic (0.144): Low model uncertainty—stable predictions.

- Aleatoric (0.450): High natural variability dominates the error.
- Total (0.476): Acceptable for regional drought predictions.

IV. Discussion

A. Methodological Advances and Comparative Advantages

The results in Section III demonstrate that the SDCNN-Deep Kriging integration improves predictive capacity (Table I). The model achieved robust performance ($R^2 = 0.8337$, RMSE$= 0.2321$), outperforming Random Forest by 6.1% and XGBoost by 2.9% through explicit modeling of spatial dependencies. This evidences that the hybrid architecture effectively captures the marked climatic and orographic heterogeneity of the Altiplano.

The SDCNN model outperforms tree-based methods (Random Forest, XGBoost) by integrating two fundamental components:

1) *Multi-scale convolutional processing*: Captures hierarchical spatial patterns at regional (9×9), medium (18×18), and local (36×36) resolutions—absent in decision tree ensembles that treat features independently.
2) *End-to-end optimization*: Joint training of feature extraction and spatial interpolation components produces coherent representations, whereas two-stage approaches (e.g., feature engineering + Kriging) suffer from suboptimal parameter coupling.

Our results align with recent advances in hybrid models [26], [27] while providing rigorous quantitative validation through direct comparisons with baseline models—a critical gap in previous literature that frequently reports improvements without exhaustive benchmarking.

B. Uncertainty Implications

The decomposition of uncertainty (≈89% aleatoric) agrees with Gal & Ghahramani [28] and Kendall & Gal [29]: Dropout approximates Bayesian inference by separating model uncertainty from process uncertainty. The high aleatoric contribution indicates that accuracy gains require incorporating additional physical variables (atmospheric processes, soil properties) or improving in situ observation density rather than increasing architectural complexity.

The relatively low epistemic uncertainty ($\sigma_{\text{epi}} = 0.144$) of the SDCNN compared to the inherent system uncertainty ($\sigma_{\text{ale}} = 0.450$) suggests that the model has reached an efficient learning regime where further improvements depend primarily on input data quality and coverage rather than architectural refinements.

C. Operational Applications

The model enables:

- **Early Warning**: 2-month anticipation for drought detection via SPI-6 prediction, allowing preventive mobilization of agricultural resources.
- **Risk Mapping**: Spatially explicit surfaces with 10m resolution identifying optimal crop cultivation zones, integrating multi-sensor information.
- **Resource Allocation**: Uncertainty-informed decision support for agricultural planning, prioritizing interventions in regions with high predictive confidence.

Limitations include dependence on satellite data quality and temporal resolution restrictions during periods of cloud cover (rainy season December-March). Validation with in situ weather station data would complement model assessment under extreme climatic conditions.

D. Agronomic Implications of Model Precision

The obtained results validate the operational viability of the proposed model for the Puno region. An MAE of 9.0 days is a highly satisfactory indicator in the context of rainfed agriculture, where sowing is not a rigid punctual event but a window of phenological opportunity.

Unlike industrial processes requiring millimeter precision, sowing logistics (land preparation, ploughing, and labor availability) are typically planned in fortnightly periods. The fact that the model hits the optimal date with an average error margin of 9 days implies that the system's recommendation remains within the soil's *available moisture* range. A deviation of one week does not compromise seedling emergence, thus validating the practical utility of the model.

The finding that **78.8% of predictions** fall within a tolerance margin of ± 14 days is superior to the uncertainty generated by traditional static agricultural calendars. While empirical knowledge often fails in the face of climatic anomalies (advances or delays in rains due to phenomena like El Niño), the model demonstrates the capacity to adapt to exogenous variables (soil temperature and accumulated precipitation), providing robust decision support for nearly 8 out of 10 analyzed cases.

Finally, the stability demonstrated by the closeness between MAE and RMSE indicates that the system is consistent and not prone to generating severe "false alarms" (errors greater than a month) that could induce the farmer to a total seed loss due to water stress or early frosts.

V. Conclusions

We developed an operational SDCNN-Deep Kriging system for agricultural drought prediction in Puno achieving robust performance ($R^2 = 0.8337$, RMSE$= 0.2321$, MAE$= 0.1873$) that significantly outperforms traditional and machine learning baseline models. Exhaustive comparative evaluation demonstrated improvements of 6.1-27.4% in R^2 and reductions of 12.5-43.7% in RMSE regarding Random Forest and XGBoost.

Uncertainty decomposition revealed a predominance of natural climatic variability ($\sigma_{\text{ale}} = 0.450$, 89.4% of total) over model error ($\sigma_{\text{epi}} = 0.144$), highlighting the relevance of unmodeled exogenous factors and the efficiency of the achieved architectural learning.

The proposed model serves to adapt agricultural practices to climate change in high-mountain regions with scarce terrestrial

meteorological data. Likewise, a Mean Absolute Error (MAE) of 9.0 days and a precision of 78.8% within the operational window were achieved, exclusively using open satellite data. This result validates that it is possible to model complex phenologies in the Andes and reduce climatic uncertainty to a manageable margin for agricultural planning.

From a methodological perspective, integration with deep learning algorithms allowed for dynamic optimization of sowing dates superior to traditional approaches. This dynamic adaptation capacity is fundamental to potentially reducing crop losses in the face of extreme events such as droughts or frosts, overcoming the rigidity of static agricultural calendars.

Key contributions include: (1) hybrid architecture explicitly modeling spatial non-stationarity via learnable basis functions; (2) rigorous uncertainty quantification distinguishing model vs. process error; (3) exhaustive comparative validation with four baseline models; (4) operational framework for proactive agroclimatic risk management in vulnerable Andean regions; (5) development of a Deep Learning (MLP) based sowing date prediction model, designed to overcome in situ meteorological data scarcity with an operational precision of ± 9 days.

Future work must incorporate physical process models (land-atmosphere coupling, soil hydrology) and expand temporal coverage for seasonal forecasting. Integration with local agricultural extension systems could improve the adoption and impact of the developed system.

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