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SOIL MOISTURE RETRIEVAL WITH VERTICAL AND HORIZONTAL POLARIZATION SATELLITE DATA USING DEEP LEARNING MODELS

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ABSTRACT

Soil moisture (SM) is a critical factor for comprehending the interactions and feedback mechanisms between the atmosphere and the Earth's surface, particularly in relation to energy and water cycles. The challenge of accurately determining the spatiotemporal distribution of land surface SM has persisted within the remote sensing field. The model proposed here incorporates various algorithms, including artificial neural networks (ANN), deep neural networks, and three support vector regression (SVR) models—namely, radial basis function (SVR_rbf), linear (SVR_linear), and polynomial (SVR_quad) kernels—as well as two tree-based techniques: random forest and eXtreme Gradient Boosting (XGBoost). A comparison of predicted and observed soil moisture values indicated that the most accurate retrievals were achieved using Sentinel-1 data at VV polarization, yielding correlation coefficients (R) between 0.68 and 0.76, along with root-mean-square errors (RMSE) of 0.05 m^3/m^3 and 0.06 m^3/m^3. Ultimately, SVR_rbf was selected for generating high-resolution soil moisture maps from Sentinel-1 data over irrigated wheat fields, owing to its favorable balance of retrieval accuracy, processing efficiency, and ease of use.

Keywords: Machine learning (ML), Deep Learning (DL), Vertical and Horizontal polarization.

1. INTRODUCTION

Soil moisture plays a vital role in land ecosystems and agricultural practices, showing high variability across different locations and over time—ranging from a few centimeters to several kilometers. Understanding soil moisture at the field scale is key for efficient irrigation management. Common methods for measuring soil moisture include point-based sensors, hydrogeophysical approaches, and satellite remote sensing using active and passive microwave data. However, there is still a noticeable gap between local and regional measurements, making it difficult to validate satellite observations and calibrate hydrological models accurately.This review introduces several **innovative methods for retrieving Surface Soil Moisture (SSM)**, such as using geostationary satellite data, all-weather retrieval techniques, and new modeling approaches like the asynchronous-assumed feature space. These methods aim to reduce dependence on soil texture and function well under varying weather conditions, offering high spatial and temporal resolution in future SSM estimates.

The main objective of this study is to evaluate the effectiveness of deep learning and machine learning algorithms in retrieving surface soil moisture using Sentinel-1 radar data. Specifically, the study analyzes backscatter and interferometric coherence data to compare models like artificial neural networks (ANN), deep neural networks (DNN), and support vector regression (SVR)—including RBF, polynomial, and linear versions—as well as tree-based models like random forest (RF) and XGBoost. The study also assesses how well these methods transfer to new conditions and compares them against traditional Water Cloud and Oh models (WCM). observatories.

2. METHODOLOGY

The study used Sentinel-1 data to estimate soil moisture, with the best results from VV polarization (R = 0.68–0.76, RMSE = 0.05–0.06 m^3/m^3). Among tested models—ANN, SVR_rbf, XGBoost, and traditional WCM/Oh—ANN and SVR_rbf performed best. **SVR_rbf** was selected for mapping soil moisture due to its strong accuracy, efficiency, and simplicity.

2.1 Dataset and Preprocessing

This research utilized Sentinel-1 radar data to extract Soil Surface Moisture (SSM), focusing on the backscattering coefficient and coherence at both VV and VH polarizations. The Sentinel-1 mission comprises two identical satellites: Sentinel-1A, which was launched on April 3, 2014, and Sentinel-1B, launched on April 25, 2016. Both satellites are equipped with a C-band Synthetic Aperture Radar (SAR) system that operates in three distinct imaging modes, enabling all-weather and continuous day-and-night imaging with a six-day revisit interval. Data from the Sentinel-1 mission is typically available through its official data hub in two formats: single look complex (SLC) and ground range detected (GRD).

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2.2 Phase 1 and Phase 2

In the first phase of the study, the goal was to **identify the best-performing machine learning model from three major categories** for retrieving Surface Soil Moisture (SSM) using only Sentinel-1 satellite data. The tested algorithms included neural networks (ANN and DNN), support vector machines with different kernels (SVR_rbf, SVR_linear, SVR_quad), and tree-based methods (Random Forest and XGBoost). These models were trained and validated using data from rainfed and irrigated wheat fields in the **Sidi Rahal** and **Kairouan** regions. The best model from each category was selected based on key performance metrics such as **RMSE, R^2, and BIAS**.

In the second phase, the selected models were tested for their **transferability** to new conditions using data from **drip-irrigated wheat fields in Chichaoua**. At the same time, the models' performance was compared with the **Water Cloud Model (WCM)**, which also uses backscatter and coherence data, along with factors like **fractional vegetation cover and surface roughness**.

3. MODELING AND ANALYSIS

The results from the machine learning models and the **Water Cloud Model (WCM)** were compared to see which model worked best with the observed data.

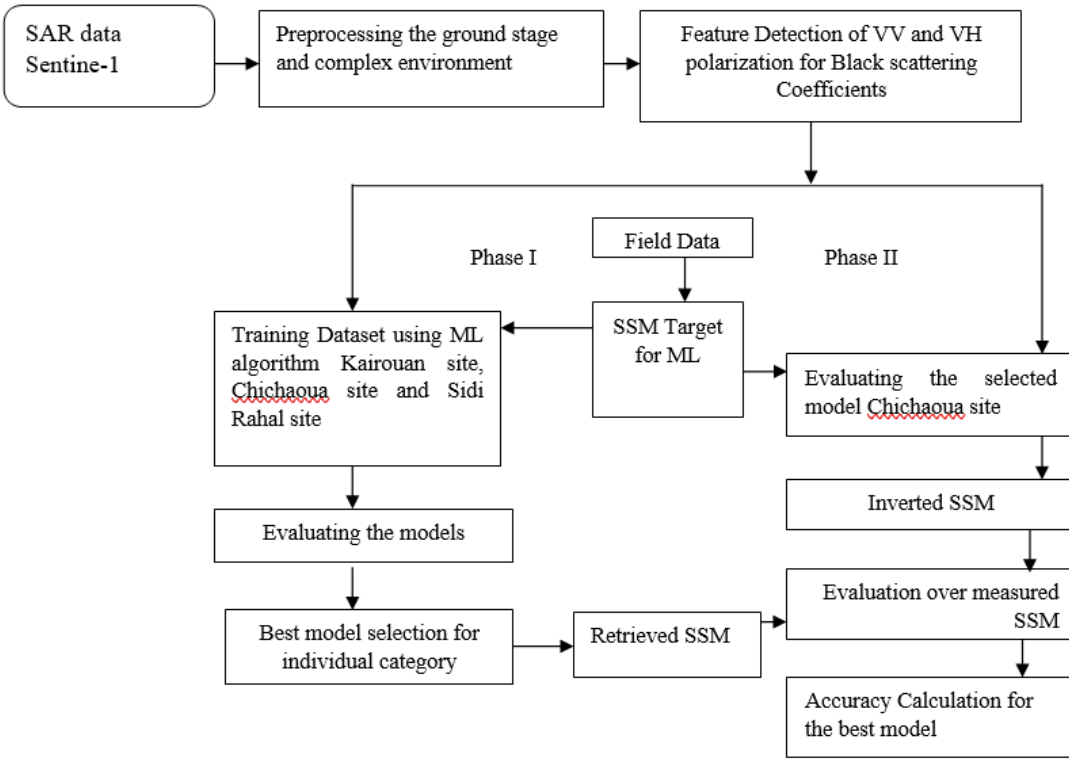


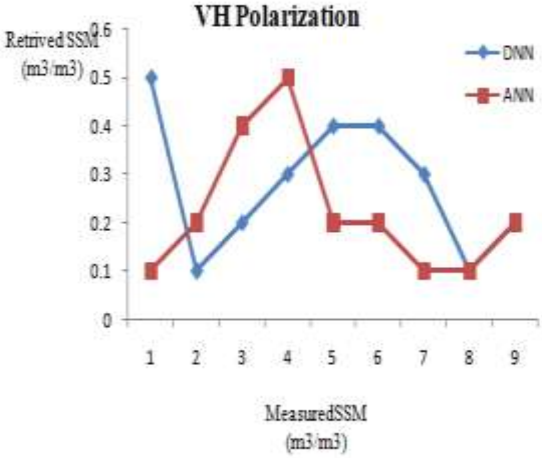
Figure1: Illustrates the proposed methodology of study

4. RESULTS AND DISCUSSION

The proposed work is implemented using the MATLABR2021aa Figures 2 and 3 illustrate that this finding aligns closely with the results derived from the ANN algorithm and previous research, which indicated that the backscatter coefficient and interferometric coherence at VV polarization can effectively estimate soil moisture using a backscattering modeling inversion approach. Furthermore, all machine learning algorithms exhibited diminished performance for both polarizations when soil moisture values surpassed 0.3 m^3/m^3.

Table 1 presents the characteristics of Sentinel-1 processed products utilized throughout this study.

Site	Season	Relative orbit number	Incident Angle	Relative orbit with Overpass time	Product	Number Of Images
Chichaoua (F1)	October 2016-July 2018	52	35.2°	Descending-06:30	GRD SLC	110 106
Sidi Rahal	November2016-June 2018	154	40°	Descending-06:28	GRD SLC	61 60



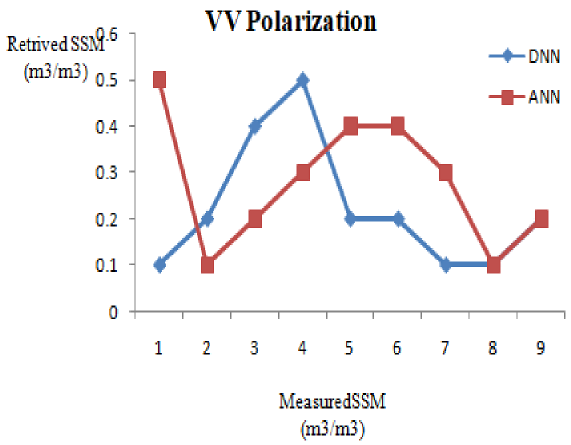


Figure 2 : VV Polarization **Figure 3** : VH Polarization

5. CONCLUSION

In the first phase, machine learning algorithms were trained and validated using data from irrigated and rainfed wheat fields in Morocco and Tunisia. The comparison of estimated and measured soil moisture content (SSM) showed that the Artificial Neural Network (ANN), Deep Neural Network (DNN), Radial Basis Function Support Vector Regression (SVR_rbf), and XGBoost were the top performers for VV polarization, with correlation values between 0.75 and 0.76 and an RMSE of 0.05 cm^3/cm^3.

In the next phase, the transferability of these models was tested using a second dataset from a drip-irrigated wheat field in Morocco. The focus shifted to ANN, SVR_rbf, and XGBoost, as the DNN gave similar results. ANN and SVR_rbf showed the best performance, with correlation values of 0.81 and RMSE of 0.034 m^2/m^2, slightly outperforming XGBoost (0.76 and 0.038 m^2/m^2). These models performed similarly to the Water Cloud Model (WCM), confirming their effectiveness in estimating SSM using just radar data.

Because of its balance of accuracy, speed, and simplicity, SVR_rbf was recommended for SSM mapping. Notably, using SVR_rbf was much faster than the WCM, as generating an SSM map for a 4 × 4 km^2 area took about 20 times longer with the WCM.

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