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Soil Moisture Content Prediction in Loam Soil with RFR Model

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ABSTRACT

Soil moisture content (SMC) is an important factor in agricultural productivity; it has an impact on crop growth, water use efficiency, and soil health. However, accurately predicting SMC, especially at deeper soil layers, remains challenging due to high variability and limited spatiotemporal data resolution. This study developed and evaluated a Random Forest Regression (RFR) model to predict SMC in loam soil at five different depths (5, 20, 40, 60, and 80 cm) utilizing meteorological data (temperature, humidity, precipitation, wind speed, and solar radiation) and vegetation indices: the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Moisture Index (NDMI). Data were collected during the maize vegetation season in 2023 in Mosonmagyaróvár, Hungary. The results showed that the mean SMC ranged from 12.61% to 16.19%. Correlation analysis demonstrated that precipitation and NDMI had the strongest positive correlation with SMC, especially at shallower depths $r = 0.78$ at 5 cm depth, Solar radiation had a moderate correlation with SMC, especially at the deeper depths. The RFR model performed well at all depths, achieving an R^2 of 0.86 at 5 cm depth; the model accuracy enhanced at deeper layers, achieving R^2 values of 0.91 and 0.94 at 60 and 80 cm depths, respectively. The most significant predictors according to the feature importance analysis were precipitation, humidity, and NDMI, with NDMI playing a crucial role in subsurface moisture retention at deeper depths. These findings highlight the potential for machine learning algorithms to optimize irrigation approaches and improve water management in precision agriculture.

Keywords: Soil moisture content, RFR, Loam soil, NDVI, NDMI, Feature importance.

1. INTRODUCTION

Soil moisture (SM) is the amount of water retained in the topsoil's active layer (Lee et al., 2023). It is an essential hydrological parameter that influences a wide range of global processes, including climate, hydrology, and the carbon cycle. In addition, soil moisture is crucial in agriculture since it

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directly affects crop yields and is utilized to monitor droughts and floods (Szám et al., 2024; Verhoest et al., 2008). In an agricultural context, soil moisture content (SMC) is a key indicator of productivity, influencing water use efficiency, crop growth, and overall soil health. Proper monitoring and prediction of soil moisture are critical for optimizing irrigation operations, especially in precision agriculture. This approach relies primarily on data-driven decision-making, which has been found to enhance sustainability and resource efficiency (Liao et al., 2018).

Internet of Things Sensors and latest data transmission technologies allow to collect big data in spatio-temporal resolutions (Neményi et al., 2023). Recent developments in sensor technology have allowed researchers to collect large-scale, continuous, and highly accurate soil moisture data from in-situ monitoring areas (Zheng et al., 2019). Along with these advancements, remote sensing technologies have become essential for large-scale soil moisture mapping (Acharya et al., 2022). Satellite data from the Landsat and Sentinel, which are freely available, have transformed soil moisture prediction by providing cost-effective and time-efficient data for regional and national-scale analysis (Peng et al., 2017). Furthermore, vegetation indices such as NDVI (Normalized Difference Vegetation Index) and NDMI (Normalized Difference Moisture Index) have emerged as useful methods for indirectly measuring soil moisture by capturing vegetation health and moisture content (Saha et al., 2018).

Much large-scale agricultural research requires accurate prediction of spatio-temporal variations of SMC. However, traditional methods of predicting soil moisture have numerous disadvantages. Many existing models, particularly those that use artificial neural networks (ANN), focus on extracting a single characteristic from the data and frequently ignoring crucial spatial and temporal dynamics (Liakos et al., 2018). Furthermore, most SMC prediction models only consider surface layers (0–20 cm) or single depth, However, these studies often focus on single-depth predictions or limited environmental parameters, leaving gaps in understanding SMC dynamics across multiple depths.

In recent years, researchers have worked to address these limitations, seeking to improve prediction accuracy and apply machine learning models that can account for both surface and subsurface soil moisture variations. Machine learning models, particularly those utilizing Random Forest Regression (RFR), have shown promise in predicting soil moisture by integrating multiple meteorological factors and vegetation indices (Ning et al., 2023). These models offer an opportunity to enhance water resource management and improve irrigation scheduling through precise and dynamic soil moisture predictions.

The objective of the research is to develop and evaluate a Random Forest Regression (RFR) model for predicting SMC in loam soil at five different depths using meteorological data (temperature, precipitation, humidity, wind speed, and solar radiation) and vegetation indices: Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI). This study aims to address the following critical inquiries: how reliably can the RFR model estimate soil moisture content at different depths, and what are the most important meteorological and vegetation features influencing soil moisture dynamics. The research highlights machine learning's potential for improving water-use efficiency, crop health monitoring, and promoting sustainable agricultural practices in the face of climate change and limited resources.

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2. LITERATURE REVIEW

Soil moisture (SM) measurement techniques are generally classified into direct and indirect methods. The only direct methods involve oven drying techniques, both gravimetric and volumetric, to determine soil moisture. In contrast, all automated systems for estimating soil moisture, such as time-domain reflectometry (TDR) and Stevens HydraProbe sensors, are considered indirect methods (Caldwell et al., 2018; Singh et al., 2024). Although in-situ observations using these sensors are accurate, they are often too costly for large-scale applications, making them impractical for observing the spatial distribution of soil moisture over wide areas (Lee et al., 2019). Satellite-based soil moisture data have thus become a valuable alternative for capturing continuous spatial and temporal variations in soil moisture (Lee et al., 2023).

In recent years, various artificial intelligence (AI) and machine learning (ML) techniques have been employed to overcome the limitations of traditional soil moisture measurement methods. Models such as Random Forest Regression (RFR), Support Vector Machine (SVM), Extreme Gradient Boosting Regression (XGBR), and CatBoost Gradient Boosting Regression (CBR) have shown great potential in accurately predicting soil moisture content (Ågren et al., 2021; Carranza et al., 2021; Senanayake et al., 2021). For instance, Shokati et al. (2024) demonstrated that soil moisture modeling using the random forest algorithm performed significantly better with hyperspectral data from the Co Spectro Cam (CSC) sensor mounted on a UAV (R^2 = 0.87), compared to multispectral data from Sentinel-2 (R^2 = 0.49) and Landsat-8/9 (R^2 = 0.66). This study also highlighted that the perpendicular index (PI) was highly sensitive to soil moisture changes across all datasets, emphasizing the importance of high-resolution multispectral data for accurate soil moisture monitoring.

In a related study, de Oliveira et al. (2021) used four machine learning algorithms to model the spatiotemporal dynamics of soil moisture in an Atlantic Forest remnant. Their results indicated that the Random Forest model performed best, achieving an R^2 of 0.51 and a Nash-Sutcliffe efficiency (NS) of 0.77. This model demonstrated its ability to generalize data effectively under varying weather conditions, with key factors influencing soil moisture being throughfall (TF), evapotranspiration (ETo), and forest structure variables such as tree diameter at breast height (DBH) and species diversity. Additionally, Hegazi et al. (2021) proposed a Convolutional Neural Network (CNN)-based approach to predict soil moisture in vegetation-covered areas using Sentinel-2 imagery. Their CNN architecture, which included six convolutional layers, one pooling layer, and two fully connected layers, produced high accuracy predictions. The study found that the combination of Sentinel-2 bands (Red, Red Edge 1–4, and NIR) was more effective for soil moisture prediction than single indices like NDVI or NDWI, achieving an R^2 of 0.71, MAE of 0.03, and RMSE of 0.04. Furthermore, models that integrated both thermal and multispectral data consistently outperformed other models in predicting soil moisture.

These studies collectively demonstrate the increasing use of machine learning and remote sensing tools to enhance soil moisture predictions. The random forest algorithm has consistently shown strong predictive performance, especially when high-resolution, multispectral, or hyperspectral data are available. With advancements in AI and sensor technology, it is now possible to address the limitations of traditional soil moisture measurement methods and achieve more accurate and scalable predictions.

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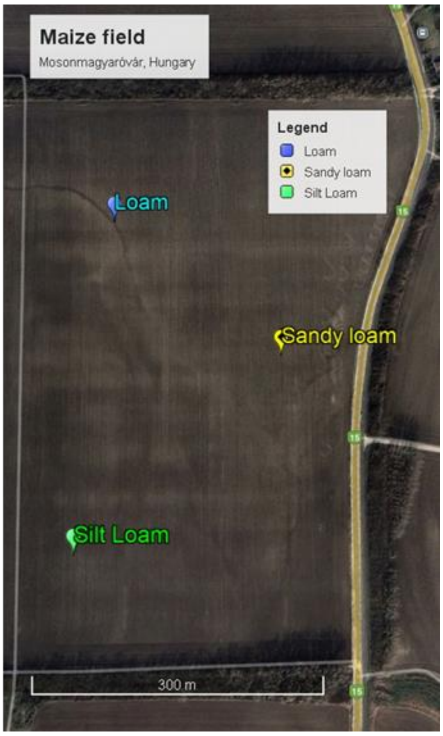
3. MATERIALS AND METHODS

3.1 Experiment location and data collection

Our research was conducted between June and October 2023 at a 23-ha maize field at Széchenyi István University in Mosonmagyaróvár, Hungary (Alahmad et al., 2023). The meteorological sensors collect data from fields using soil, crops, environment, and atmospheric sensors (*Figure 1a*). Data collection was performed at 10–15-minute intervals via LoRaWAN (Low Power, Wide Area Network protocol). The meteorological parameters included temperature [°C], relative humidity [%], precipitation [mm], wind speed [km/h], and solar radiation [W/m²] The data was grouped by depth and time for detailed analysis.



1a *1b*

Figure 1a: Meteorological sensor station at the maize field

Figure 1b: The three soil types in the field

The field has three soil types (loam, sandy loam and silt loam) (*Figure 1b*). The soil samples have been collected from the loam soil at five different depths (5, 20, 40, 60 and 80 cm). More than 135 samples have been collected during the maize vegetation season with three replications every two weeks starting from 14/06/2023 to 18/10/2028.

Two vegetation indices have been collected from Sentinel 2A using the Sentinel Hub platform (Sentinel Hub, 2024): the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Moisture Index (NDMI). The band data were downloaded on several dates (16/6, 26/6, 11/7, 16/7, 10/8, 20/8, 04/9, 09/9, 29/9, 14/10 in 2023, and 01/5, 15/6, 25/6, 10/7 in 2024) (*Figure 2 a, b*). The data and the images were downloaded to reflect the changes in vegetation and soil moisture dynamics across the maize vegetation season. The mapping and data extraction for both

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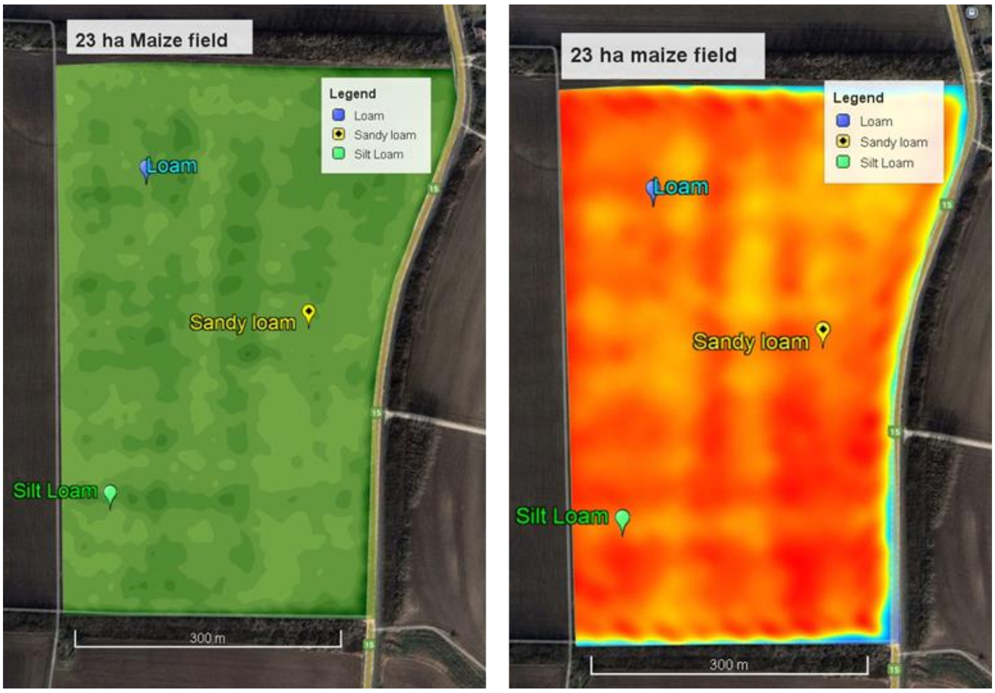
indices (NDVI and NDMI) were done using QGIS (version 3.36.2) and the NDVI and NDMI values were calculated using the following equations (*Eq. 1* and *Eq. 2)* (Strashok et al., 2022):

$$NDVI = \frac{NIR-Red}{NIR+Red} \quad (1)$$

$$NDMI = \frac{Red\ edge4-SWIR\ 1}{Red\ edge4+SWIR\ 1} \quad (2)$$



2a *2b*

Figure 2a: NDVI index on October 14, 2023

Figure 2b: NDMI index on October 14, 2023

3.2 Gravimetric Technique for Soil Moisture Content Measurements

The samples were placed in pre-weighed containers, which were then weighed using a digital scale to record their initial weights. The samples were transported to the laboratory and oven-dried at 105°C for 24 hours. After drying, the samples were weighed again to obtain their post-drying weights. Finally, the empty weights of the soil moisture containers were measured (Shukla et al., 2014). Soil moisture content based on dry weight calculated using *Eq. 3*:

$$\boldsymbol{\theta} = \frac{Mw}{Md} \times 100 \quad (3)$$

Where: θ = Soil Moisture Content (%), Mw = Mass of water (g) = (Wet weight – Dry weight), Md = Mass of dry soil (g)

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3.3 Data Random Forest Regression (RFR)

To predict soil moisture content, a Random Forest Regression (RFR) model was applied. The dataset has been divided into two categories: predictors (temperature, humidity, precipitation, wind speed, and solar radiation) and target variables (soil moisture content). The data was divided into two sets: training and testing, with training taking in 80% and testing for 20%. The RFR model was trained using different hyperparameters: n_estimators, max_depth, min_samples_split, and min_samples_leaf, and grid search was applied to find the best combination that provided the higher model accuracy. Feature importance analyses have been done to emphasize the importance of each predictor in the prediction process.
Python (version 3.10.12) (Python Software Foundation, 2024) and Google Colab (Google Inc., USA) (Bisong, 2019) were used to run the model, and we used Pandas (McKinney, 2010), NumPy (Harris et al., 2020), Matplotlib (Hunter, 2007), and the Scikit-learn (Pedregosa et al., 2011) libraries.

3.4 Performance Evaluation Measures

Four indicators were calculated to quantify the performance of the different models.
Mean Squared Error (MSE): *Eq. 4* (Willmott et al., 1985)

$$MSE = {}^{1}\!/_{n} \sum_{t=1}^{n} (y_t - \hat{y}t)^2 \qquad (4)$$

Mean Absolute Error (MAE): *Eq. 5* (Willmott et al., 1985)

$$MSE = {}^{1}\!/_{n} \sum_{t=1}^{n} (y_t - \hat{y}t)^2 \qquad (5)$$

R-squared: *Eq. 6* (Wright, 1921)

$$R^2 = 1 - \frac{\sum_{t=1}^{n} (y_t - \hat{y}t)^2}{\sum_{t=1}^{n} (y_t - \bar{y})^2} \qquad (6)$$

4. RESULTS AND DISCUSSIONS

4.1 General Statistical Analysis

The statistical analysis provides an overview of the variability in soil moisture content and meteorological parameters (temperature, humidity, precipitation, wind speed, and solar radiation) across depths, as well as the NDVI and NDMI indices. SMC showed substantial variation across the five depths, especially at the deeper layers (40 to 80 cm) (*Figure 3*), with a mean SMC ranged from 12.61% to 16.19% and a standard deviation of 4.18%. The coefficient of variation (CV) was 22.20%, highlighting the moderate variability of SMC. The highest SMC was recorded at 20 cm depth (22.01%), while the lowest values were found at 60 cm and 80 cm depths with 5.49%.
This variability is essential for understanding the dynamic nature of soil moisture retention in loam soils under various meteorological conditions. The use of NDVI and NDMI provides insight into how vegetation health and moisture content relate to SMC, particularly in the topsoil (Saha et al., 2018; Wang et al., 2007).

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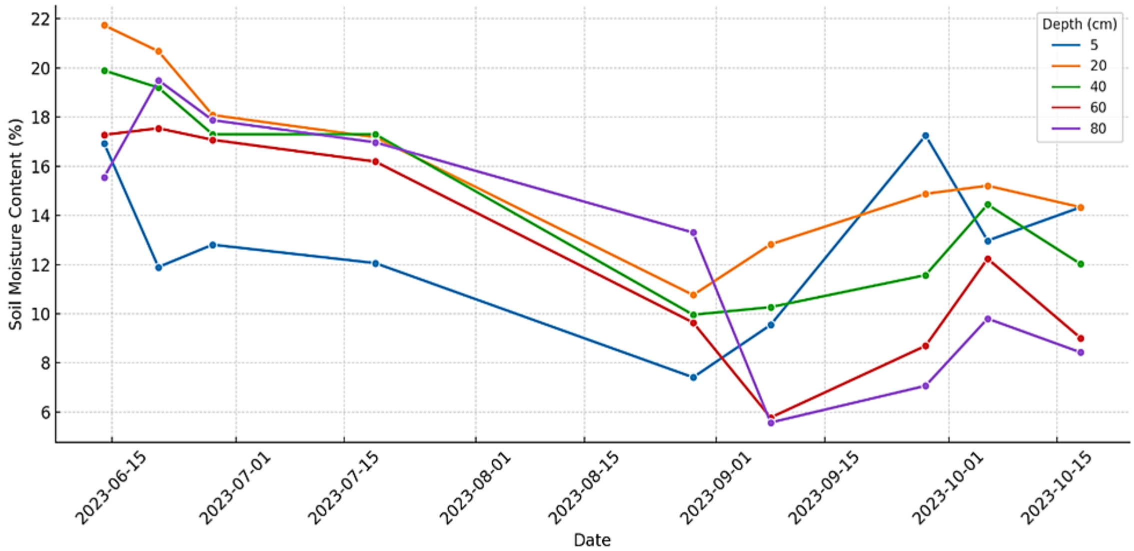

Figure 3: Soil moisture content variation across the depths during the maize vegetation season

4.2 Correlation Analysis by Depth

The study found significant correlations between soil moisture content and the studied features. The precipitation had the highest positive correlation with SMC across all the depths; at 5 cm depth, precipitation is the most significant factor impacting the SMC in the surface layer with a correlation value of 0.78 (*Figure 4*), temperature had a negative correlation with SMC due to its rule in evapotranspiration; vegetation indices, particularly NDVI and NDMI, exhibited a weak negative correlations (-0.17 and -0.06, respectively), indicating that they are poor predictors of surface SMC. At 20 and 40 cm depths also, precipitation had a positive significant correlation with SMC with a value of 0.61 and 0.47, respectively; solar radiation also had a moderate correlation with SMC at the two depths with a value of 0.31 and 0.44, respectively, showing its rule in evapotranspiration.

At 60 and 80 cm depth also, precipitation and solar radiation had a positive correlation with SMC; NDMI also had a moderate positive correlation at these deep layers, with a value of 0.03 at 60 cm and 0.15 at 80 cm, emphasizing its rule in deep layers water retention.

These depth-wise variations highlight that, while meteorological parameters such as precipitation and temperature influence SMC at shallow depths (Mohseni & Mokhtarzade, 2020), vegetation indices, particularly NDMI, consistently play an essential role in soil moisture retention at all depths. This shows that NDMI could play an important role in monitoring the SMC in large-scale area (Zhang & Zhou, 2016).

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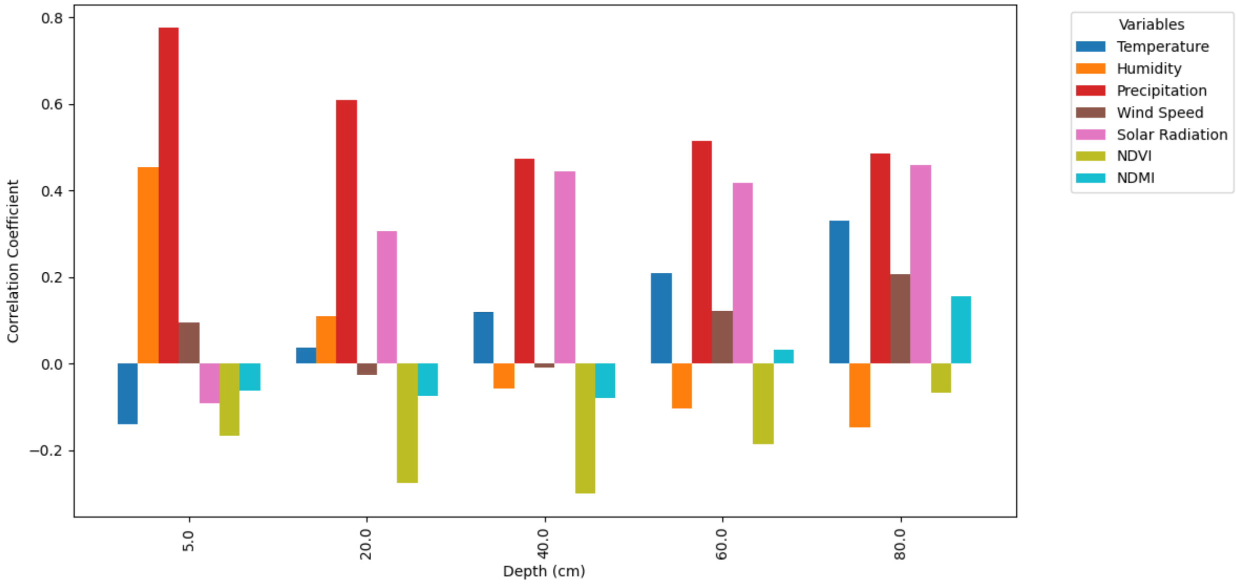

Figure 4: Correlations between soil moisture content and studied features across the depths

4.3 Random Forest Regression (RFR) Analysis

The RFR model was used to predict SMC at different depths utilizing meteorological data and vegetation indices. The results of performance metrics showed that the model accuracy varied across the different depths, highlighting the impact of studied features on SMC at the five depths.
At 5 cm depth, the model has R^2 of 0.86, MSE of 3.35, and MAE of 1.31 (*Figure 5*). the model accuracy showed that there were some challenges in capturing SMC variation at this depth due to the significant variability of SMC, which is affected by short-term variations in precipitation temperature, wind speed, and solar radiation. These constantly changes making accurate predictions is a challenge in this depth (Li et al., 2022). At 20 cm depth, the model's accuracy improved, achieving an R^2 of 0.90, MSE of 1.95, and MAE of 1.13.
The 40 cm depth is a transition zone where both meteorological features and other features such as soil texture and water dynamics impact moisture retention, making prediction more challenging with R^2 of 0.85, MSE of 3.01, and MAE of 1.33. At 60 cm and 80 cm depths, the model captured SMC variation with the highest accuracy, achieving R^2 values of 0.91 and 0.94, respectively
The model's consistent performance at all depths highlighted its capacity to capture meteorological and vegetation indices variations in soil moisture (Ning et al., 2023; Teshome et al., 2023). The model performed the best at deeper depths of 60 and 80 cm due to the stability of SMC at these depths and the influence of other factors on SMC variation than the environmental features. In contrast, the model performance at the shallower depths of 5 to 40 cm was less accurate regarding the rapid environmental features variation (Du et al., 2021).

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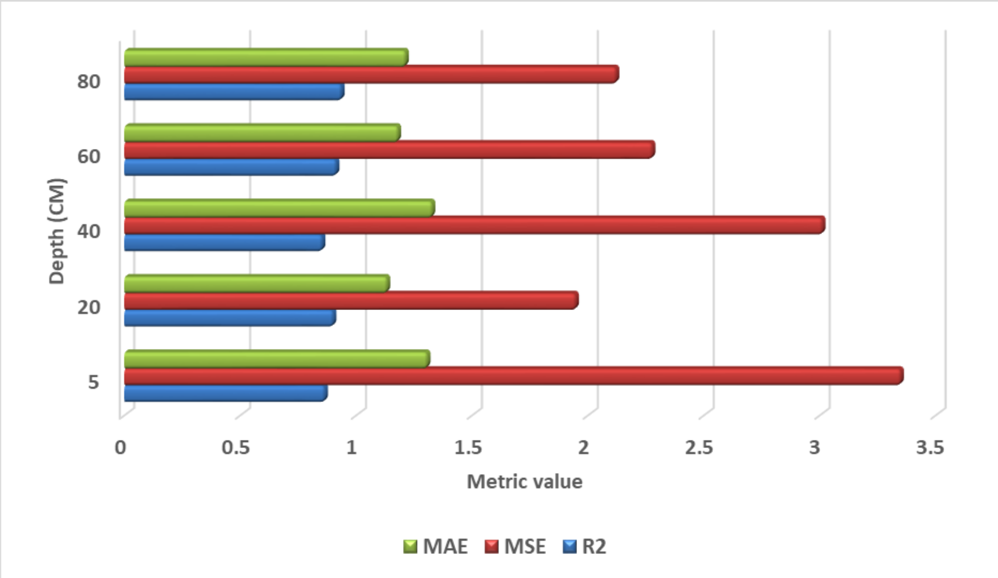

Figure 5: Performance metrics values of the RFR across he five depths

4.4 Feature importance analysis

The analysis showed that precipitation was the most influencing factor in SMC prediction across all the depths, particularly at 5 cm depth, where it contributed to 62.4 % of the prediction, followed by humidity, solar radiation and NDMI (*Figure 6*). Precipitation is the key factor for predicting SMC in the surface depths due to its direct effect on soil moisture level in the topsoil. Humidity was the second most important feature, especially at 20 cm depth, where it contributed to 35.4 % of SMC prediction. NDMI had a crucial role in SMC prediction across all depths, despite the importance of meteorological features. The results showed that vegetation indices, particularly NDMI, at 5 cm depth contributed to 6.1 % of SMC prediction, the impact decreased at 20 and 40 cm depths. NDMI got a higher impact on SMC prediction at deeper depths (60 and 80 cm), achieving 8.3 % at 80 cm depth.

These results showed that precipitation and humidity are the most significant features in SMC prediction, especially at the shallower depths where surface water dynamics influence the SMC variations (Li et al., 2022). NDMI was consistently a significant feature at all depths, highlighting its potential as a key factor for soil moisture prediction models (Ahmed et al., 2021). This is especially important in agricultural practices, where understanding the impact of vegetation on soil moisture retention may assist in optimizing irrigation scheduling and water resource management (Fu et al., 2023).

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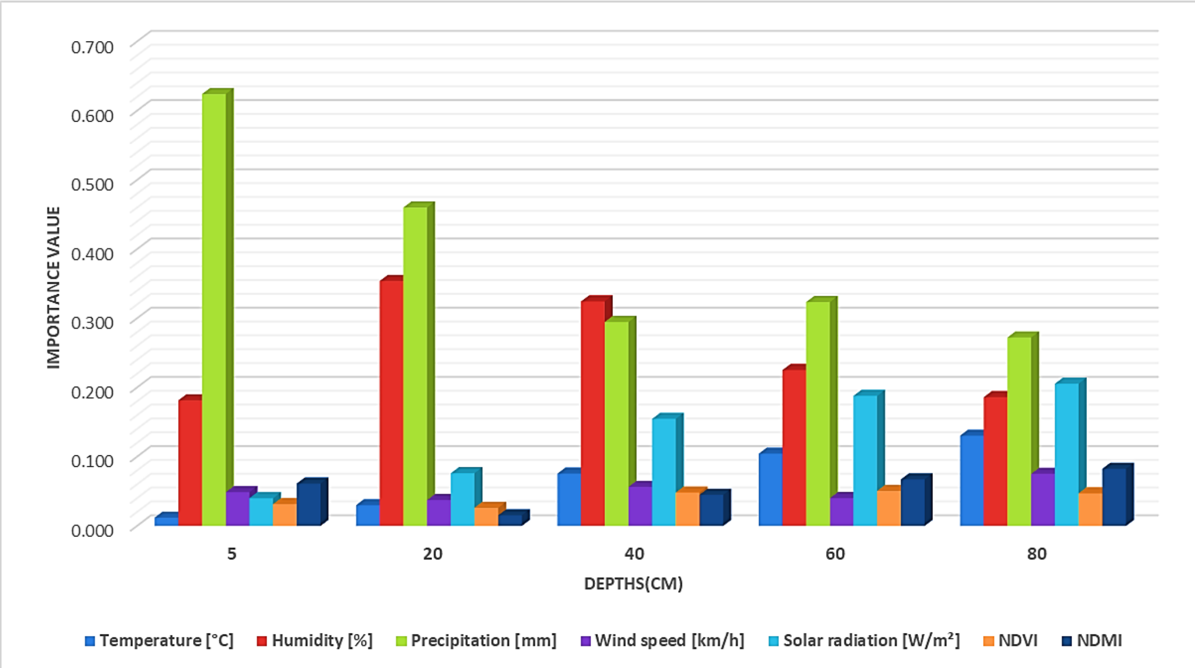

Figure 6: Features importance by depths for RFR

5. CONCLUSION

The research highlights significant findings of SMC predictions using the RFR model in loam soil at five depths using meteorological data and vegetation indices. The analysis results showed that SMC varied across the five depths. The correlation results showed a strong positive correlation of SMC with precipitation and solar radiation, while NDMI showed a strong correlation with SMC, particularly in deeper depths. The RFR model performed well at all depths, achieving high accuracy, and it was effective in capturing surface soil moisture dynamics. In the deeper depths (40 to 80 cm) the prediction accuracy was higher due to the effect of other features on soil moisture dynamics than the meteorological features. Feature importance analysis highlighted that both meteorological variables and vegetation indices, especially precipitation, were the most important features in SMC prediction at all depths. NDMI played a consistently important role in moisture retention, particularly in deeper depths. These results highlighted the importance of integrating vegetation indices and meteorological data with ML models to enhance the SMC prediction accuracy, which will allow for practical implementation in optimizing irrigation systems and improve sustainable agricultural practices. Further research and model training should be conducted considering more features that could affect SMC, especially in the deeper layers, such as soil texture parameters or real-time satellite data, that will lead to better model optimization and accuracy.

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A talajnedvesség tartalom előrejelzése vályogtalajban RFR modellel

ÖSSZEFOGLALÁS

A talajnedvesség tartalom (soil moisture content, SMC) fontos tényező a mezőgazdasági termelékenység szempontjából, mivel hatással van a növények növekedésére, a vízfelhasználási hatékonyságra és a talaj egészségére. Az SMC előrejelzésére szolgáló hagyományos módszerek, különösen a mélyebb talajrétegek esetében, gyakran korlátozottak. Jelen kutatás célja a Random Forest Regression (RFR) gépi tanulási modell fejlesztése és validálása volt az SMC előrejelzésére vályogtalajban, öt különböző mélységben (5, 20, 40, 60 és 80 cm) meteorológiai adatok (hőmérséklet, páratartalom, csapadék, szélsebesség és globálsugárzás) és vegetációs indexek, mint a Normalizált Vegetációs Index (NDVI) és a Normalizált Nedvesség Index (NDMI) felhasználásával. Az adatokat a 2023-as kukorica vegetációs szezonban gyűjtöttük Mosonmagyaróváron. Az SMC eredmények átlagértékei 12,61% és 16,19% között változtak. A korrelációs elemzés alapján a csapadékmennyiség és az NDMI erős pozitív korrelációt mutattak az SMC-vel, különösen a sekélyebb rétegekben, r = 0,78 értéket elérve 5 cm mélységben, míg a sugárzási érték közepes korrelációt mutatott, különösen a mélyebb talajrétegek esetében. Az RFR modell minden mélységnél jól teljesített, 5 cm mélységnél R^2 = 0,86 értéket ért el, míg a mélyebb rétegeknél a modell pontossága nőtt, 60 és 80 cm mélységben R^2 = 0,91 és 0,94 eredményeket realizálva. Az elemzésbe vont változók fontossági sorrendje szerint a legjelentősebb faktor a csapadék, a páratartalom és az NDMI voltak, utóbbi tényező fontos szerepet játszik a mélyebb rétegek nedvességmegőrzésében és a modellezésben. Ezek az eredmények hangsúlyozzák a mesterséges intelligencia, valamint a gépi tanulási algoritmusok alkalmazásának lehetőségeit az öntözési technológiák optimalizálásában és a vízgazdálkodás fejlesztésében.

Kulcsszavak: talajnedvesség tartalom, RFR, vályogtalaj, NDVI, NDMI, jellemzők fontossága

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