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AI-based deep soil moisture prediction to assess past and future consistency of NOAA data

Predicción de la humedad del suelo profundo basada en IA para evaluar la coherencia pasada y futura de los datos de la NOAA

Previsão da umidade profunda do solo baseada em IA para avaliar a consistência passada e futura dos dados da NOAA

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Abstract

Accurate deep soil moisture modeling is essential for agriculture, especially in regions with unpredictable precipitation impacting crop health and yield. Understanding these dynamics is crucial for assessing drought vulnerability and promoting sustainable agricultural practices. This study evaluated the consistency of NOAA climate data over five years using an AI-developed deep soil moisture model. The objectives were to assess historical and future NOAA data reliability and predict soil moisture at 40 cm and 100 cm depths in Panama's western region. The CNN-BiLSTM regression model integrated meteorological and soil property data (clay, silt, sand) from NOAA and the International Soil Reference and Information Centre. It transformed data into spatial and temporal features, with training, validation, and testing sets using 2021 data. The generalization capability of the model was assessed using data from 2019, 2020, 2022, and 2023, validating predictions with two preceding and two subsequent years. Results show the 40 cm model achieved MAE, RMSE, MAPE, and R^2 of 0.007112 $m^3.m^{-3}$, 0.012662 $m^3.m^{-3}$, 3.55 %, and 0.97, respectively. The 100 cm model recorded 0.011019 $m^3.m^{-3}$, 0.017334 $m^3.m^{-3}$, 4.92 %, and 0.95, respectively. The model demonstrated coherence over five years, confirming NOAA data consistency.

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Resumen

La modelación precisa de la humedad del suelo profundo es fundamental para la agricultura, especialmente en regiones con precipitaciones impredecibles que afectan la sanidad y el rendimiento de los cultivos. Comprender esta dinámica es crucial para evaluar la vulnerabilidad a la sequía y promover prácticas agrícolas sostenibles. Este estudio evaluo la consistencia de los datos climáticos de la NOAA a lo largo de cinco años mediante un modelo de humedad del suelo profundo desarrollado con inteligencia artificial. Sus objetivos incluyeron la evaluación de la coherencia de los datos históricos y futuros de la NOAA y la predicción de la humedad del suelo a profundidades de 40 cm y 100 cm en la región occidental de Panamá. El modelo de regresión CNN-BiLSTM integró datos meteorológicos y propiedades del suelo (arcilla, limo y arena) provenientes de la NOAA y del Centro Internacional de Referencia e Información de Suelos. El modelo transformó estos datos en características espaciales y temporales, y los conjuntos de entrenamiento, validación y prueba se basaron en los datos de 2021. La capacidad de generalización del modelo se evaluó con datos de 2019, 2020, 2022 y 2023, validando predicciones con dos años anteriores y dos años posteriores. Los resultados indicaron que el modelo de 40 cm alcanzó valores de MAE, RMSE, MAPE y R^2 de 0,007112 $m^3.m^{-3}$, 0,012662 $m^3.m^{-3}$, 3,55 % y 0,97, respectivamente. El modelo de 100 cm registró valores de 0,011019 $m^3.m^{-3}$, 0,017334 $m^3.m^{-3}$, 4,92 % y 0,95, respectivamente. El modelo demostró coherencia a lo largo de cinco años, lo que confirma la consistencia de los datos de la NOAA.

Palabras clave: contenido de humedad profunda del suelo, propiedades del suelo, inteligencia artificial.

Resumo

A modelagem precisa da umidade profunda do solo é essencial para a agricultura, especialmente em regiões onde a precipitação imprevisível impacta a saúde e a produtividade das culturas. Compreender essas dinâmicas é crucial para avaliar a vulnerabilidade à seca e promover práticas agrícolas sustentáveis. Este estudo analisou a consistência dos dados climáticos da NOAA ao longo de cinco anos, utilizando um modelo de umidade profunda do solo desenvolvido com inteligência artificial. Os objetivos foram avaliar a confiabilidade dos dados históricos e futuros da NOAA e prever a umidade do solo nas profundidades de 40 cm e 100 cm na região oeste do Panamá. O modelo de regressão CNN-BiLSTM integrou dados meteorológicos e propriedades do solo (argila, silte e areia) provenientes da NOAA e do Centro Internacional de Referência e Informação sobre Solos. Transformou esses dados em características espaciais e temporais, utilizando conjuntos de treinamento, validação e teste com dados de 2021. A capacidade de generalização do modelo foi avaliada com dados de 2019, 2020, 2022 e 2023, validando as predições com dois anos precedentes e dois anos subsequentes. Os resultados mostram que o modelo de 40 cm obteve valores de MAE, RMSE, MAPE e R^2 de 0.007112 $m^3.m^{-3}$, 0.012662 $m^3.m^{-3}$, 3,55 % e 0,97, respectivamente. O modelo de 100 cm registrou valores de 0.011019 $m^3.m^{-3}$, 0.017334 $m^3.m^{-3}$, 4,92 % e 0,95, respectivamente. O modelo demonstrou coerência ao longo de cinco anos, confirmando a consistência dos dados da NOAA.

Palavras-chave: conteúdo de umidade profunda do solo, propriedades do solo, inteligência artificial.

Introduction

Deep soil moisture content is crucial for agricultural land management, soil and water conservation, and ecological processes (Tong *et al*., 2020). It significantly influences plant growth and water resource management, serving as a key indicator of agricultural productivity since soil water is the main accessible component of the hydrological cycle for plants (Munro *et al*., 1998). Soil texture has a significant impact on deep soil water content (SWC), with soil texture-based models enabling the prediction of SWC profiles-critical for monitoring water depletion and informing sustainable land-use decisions. Estimating deep soil moisture is essential for sustainable land use in dry and semi-arid regions, as well as for soil and water conservation (Wang *et al*., 2016). Understanding the interaction between soil texture and moisture content, along with the influences of climate and land use, is crucial for effective agricultural resource management. Pan *et al*. (2015) proposed a soil moisture diagnostic equation to estimate the soil moisture at depths of 5, 10, 20, 50, and 100 cm in arid and semiarid regions using only precipitation data. The authors incorporated the daily mean air temperature, precipitation, and solar radiation to calculate the parameters of the soil moisture diagnostic equation.

Much research in the literature addresses artificial intelligence-based modeling of soil moisture content. Han *et al*. (2021) developed two data-driven models-an artificial neural network (ANN) and a Long Short-Term Memory (LSTM) model-to predict soil moisture up to six days ahead at depths of 100, 200, 500, and 1,000 mm. Using weather data (air temperature, precipitation, vapor pressure, soil temperature, and relative humidity) and soil characteristics, these models were tested at the Eagle Lake Observatory in California, USA. The study concluded that the LSTM model consistently outperformed the ANN model across all depths. Basir *et al*. (2024) conducted a subsurface soil moisture forecasting study in Fort Wayne, Indiana, USA, using nine years of weather data and historical soil moisture measurements. They developed two models-Vector Auto Regression and LSTM-to predict subsurface soil moisture at a depth of 20 cm, utilizing inputs such as total rainfall, ambient temperature, wind speed, relative humidity, solar radiation, and volumetric water content at 30 cm depth. The study concluded that the LSTM model outperformed traditional statistical approaches in forecasting subsurface soil moisture. Geng *et al*. (2024) proposed a method that combines machine-learning techniques with physical laws to improve soil moisture predictions. They integrated physical concepts and prior knowledge into the model design and training process to capture multiscale soil moisture dynamics, thereby predicting soil moisture between 0 and 7 cm using the ERA5-Land reanalysis dataset. Filipović *et al*. (2022) developed an LSTM model to predict soil moisture three days ahead using the ERA5 reanalysis dataset developed by Muñoz-Sabater *et al*. (2021) and Yr database (https://www.yr.no/nb) data from 28 locations in Serbia across four different soil types. Input variables included daily temperature, precipitation, vapor pressure deficit, and soil moisture content. Trained on 15- to 60-day historical data in 15-day increments, the LSTM model outperformed random forest and ARIMA models, achieving the lowest mean absolute error. Yu *et al*. (2020) developed a modified Residual Bidirectional Long Short-Term Memory (ResBiLSTM) model, integrating Residual Networks (ResNet) and Bidirectional Long Short-Term Memory (BiLSTM), to predict soil moisture at 10, 20, 30, 40, and 50 cm depths during maize (*Zea mays* L.) growth stages. Using data from seven agrometeorological stations in Hebei, China (2016-2018), including soil water content and meteorological variables, the model employed three-day input data to forecast soil moisture for 1- to 6-day horizons.

Deep soil moisture modeling is vital in Panama due to variable precipitation, enabling optimized agricultural practices, drought vulnerability assessment, and proactive mitigation for sustainability. It also supports hydrological assessments by informing groundwater recharge, soil erosion risks, and ecosystem health.

As a data-handling strategy, we have designed a temporal-multivariate framework that integrates ten days of prior and current meteorological data as model inputs. These include precipitation, maximum and minimum temperature, dew point, field capacity, evaporation rate, humidity, heat flux, surface soil moisture, soil temperature, and surface texture (clay, silt, and sand fractions at 5 cm depth) obtained from the National Oceanic and Atmospheric Administration (NOAA) (National Centers for Environmental Prediction, 2015) and the International Soil Reference and Information Centre (ISRIC) (Poggio *et al*., 2021). The Convolutional Neural Network-Bidirectional Long Short-Term Memory (CNN-BiLSTM) models have been trained using 2021 data and validated with independent datasets from 2019-2020 and 2022-2023.

A key feature of this strategy is the explicit incorporation of soil surface texture variables-strongly correlated with soil moisture-which enhances both accuracy and robustness. In contrast to prior studies (Yu *et al*., 2020; Filipović *et al*., 2022) that excluded these parameters and therefore limited model generalization to similar soil types, our approach extends applicability across diverse agricultural environments, representing a meaningful methodological advancement.

In this study, we developed and validated two CNN-BiLSTM regression models capable of estimating deep volumetric soil moisture ($m^3.m^{-3}$) at 40 cm and 100 cm depths, demonstrating their applicability to Panama's agricultural western region.

Material and methods

Study site

Panama, located in the intertropical region (7°11'34.10"-9°39'44.70" N, 77°09'30.58"-83°03'3" W) with an area of 75,517 km², is bordered by the Caribbean Sea, Pacific Ocean, Colombia, and Costa Rica. Its S-shaped topography features a central mountain range (Talamanca and San Blas), dividing Atlantic and Pacific slopes, with 1,290 km and 1,700 km of coastline, respectively. It has a tropical climate with high humidity, temperatures of 20 34.5 °C, and rainfall of 1,000-3,000 mm, varying by topography and ocean currents. It includes a rainy season (May-mid-December) and a dry season (mid-December-late April), with the Caribbean side receiving more rain (Ministerio de Ambiente de Panamá, 2020).

Selection of the agricultural region for this study

The research focuses on western Panama's agricultural region, encompassing Chiriquí, Veraguas, Herrera, Coclé, Los Santos, Bocas del Toro, and Ngöbe-Buglé Comarca (7°24'-9°07' N, 79°55'-82°55' W, 100 to 300 m a.s.l.), notable for fertile soils, diverse crops, and robust infrastructure. The agricultural map (Figure 1a) was created using the GFSAD1KCD v001 dataset (Thenkabail *et al*., 2016), with a 1 km resolution, identifying nine dominant crop types through integrated remote sensing data from global irrigated and rainfed croplands.

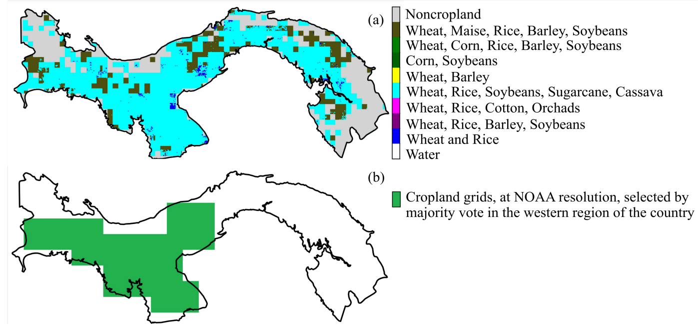

Figure 1. (a) Crop dominance map from dataset "GFSAD1KCD v001". (b) The NOAA-resolution western agricultural region, cropland selected by majority vote. (b) illustrates green cells at the NOAA resolution of 0.25x0.25 degrees for the western agricultural region of the country. These cells were obtained by counting the 784 cells of the "GFSAD1KCD v001" product within each cell of the NOAA grid and classifying each cell as agricultural or non-agricultural based on a majority vote.

NOAA variables

Climate variables for this study were obtained from NOAA's ds083.3 dataset (National Centers for Environmental Prediction, 2015; https://rda.ucar.edu/datasets/d083003/). This global dataset integrates atmospheric, oceanic, and land data from satellites, weather balloons, and ground stations on 0.25° x 0.25° grids, updated every six hours via the Global Data Assimilation System (GDAS), covering the period from July 8, 2015, to the present.

NOAA's Climate Forecast System version 2 model, developed by National Centers for Environmental Prediction (NCEP), estimates surface and deep volumetric soil moisture by simulating water balance through precipitation, evapotranspiration, and runoff. NOAA's deep soil moisture measurements, derived from North-American Land Data Assimilation System (NLDAS) and Global Land Data Assimilation System (GLDAS) models (https://ldas.gsfc.nasa.gov/gldas), integrate satellite data, ground observations, and climate inputs, achieving an accuracy of ±0.05 to ±0.08 $m^3.m^{-3}$. These estimates offer a spatial resolution of 12-25 km and are updated daily.

NOAA provided the climate data for Panama, and table 1 lists all the variables used in this study.

Soil property variables

Soil texture variables (clay, silt, sand) at 5 cm depth, defined by the soil texture triangle, were sourced from ISRIC at a 0.25° resolution, matching NOAA grid cells, downscaled from 0.0025° (Poggio *et al*., 2021). These static data remain constant within each grid cell over time.

Dataset

The study utilizes 16 input variables from NOAA, including climatic and soil variables listed in table 1, with surface soil texture (clay, silt, sand) treated as static. Temperature variables were converted from Kelvin to Celsius. The two CNN-BiLSTM models target volumetric soil moisture content at 40 cm and 100 cm depths, with depth intervals simplified to specific depths to enhance result interpretability and comparability with other studies. The study region covers 44 NOAA grid cells (Figure 1b), with NOAA variables recorded every six hours, yielding 1,460 annual samples per variable per cell, averaged daily. Two CNN-BiLSTM models, estimating deep soil moisture at 40 cm and 100 cm depths, were trained on 2021 data and evaluated for generalization using data from 2019-2020 and 2022-2023.

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Table 1. NOAA variables used in this study.

Description	Vertical Levels	Unit
Wind speed	Ground or water Surface	$m.s^{-1}$
Temperature	Ground or water surface	K
Maximum temperature	Specified height above ground: 2 m	K
Minimum temperature	Specified height above ground: 2 m	K
Dewpoint temperature	Specified height above ground: 2 m	K
Sensible heat flux	Ground or water surface	$W.m^{-2}$
Specific humidity	Specified height above ground: 2 m	$kg.kg^{-1}$
Relative humidity	Specified height above ground: 2 m	%
Total precipitation	Ground or water surface	$kg.m^{-2}$ (*)
Potential evaporation rate	Ground or water surface	$W.m^{-2}$
Soil temperature. Layer 1	0 to 0.1 m	K
Field capacity	Ground surface	fraction
VSMC (**). Layer 1	0 to 0.1 m	$m^3.m^{-3}$
VSMC (**). Layer 2	0.1 to 0.4 m	$m^3.m^{-3}$
VSMC (**). Layer 3	0.4 to 1 m	$m^3.m^{-3}$

(*) 1 $kg.m^{-2}$ is equivalent to a precipitation of 1 mm. (**) VSMC: Volumetric soil moisture content

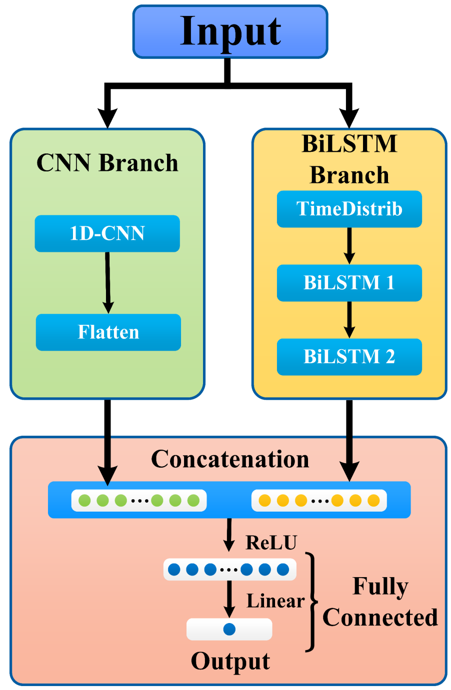

Figure 2. Block diagram of the CNN-BiLSTM model for regression proposed by the authors.

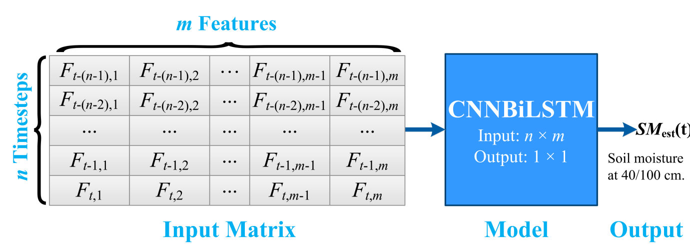

Figure 3. A general diagram of the model proposed by the authors.

CNN-and-bidirectional-LSTM: CNN-BiLSTM model

The CNN-BiLSTM model inspired by Yu *et al.* (2020) ResBiLSTM, which used parallel ResNet and bidirectional LSTM (BiLSTM) branches for soil moisture forecasting, features a simplified architecture. It includes a parallel structure with a single 1D-CNN layer and two BiLSTM layers, omitting fully connected layers in each branch. The branches are concatenated, followed by a fully connected layer and an output neuron (Figure 2). ReLU activation is used for the 1D-CNN and fully connected layers, with a linear function for the output neuron. The CNN-BiLSTM model integrates complementary 1D-CNN and BiLSTM branches for deep soil moisture prediction. The 1D-CNN branch detects spatial patterns in climate data, soil texture, and soil moisture, capturing input-target dependencies. The BiLSTM branch models temporal dynamics, leveraging bidirectional learning to identify long-term dependencies and nonlinear patterns in time-series data. The concatenation of both branches' outputs merges spatial and temporal insights, feeding into final layers for a richer data representation, enhancing generalization and prediction accuracy. The architectures of the models were implemented in Python 3.10.12 using TensorFlow 2.12.0 within the Google Colab environment.

Dataset preprocessing

The data is organized into an $n \times m$ matrix, combining meteorological time series and static soil texture data (Figure 3). Columns represent $m = 16$ features, and rows indicate $n = 11$ time-steps (the current day plus 10 prior days), determined by Partial Autocorrelation Function analysis that identifies 10 significant lags across 44 study cells (Figure 1b). For a non-leap year, 355 $n \times m$ matrices per cell are paired with soil moisture values at 40 cm and 100 cm depths.

The dataset was randomly shuffled and split into three subsets: 70 % for training, 15 % for validation, and 15 % for testing. Training set variables were normalized using the Z-score method, $x_{i,j,norm} = (x_{i,j} - x_{j,mean})/x_{j,std}$, where $x_{i,j}$ represents the *i*th sample of the *j*th variable, and $x_{j,mean}$ and $x_{j,std}$ are the mean and standard deviation of the *j*th variable, respectively. The output variable was similarly normalized. The validation and testing sets were normalized using the mean and standard deviation of the training set.

The optimization algorithm, loss function, and evaluation metrics

The Adam optimization algorithm and Mean Squared Error (MSE) loss function were used for training. The models' performance metrics are Root Mean Square Error (RMSE), $RMSE = \sqrt{1/N \sum_{i=1}^{N} (y_i - y_{i,est})^2}$, Mean Absolute Error (MAE), $MAE = 1/N \sum_{i=1}^{N} |y_i - y_{i,est}|$, Mean Absolute Percentage Error (MAPE), $MAPE = 1/N \sum_{i=1}^{N} |y_i - y_{i,est}/y_i|$, and coefficient of determination $R^2 = 1 - \sum_{i=1}^{N} (y_i - y_{i,est})^2 / \sum_{i=1}^{N} (y_i - y_{mean})^2$, where y_i is the true value, $y_{i,est}$ is the estimated value, y_{mean} is the mean value, and N is the number of samples.

Training of the CNN-BiLSTM models

Hyperparameter tuning was performed using the Keras-Tuner library to identify the optimal parameter combinations (O'Malley *et al.*, 2019). The search space for each hyperparameter is detailed in table 2. Hyperparameter tuning utilized the "BayesianOptimization" tuner class with 20 "max_trials" and 3 "executions_per_trial" for stability. The training spanned 100 epochs with early stopping based on validation loss after a 10-epoch patience period, retaining the best weights. Optimal hyperparameter values are presented in table 2.

Table 2. Hyperparameters and their optimal values used during the tuning of the model.

Hyperparameters	Search space	Optimal values	
		at 40 cm	at 100 cm
No. of CNN filters	16, 32, 64	32	32
No. of LSTM neurons	32, 64, 128	64	64
No. of FC neurons	32, 64, 128	64	32
Learning rate	0.0001, 0.001, 0.01	0.001	0.001
Regularization constant (L_2)	0.0001, 0.001, 0.01	0.001	0.001
Batch size	32, 64, 128, 256, 512	32	32

Models for 40 cm and 100 cm depths were trained using optimal hyperparameters from the tuning stage, with identical epoch counts and early stopping strategies. Training data was shuffled per epoch to prevent local minima convergence.

Results and discussion

Evaluation of the model at 40 cm for the years 2019, 2020, 2022 and 2023

Figure 4 reveals optimal prediction performance in 2021, with symmetrical behavior across MAPE, MAE, and RMSE. MAPE values were 4.9 % (2019), 1.7 % (2021), and 4.7 % (2023), indicating better future prediction performance. R^2 values were 0.95, 0.99, and 0.97 for 2019, 2021, and 2023, respectively, showing asymmetry. This is attributed to changing climatic conditions, like extended drought, and complex environmental interactions affecting soil moisture.

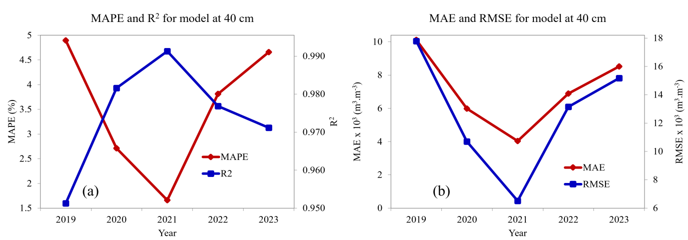

Figure 4. Metrics of the model at 40 cm. (a) R^2 and Mean Absolute Percentage Error (MAPE). (b) Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Figures 5a to 5e present scatter plots showing the 40 cm model fit to the deep soil moisture data across 44 NOAA grid cells over five years 2019 to 2023, respectively. The dashed line represents the ideal model (R^2= 1), and the solid line corresponds to a linear fit using the RANSAC algorithm (Fischler & Bolles, 1981). RANSAC-based equations are shown. High R^2 values (Figure 4a) for the 40 cm model across four test years beyond the training year demonstrate robust generalization capability.

Evaluation of the model at 100 cm for the years 2019, 2020, 2022 and 2023

Figure 6 displays performance metrics for the 100 cm depth model across all study years, with error graphs (MAPE, MAE, RMSE) showing symmetrical behavior and better future prediction performance. Asymmetries in R^2 values around 2021 (Figures 4a and 6a) contrast with symmetrical error graphs, possibly due to extended drought seasons. The metrics MAPE and 1-R^2 are normalized errors, with MAPE based on variable value and 1-R^2 on variance. Increased variance, potentially from prolonged drought (up to 45 days in some agricultural regions, per Sentinel-1 imagery), may correlate with higher R^2.

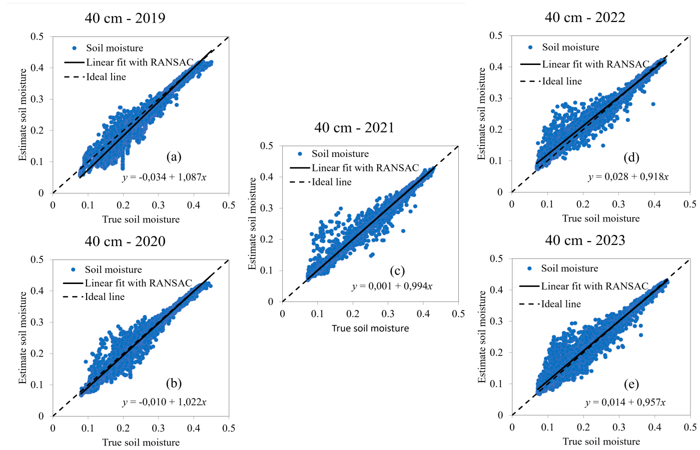

Figure 5. Soil moisture scatter plots at 40 cm. (a) 2019, (b) 2020, (c) 2021, (d) 2022, (e) 2023.

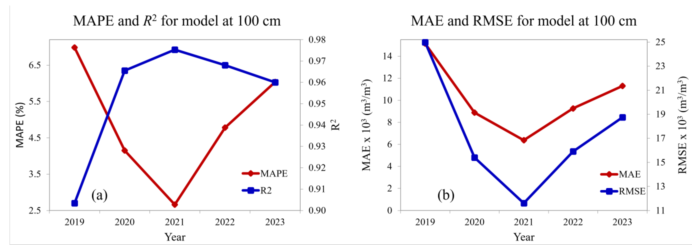

Figure 6. Metrics of the model at 100 cm. (a) R^2 and Mean Absolute Percentage Error (MAPE). (b) Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Two sequences of 12 zeros and ones, representing dry (0) and wet (1) months over 12 months, were analyzed. Sequences with 4 and 5 drought months followed by 8 and 7 rainy months yield variances of 0.222 and 0.243, respectively, indicating a 9.4 % variance increase with an additional drought month. R^2 is expected to increase proportionally, but the observed R^2 increase between 2019 and 2023 (Figures 4a and 6a) is lower, as drought duration interacts with other factors, such as delayed precipitation, affecting R^2.

Figure 7 presents scatter plots for the 100 cm model across study years, showing similar behavior to the 40 cm model but with underestimation in 2019 and 2020 (RANSAC-fit line below ideal) and slight overestimation in 2022 and 2023 (RANSAC-fit line above ideal). The model exhibits strong generalization, as shown in figures 6 and 7. Increased depth correlates with greater deviation from true values, likely due to the reduced influence of climatic conditions on water movement in deeper soil layers.

Consistency of the NOAA data

The deep soil moisture models developed for 40 cm and 100 cm depths were trained using NOAA climatic and soil data from 2021 and subsequently applied to data from 2019, 2020, 2022, and 2023 to evaluate their interannual consistency. This methodological framework-centred on training with a single reference year-constitutes an interannual consistency analysis aimed at assessing the temporal stability and persistence of climatic patterns around an analytical baseline.

The 2021 model is not an optimised predictive tool based on multi-year data aggregation, but rather as a methodological anchor for quantifying the degree of temporal drift and the stability of the climatic system in agricultural regions of central-western Panama.

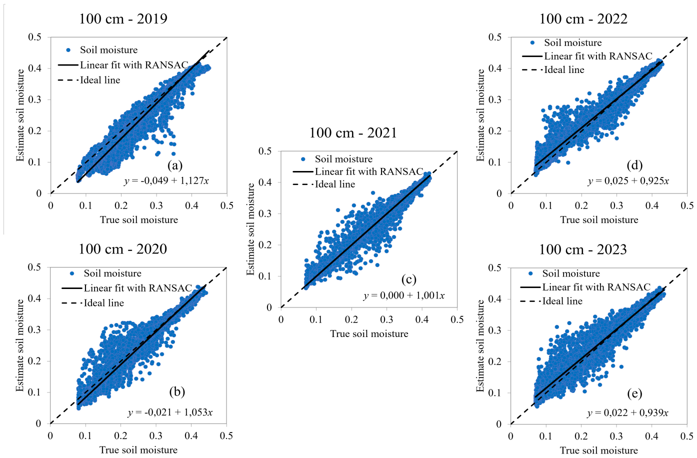

Figure 7. Soil moisture scatter plots at 100 cm. (a) 2019, (b) 2020, (c) 2021, (d) 2022, (e) 2023.

The models demonstrated strong consistency with the NOAA data across all evaluated years, yielding high correlation coefficients and low MAE, MAPE, and RMSE values. These outcomes validated both the robustness of the trained models and the temporal stability and reliability of the NOAA dataset over the five-year period. Each annual dataset incorporated six-hourly climatic variations, ensuring sufficient temporal resolution to capture the underlying dynamics of the system. Notably, the study encompassed a broad and diverse geographical region characterised by high temporal and spatial variability in meteorological and soil conditions. Despite these complexities, the NOAA climate data maintained a high degree of structural consistency, supporting the conclusion that the 2021-based models effectively quantify interannual stability and detect potential temporal drift in the climatic and soil moisture dynamics governing the region.

The validated model demonstrates that a single-year baseline can accurately assess the degree of climate stability during the study period, offering a practical framework for efficient, resource-light agricultural water management. From a theoretical perspective, this temporal persistence confirms that the underlying climate-soil system in the region operates with significant predictability, allowing such a baseline to serve not only for estimation but also as a robust detector of future climatic regime shifts.

Conclusions

This study presents an innovative artificial intelligence framework for estimating root zone soil moisture at 40 cm and 100 cm depths by integrating NOAA's globally recognized climatic data with soil information from the International Soil Reference and Information Centre (ISRIC). The approach combines a one-dimensional convolutional neural network (1D-CNN) with a bidirectional long short-term memory (BiLSTM) network, effectively capturing both spatial and temporal dependencies that govern soil moisture variability. The models were trained exclusively on 2021 data and validated against 2019-2020 and 2022-2023 datasets to evaluate their interannual consistency and temporal stability. Results show that the 40 cm model achieved MAE, RMSE, MAPE, and R^2 values of 0.007112 $m^3.m^{-3}$, 0.012662 $m^3.m^{-3}$, 3.55 %, and 0.97, respectively, while the 100 cm model recorded 0.011019 $m^3.m^{-3}$, 0.017334 $m^3.m^{-3}$, 4.92 %, and 0.95, respectively. These metrics confirm the models' high predictive accuracy and minimal temporal bias across diverse climatic and soil conditions in central-western Panama. The use of 2021 as a reference year was not intended to optimize predictive performance through multi-year aggregation but rather to assess the persistence and temporal validity of the learned climatic–soil relationships. Overall, the findings confirm the structural consistency of NOAA climatic data and demonstrate that the 2021 reference model effectively quantifies temporal drift, providing a robust methodological tool for evaluating the stability of climatic–soil interactions in tropical agricultural systems.

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