# Enhancing Agricultural Sustainability using AI-Driven Soil Moisture Modeling: A Soil-Type and Depth Approach with SHAP Interpretability

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**ABSTRACT**

The accurate prediction of soil moisture content (SMC) is important for optimizing irrigation, reducing water wastages and enhancing sustainability in agriculture. This study developed a Random Forest Regression model for soil-depth-specific prediction of SMC during two vegetation seasons. The model was applied to two soil types (loam and silt loam) at five depths with two different scenarios based on the used inputs: the first used only vegetation indices and the second integrated meteorological data with the vegetation indices. The results showed a significant rise in model's accuracy in the second scenario in both soil types at all depths, highlighting the importance of integrating meteorological features. In loam soil, $R^2$ increased from 0.65, 0.61, and 0.82, in the first scenario, to 0.94, 0.83 and 0.87, in second scenario, at 5, 20 and 40 cm depth, respectively. Similarly in silt loam, at 5, 20 and 40 cm depths the $R^2$ in the second scenario improved to get an $R^2$ of 0.97, 0.96 and 0.94, respectively, compared with an $R^2$ of 0.88, 0.94 and 0.82 in the first scenario at same depths, respectively. SHAP (SHapley Additive ExPlanations) research revealed that the most influential features on SMC prediction were precipitation, humidity, Normalized Difference Vegetation Index (NDVI) in loam soil, and solar radiation and NDVI in silt loam. These results emphasized that integrated meteorological data increases the model's performance in SMC prediction, and the importance of SHAP explainability for enhancing model interpretability and support real-time irrigation decision making. This research allows for better water resource management and enhances sustainability.

*Keywords: soil moisture content prediction, Random Forest Regression (RFR), IoT sensors, soil-depth specific modelling, irrigation strategies*

## 1. INTRODUCTION

One of the most important parameters determining agricultural and hydrological cycles is soil moisture content (SMC), providing important information regarding the available water for crops (Luo et al., 2019), transpiration, and evaporation (Ågren et al., 2021). A thorough understanding of the spatio-temporal patterns of SMC is crucial for managing water resources in hydrological systems, helping to reduce the effects of agricultural drought (Tarolli & Zhao, 2023), addressing water scarcity, and improving crop production. (Bibek Acharya, 2025). To ensure long-term production, recent advancements, such as artificial intelligence (AI) and the Internet of Things (IoT) and their applications, need to be utilized in agriculture. Additionally, by providing essential data for informed decision-making, real-time monitoring of IoT sensors could increase the effectiveness of agricultural operations (Alahmad et al., 2025a).

Unlike prior studies, which focus on single-layer or generalized SMC prediction, this study introduces depth-specific RFR modeling with SHAP-based interpretation across two soil types, advancing transparency in prediction. The objectives of this research are to develop depth- and soil-specific Random Forest Regression (RFR) models for predicting SMC in loam and silt loam soils at five depths (5-80 cm); to evaluate model performance in two input scenarios using different predictors combinations; and to identify the main factors influencing SMC prediction using SHAP-based feature importance analysis. The findings will support farmers for better irrigation management, demonstrating how specific model outputs could reduce water waste by aligning irrigation timing/depth with real-time soil moisture dynamics, which will enhance agricultural sustainability.

## 2. LITERATURE REVIEW

By allowing for real-time data, IoT sensors address the limitations of conventional soil moisture measuring methods, for instance their time consuming and lack of real-time monitoring (Songara & Patel, 2022). Additionally, by capturing the health and moisture content of vegetation, vegetation indices such as NDMI Normalized Difference Moisture Index (NDMI) and Normalized Difference Vegetation Index (NDVI) have become effective tools for indirectly assessing soil moisture (Alahmad et al., 2025b; Saha et al., 2019). Accurate prediction of SMC is essential to improve irrigation management and optimize crop production (Zhu et al., 2024). At the same time, the traditional methods fail to capture the multivariate and nonlinear relations between factors that affect SMC (Zheng et al., 2024). In contrast, Machine Learning (ML) algorithms could handle these complex interactions providing a high potential in high accurate SMC predicting (Li et al., 2024). Recently, the integration of artificial intelligence with prediction models enhances model performance and accuracy (Nyéki et al., 2021).

However, recent research has the limitation of soil-depth-specific modeling, which considers vital factors due to their high impact on SMC. In contrast to soil with high sand content, the soils with higher clay and silt content, which have higher water holding capacity and this leads to higher SMC (Celik et al., 2022). Furthermore, SMC is significantly impacted by soil depth. To address these limitations, researchers have been working to improve prediction accuracy and utilize ML models that could consider SMC variation in both surface and subsurface soil. By combining several meteorological features and vegetation indices, machine learning models, in particular, those that use Random Forest Regression (RFR) have demonstrated potential in predicting SMC (Alahmad et al., 2024; Ning et al., 2023). Chen et al. (2025) in in their research predicted 1-2-day hourly soil water content (SWC) at 10 cm and 20 cm depths in Taichung, Taiwan, using Random Forest (RF) model


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utilizing precipitation data. With cumulative precipitation of (6-8 days), the model achieved low number of errors with MAE of 0.6 % at 10 cm, and 1.0 % at 20 cm depth, along with a high accuracy with $R^2$ of 0.5 and 0.9, MAPE 5.1-25.2 %, and RMSE 2.0-2.4 % at 10 and 20 cm depth, respectively. RF performed well, offering guidelines for SMC prediction and irrigation management.

## 3. MATERIALS AND METHODS

### 3.1 Experiment location and data collection

A field study was conducted in a 23 ha rainfed maize field in Mosonmagyaróvár, Hungary (47°54'11.8"N 17°15'08.9"E), with several soil types according to USDA soil taxonomy classification (USDA. ND., 2020). Two soil types of loam, and silt loam were selected for this research (*Figure 1A*). The region has moderate precipitation and temperate climate, characteristic of Central Europe. The terrain has a slight slope of 5 % with elevation varying between 133 and 138 m, soil pH ranged between 7.12-7.8 (Nyéki et al., 2021). Soil samples were collected from six locations around the sensor station (three per soil type) across two growing seasons (2023-2024) on 23 dates. At each site, samples were taken at five depths (5, 20, 40, 60, 80 cm), yielding 30 samples per date. Depths of 5-40 cm corresponded to maize root zones (Gao et al., 2014), while 60-80 cm represented deep layers. Soil samples were sealed and moved to the laboratory, and SMC was calculated using the gravimetric method (Dirksen, 1999). An IoT-based meteorological sensor was utilized to collect meteorological data (*Figure 1B*). The LoRaWAN communication protocol was used at intervals of 10 to 15 minutes. For model training, meteorological characteristics including temperature (°C), precipitation (mm), wind speed (km/h), humidity (%), and solar radiation (W/m$^2$) were collected. The data was allocated to each sample point and represents the field average. Vegetation indices were downloaded using Sentinel-2A satellite image from Sentinel hub platform (Sentinel Hub, 2024) provide multispectral data in 13 bands at spatial resolutions of 10, 20, and 60 m. The data utilized in this study has a spatial resolution of 10 m. The NDVI and the NDMI were derived utilizing the Near-Infrared (NIR), Red, Red Edge 4, and Shortwave Infrared (SWIR1) bands (Drusch et al., 2012). The data collection dates represent most of maize growth stages in the two seasons with different ground coverage percentages. The mapping and data extraction for both NDVIs was done by QGIS (version 3.36.2) (QGIS, 2024).

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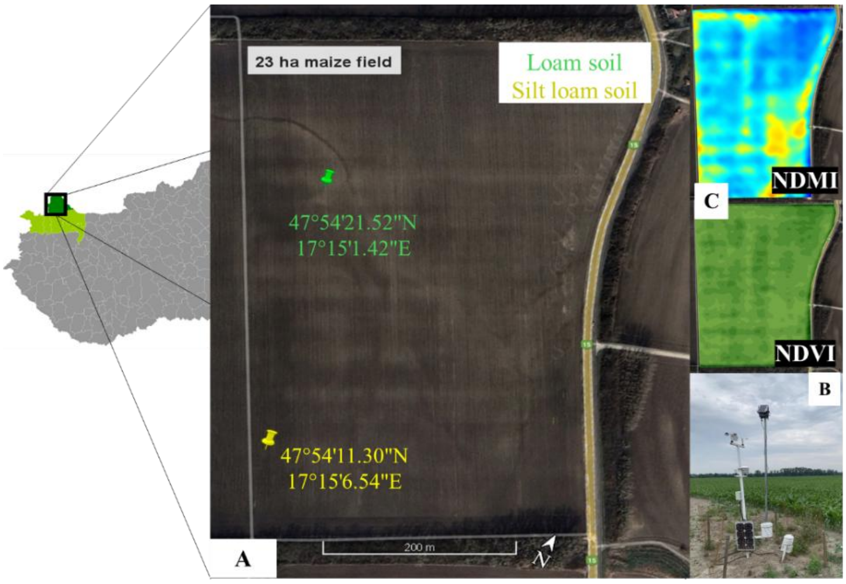


*Figure 1: (A) Maize field with GPS location of soil sampling and soil types, (B) NDVI and NDMI indices from sentinel 2A, (C) IoT-based sensor station for meteorological data*

### 3.2 Data preprocessing, feature engineering and model development

The dataset was preprocessed using Python (v3.10.12) (Python Software Foundation, 2024). Data cleaning, imputation, and synchronization were performed to align meteorological, remote sensing and soil measurements. Soil type and depth were used to subset the data for soil- and depth-specific modeling. Two feature input scenarios were tested: Scenario 1 which used NDVI and NDMI; Scenario 2 which used NDVI, NDMI and meteorological features. Features and target variables (SMC %) were scaled using MinMaxScaler to normalize data distributions. The target variable was reshaped before scaling and inverse-transformed after prediction for interpretability. Since its ability to capture the nonlinear relationships between the features used in this research, the RFR model was used to predict SMC. To improve soil-depth-specific prediction, the model was trained independently for each soil type and each depth. GridSearchCV was used to optimize the models' hyperparameters, eliminate overfitting, and improve robustness (n_estimators': [50, 100, 200], 'max_depth': [None, 10, 20, 30], 'min_samples_split': [2, 5, 10]). A three-fold cross validation was also used to validate performance. 20 % of the dataset was used for testing and the remaining 80 % was used for training. To interpret model predictions and understand feature contributions, SHAP values were calculated using the TreeExplainer method. Mean absolute SHAP values were computed per feature, soil type, depth, and scenario. Python was used in modeling and visualization. For evaluating the models' performance, three metrics were calculated using the hold-out test set and cross-validation.

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{{}^{1}/_{n}\sum_{t=1}^{n}(y_t - \hat{y}t)^2} \qquad \text{(1) (Willmott et al., 1985)}$$

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Mean Absolute Error (MAE):

$$MAE = {}^{1}/_{n} \sum_{t=1}^{n} |y_t - \hat{y}t| \qquad \textit{(2) (Willmott et al., 1985)}$$

Coefficient of Determination ($R^2$):

$$R^2 = 1 - \frac{\sum_{t=1}^{n} (y_t - \hat{y}t)^2}{\sum_{t=1}^{n} (y_t - \bar{y})^2} \qquad \textit{(3) (Wright, 1921)}$$

Where, $n$ is the total number of observations in the dataset, $t$ is the time index or sequence index of an observation, $y_t$ is the observed value at time t, $\hat{y}t$ is the predicted value by the model at time t, and $\bar{y}$ is the mean of observed values.

## 4. RESULTS AND DISCUSSIONS

### 4.1 Model performance results

The results demonstrated that RFR performed well in predicting SMC in both soil types. The model performance was evaluated using test data and validated by using 3-fold cross-validation. Model performance in the second scenario was the best over both soil types emphasizing the importance of integrating meteorological factors in SMC along with vegetation indices (*Table 1*).

*Table 1: Performance metrics results for the RFR model across soil types, depths and input scenarios*

| Soil type | Depth (cm) | Input Scenario | RMSE | MAE | $R^2$ |
|---|---|---|---|---|---|
| **Loam** | 5 | Vegetation indices | 2.45 | 1.75 | 0.65 |
| **Loam** | 5 | Meteorological and vegetation indices | 0.94 | 0.63 | 0.95 |
| **Loam** | 20 | Vegetation indices | 1.97 | 1.48 | 0.61 |
| **Loam** | 20 | Meteorological and vegetation indices | 1.30 | 0.95 | 0.83 |
| **Loam** | 40 | Vegetation indices | 1.40 | 1.07 | 0.82 |
| **Loam** | 40 | Meteorological and vegetation indices | 1.20 | 0.80 | 0.87 |
| **Loam** | 60 | Vegetation indices | 1.69 | 1.20 | 0.81 |
| **Loam** | 60 | Meteorological and vegetation indices | 1.40 | 1.06 | 0.87 |
| **Loam** | 80 | Vegetation indices | 1.69 | 1.42 | 0.85 |
| **Loam** | 80 | Meteorological and vegetation indices | 1.21 | 0.98 | 0.92 |
| **Silt loam** | 5 | Vegetation indices | 1.40 | 1.07 | 0.88 |
| **Silt loam** | 5 | Meteorological and vegetation indices | 0.70 | 0.52 | 0.97 |
| **Silt loam** | 20 | Vegetation indices | 0.94 | 0.77 | 0.94 |
| **Silt loam** | 20 | Meteorological and vegetation indices | 0.74 | 0.58 | 0.96 |
| **Silt loam** | 40 | Vegetation indices | 1.97 | 1.47 | 0.82 |
| **Silt loam** | 40 | Meteorological and vegetation indices | 1.12 | 0.85 | 0.94 |
| **Silt loam** | 60 | Vegetation indices | 1.95 | 1.53 | 0.91 |
| **Silt loam** | 60 | Meteorological and vegetation indices | 1.72 | 1.41 | 0.93 |
| **Silt loam** | 80 | Vegetation indices | 2.37 | 1.93 | 0.88 |
| **Silt loam** | 80 | Meteorological and vegetation indices | 2.10 | 1.66 | 0.91 |


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The model performance in loam soil had a higher accuracy in the second scenario, achieving an $R^2$ of 0.95 and RMSE of 0.94 % at 5 cm depth compared with an $R^2$ of 0.65 and RMSE of 2.45 % in the first scenario (*Figure 2*).

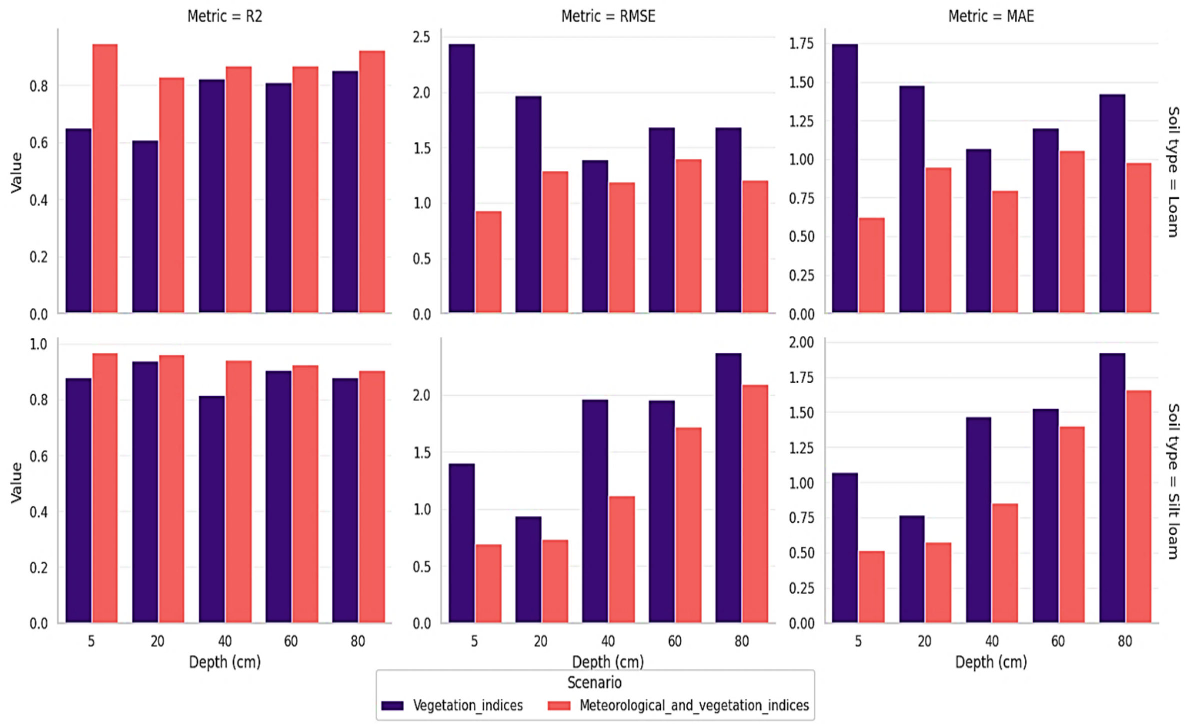


*Figure 2: Evaluation metrics values ($R^2$, MSE, RMSE, MAE, NSE)*
*in both soil types (loam and silt loam) at 5 depths in two scenarios with an RFR model*

Integrating meteorological data significantly enhanced prediction accuracy, especially in loam soil in which there is a relatively balanced texture that actively responds to environmental changes (Sihag et al., 2019). Vegetation indices (NDVI, NDMI) alone were not able to capture all the variability in the SMC (Bramley et al., 2024). Integrating meteorological data increased accuracy in the upper layers of 5 and 20 cm, where $R^2$ increased from 0.61 to 0.83 and RMSE from 1.97 % to reach 1.30 % after integrating the meteorological data at a 20 cm depth. In contrast, in the deeper layers (40, 60, and 80 cm) the model had a slight improvement in predicting SMC, regarding the influence of other factors in SMC variation. The model had an $R^2$ of 0.82, 0.81 and 0.85 with RMSE 1.4 %, 1.69 % and 1.69 % at 40, 60 and 80 cm depths, respectively, in the first scenario and improved to get an $R^2$ value of 0.87, 0.87 and 0.92 and RMSE of 1.20, 1.40 and 1.21 at the same depths, respectively. In silt loam soil, the RFR model showed a consistently strong performance particularly in the second scenario, due to the soil's higher water retention and balance structure. The model had the highest accuracy in the upper soil layers of 5 and 20 cm, achieving an $R^2$ of 0.97, 0.96 and RMSE of 0.7 %, 0.74 %, respectively, compared with an $R^2$ of 0.88, 0.94 and RMSE of 1.4 %, 0.94 %, respectively, in the first scenario. The utilization of meteorological data, which significantly impacts the dynamics of soil moisture content in these layers, is the reason for this model improvement. In deeper layers (40, 60, and 80 cm) the model also had a slightly higher accuracy, regarding the high-water retention and less SMC variability in silt loam. The model achieved an $R^2$ value of 0.82, 0.91 and 0.88 with RMSE 1.97 %, 1.95 % and 2.37 % at 40, 60 and 80 cm depths, respectively, in the first scenario, and

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improved to get an $R^2$ value of 0.94, 0.93 and 0.91 with RMSE 1.12 %, 1.72 % and 2.10 % at the same depths, respectively.

### 4.2 SHAP analysis results

For better understanding the influence of meteorological features and soil depth on SMC prediction, SHAP (SHapley Additive exPlanations) analysis was conducted across all models, soil types, depths, and feature scenarios. This explainable AI approach quantifies the average marginal contribution of each feature to the prediction, enabling the interpretation of complex nonlinear models like Random Forest Regressor.

In loam soil, SHAP analysis highlighted significant variability in feature importance between the two scenarios and across depths. In the first scenario, NDVI consistently ranked higher than NDMI, especially at shallow depths of 5 and 20 cm with values of 1.12, and 1.14, respectively, compared with NDMI that had values of 1.11 in both depths (*Figure 3*). This suggests that the NDVI is more responsive to moisture variations near the surface, likely due to its sensitivity to canopy water content and its stronger correlation with soil water compared to NDVI. In the second scenario, when meteorological features were introduced, precipitation and humidity emerged as the dominant features in most depths, with precipitation values of 0.12, 0.08 and 0.05 at 5, 20 and 80 cm and humidity with values of 0.05, 0.05 and 0.04 at same depths, respectively (*Figure 4*). This aligns with the physical behavior of loam soils, which have moderate water-holding capacity and are highly responsive to recent precipitation and atmospheric moisture. At deeper depths, depth itself and precipitation gained importance, highlighting the role of infiltration dynamics and reduced influence of surface-level vegetation.


*Figure 3: SHAP analysis results of the RFR model in loam and silt loam soils in the first scenario at five depths*

Silt loam soil, known for its superior water retention and balanced texture, showed a different pattern of feature importance especially in the second scenario, where solar radiation was the most influential feature across nearly all depths, with the highest SHAP values of 0.1 and 0.08 at 60 and


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80 cm depths, respectively. This dominance reflects the strong control of evapotranspiration processes in this soil type, where retained moisture is highly influenced by energy input at the surface. In the upper layers precipitation had relatively high impact at all depths with an average impact value of 0.05 at all depths. NDVI also showed high impact at all depths especially at 20, 60 and 80 cm with values of 0.12, 0.07 and 0.06, respectively. At shallower depths of 5 and 20 cm, humidity with precipitation were the most influential factors. Humidity had a higher impact at 5 cm depth with a value of 0.08. In the first scenario, NDVI also had the highest impact at most depths with values of 0.20, 0.19 and 0.18 at 60, 80 and 20 cm, respectively.

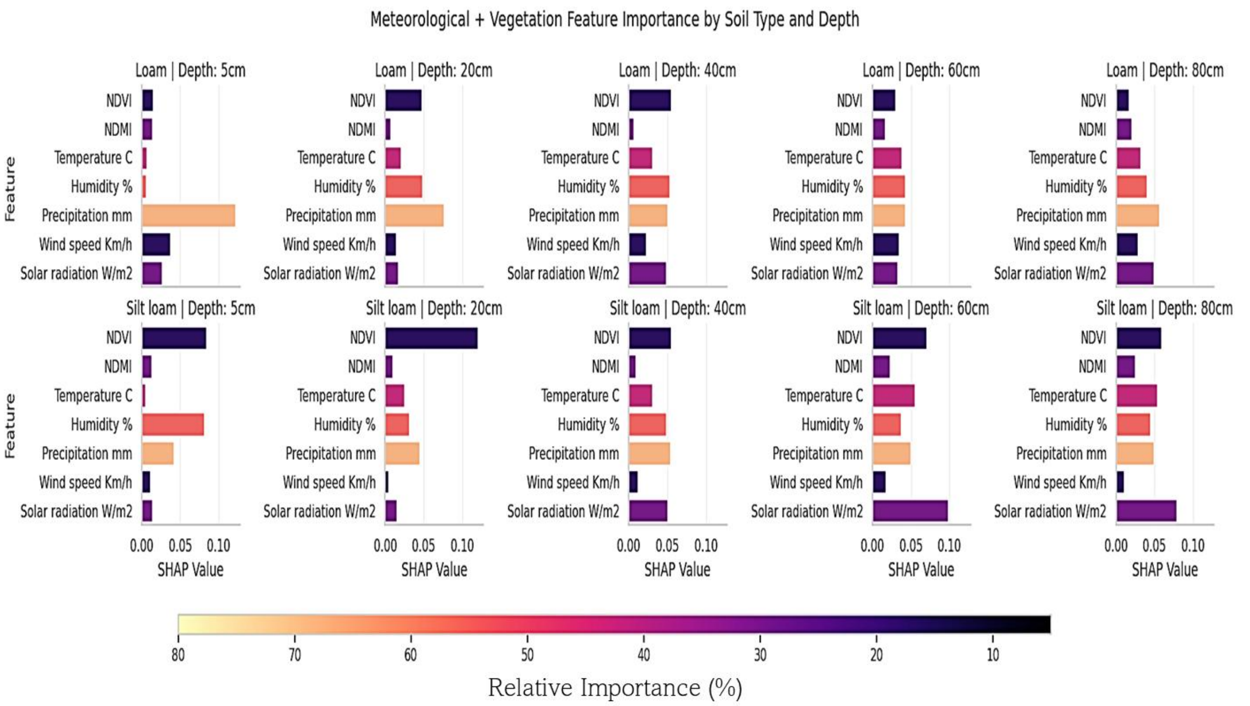


*Figure 4: SHAP analysis results of the RFR model in loam and silt loam soils in the second scenario at five depths*

These results highlighted the ability of the RFR model to capture nonlinear relations in SMC dynamics across studied soil types and depths. Also, the significant rise in model accuracy in the second scenario showed that vegetation indices alone are not enough to capture all variations in SMC (Guo et al., 2024). SHAP analysis revealed soil-specific drivers: precipitation and humidity dominated in loam soil, while solar radiation and NDVI were key in silt loam, especially below 40 cm. This reflects their distinct water behaviors. The utilization of SHAP analysis validated the choice of input features and enhanced the model transparency (Hussein et al., 2024). These findings underscore the necessity of soil- and depth-specific modeling, particularly for optimizing irrigation strategies in surface layers (5-40 cm), where meteorological factors dominate. The results successfully addressed objectives by establishing RFR's capability to accurately predict SMC (Alahmad et al., 2024), and providing actionable insights for reducing water waste through tailored irrigation scheduling. While deeper layers (60-80 cm) showed reduced meteorological dependency, future research should incorporate soil hydraulic properties and broader spatial validation to

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enhance generalizability. This research advances precision agriculture by linking AI-driven predictions with sustainable water management practices.

## 5. CONCLUSION

This study showed that soil- and depth-specific RFR models, incorporating meteorological data with vegetation indices (NDVI/NDMI), significantly improve SMC prediction accuracy across loam and silt loam soils at all studied depths of 5 to 80 cm. Integrating meteorological inputs (Scenario 2) significantly improved model performance in all depths, achieving $R^2$ values of 0.95, 0.92 (loam) and 0.97, 0.91 (silt loam) at 5 and 80 cm depths, respectively, compared to vegetation indices alone (Scenario 1). According to their different hydrological systems, SHAP analysis highlighted soil-dependent drivers in which precipitation and humidity were important in dynamic loam soils and solar radiation and NDVI were crucial in water-retentive silt loam. While upper soil layers (5 to 40 cm) showed higher sensitivity to meteorological features, the deeper layers (60-80 cm) were influenced by other factors, such as soil properties and other soil hydrological factors. These findings highlight the importance of tailored feature selection to optimize prediction accuracy and align irrigation strategies with real-time soil moisture dynamics. By integrating AI-driven insights into precision water management, this framework advances agricultural sustainability through reduced water wastage. Future studies should integrate soil hydraulic properties for deeper layers and expand spatial validation to enhance model generalizability across diverse agronomic systems.

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# A mezőgazdasági fenntarthatóság javítása MI-alapú talajnedvesség-modellezéssel: talajtípusra és -mélységre vonatkozó elemzés SHAP-modellel

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**ÖSSZEFOGLALÁS**

A talajnedvesség-tartalom (SMC) pontos előrejelzése elengedhetetlen az öntözés- és a vízfelhasználás optimalizálása, összességében a mezőgazdaság fenntarthatóságának javítása érdekében. A tanulmányban egy Random Forest regressziós modellt alkalmaztak a talajnedvesség-tartalom talajmélység-specifikus előrejelzésére két vegetációs időszak alatt (2023, 2024). A modellt két fizikai talajtípuson (vályog és iszapos vályog) öt mélységben tesztelték. Az elemzésben két forgatókönyvet alkalmaztak, melyben az első kizárólag vegetációs indexeket, a második pedig a vegetációs indexeket mellett meteorológiai adatokat is integrált. Az eredmények mindkét talajtípuson és mélységnél szignifikáns különbséget mutattak a második forgatókönyvben, bizonyítva ezzel a meteorológiai adatok integrálásának fontosságát. Vályog talaj esetén az $R^2$ érték az 5, 20 és 40 cm-es mélységeken az első forgatókönyvben 0,65; 0,61 és 0,82-ről; a második forgatókönyvben 0,94; 0,83 és 0,87-re nőtt. Hasonlóképpen, az iszapos vályog talajnál ugyanezen mélységek (5, 20, 40 cm) esetén az $R^2$ a második forgatókönyvben 0,97; 0,96 és 0,94 értékre javult, szemben az első forgatókönyvben prognosztizált 0,88; 0,94 és 0,82 adatokkal. A SHAP (SHapley Additive exPlanations) elemzés feltárta, hogy a talajnedvesség előrejelzésére legnagyobb hatással bíró jellemzők a vályog talajnál a csapadék, a páratartalom és az NDVI, míg az iszapos vályognál a napsugárzás és az Normalizált Differenciált Vegetációs Index (NDVI) voltak. Ezek az eredmények hangsúlyozzák, hogy a meteorológiai adatok integrálása jelentősen javítja a modell teljesítményét a talajnedvesség előrejelzésében.

*Kulcsszavak: talajnedvesség-tartalom előrejelzése, random forest regresszió, IoT-érzékelők, talajmélység-specifikus modellezés, öntözési stratégiák*

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