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ASSESSING THE ROLE OF RAINFALL AND ANTECEDENT SOIL MOISTURE CONDITIONS ON SOIL MOISTURE INCREASE

ANALIZA VLOGE PADAVIN IN PREDHODNE NAMOČENOSTI ZEMLJINE NA NARAŠČANJE VLAŽNOSTI TAL

Elisa Vialette[1], Katarina Zabret[1]

[1] Faculty of Civil and Geodetic Engineering, University of Ljubljana, Jamova 2, Ljubljana

Abstract

Soil moisture plays an important role in regulating natural processes, including water movement in the hydrological cycle. One of the main factors affecting soil moisture wetting and drying patterns is precipitation, but the response of soil moisture depends not only on its characteristics but also on other indicators such as soil depth, soil water-retention properties, land cover, and land use. These indicators determine the dynamics of the increase in soil moisture, which does not usually follow the dynamics of measured precipitation. In order to evaluate the rate of soil moisture response to rainfall input, as well as the influence of rainfall indicators and previous soil moisture conditions on the increase, we applied a decision tree model and a random forest model. Data collected during two years of measurements at three different depths in a grassy area of a small park in Ljubljana were considered. The increase in soil moisture at depths of 16 cm and 51 cm is mainly determined by the maximum 20-minute intensity recorded in the period of 6 hours before the increase. In deeper layers (74 cm), however, the response is determined by the previous moisture conditions at least 24 hours earlier or by precipitation in the previous 7 days.

Keywords: soil moisture, precipitation, antecedent conditions, decision trees, random forests.

Izvleček

Vlažnost tal ima pomembno vlogo pri uravnavanju naravnih procesov, vključno z gibanjem vode v hidrološkem krogu. Eden od glavnih dejavnikov, ki vplivajo na vsebnost vode v tleh, so padavine, odziv vlage v tleh pa je poleg lastnosti padavin odvisen še od drugih kazalnikov, kot so globina, vodozadrževalne lastnosti tal, tip dal, pokrovnost in raba tal. Ti kazalniki določajo, s kakšno dinamiko bo prišlo do dviga vsebnosti vode v tleh, ki običajno ne sledi dinamiki merjenih padavin. Z namenom ocene hitrosti odziva vlažnosti tal na padavine ter analizo vpliva kazalnikov padavin in predhodne namočenosti tal na povečanje vsebnosti vode v tleh smo uporabili model odločitvenih dreves in model naključnega gozda. Upoštevali smo podatke, zbrane v dveh letih meritev na treh različnih globinah na travnati površini majhnega parka v Ljubljani. Naraščanje

[1] Stik / *Correspondence*: katarina.zabret@fgg.uni-lj.si

vsebnosti vode v tleh na globinah 16 cm in 51 cm je pogojeno predvsem z maksimalno 20-minutno intenziteto, zabeleženo v obdobju 6 ur pred pričetkom naraščanja vrednosti. V globljih plasteh (74 cm) pa je odziv pogojen s stanjem predhodne vlažnosti vsaj 24 ur prej oziroma s padavinami v preteklih 7 dneh.

Ključne besede: vsebnost vode v tleh, padavine, predhodne razmere, odločitvena drevesa, naključni gozd.

1. Introduction

Soil moisture is an important variable in hydrological processes, influencing the partitioning of precipitation into infiltration, surface runoff, and evapotranspiration. It plays a crucial role in maintaining terrestrial ecosystems, supporting plants and regulating natural processes (Peng et al., 2023). Moist soils promote plant growth by providing the necessary water for photosynthesis and nutrient transport, while also contributing to temperature regulation and erosion reduction (Haiyan and Haimei, 2021).

Rainfall amount is the most direct and immediate factor in soil moisture wetting patterns (Haiyan and Haimei, 2021). Rainfall events increase soil moisture by introducing water into the soil, but the extent and rate of this increase depend on multiple factors, including rainfall intensity, duration, and frequency. Furthermore, the wetting response of soil to rainfall depends on antecedent soil moisture, soil properties (e.g. texture, structure, organic content, and water-holding capacity), land use and cover, as well as topographic features (e.g. slopes and depressions) (Dong and Ochsner, 2018; Zhu et al., 2022).

Peng et al. (2023) investigated the driving mechanisms of soil moisture trends globally and observed that precipitation and vegetation in general have a greater influence on soil moisture wetting and drying trends than temperature does. Precipitation's role in moisture replenishment dominates in areas with relatively high soil moisture values. It was thus evaluated that, for Slovenia, where our study is located, the strongest correlation coefficient between influencing factors and soil moisture is precipitation (Peng et al., 2023). The impact of precipitation input for typical grassland in northern China was analyzed in detail by Haiyan and Haimei (2021), who reported that events below 7 mm are ineffective at increasing soil moisture values, while at least 29 mm of rainfall was needed to observe an increase at a typical root depth of 0–30 cm. The improvement of soil moisture was greatest one day after the rainfall event. In addition to rainfall, Zhu et al. (2022) observed combined drivers for relative soil moisture in China's agroecosystem areas, consisting of climate (temperature and precipitation) and management practices (fertilizer amount, NDVI as an indicator of plant cover, and annual grain output as an indicator of production intensity). For soils typical of Poland, Gruchot et al. (2022) conducted laboratory experiments showing that soil moisture content increases with depth and that the onset of overland flow depends not only on rainfall amount but also strongly on initial soil moisture content. Gimbel et al. (2016), who performed field experiments in forests across Germany, additionally concluded that drought history is more important than the actual antecedent soil moisture status as regards hydrophobicity and soil infiltration behavior. This also highlights the effect of a changing climate that may alter the response of soil moisture. For example, Nielsen et al. (2024) showed that surface soil moisture becomes more sensitive to a given precipitation input: relatively small precipitation deficits can trigger drying, whereas larger and more sustained surpluses are needed to restore wet conditions.

Monitoring and understanding increases in soil moisture following precipitation events is important for assessing water availability and its effect on ecosystems' health (Ochsner et al., 2013), for understanding agricultural productivity (Sušnik et al., 2010), and for understanding the triggers of flood (Marchi et al., 2010) or landslide generation (Whiteley et al., 2019). Soil moisture generally responds non-linearly to precipitation, as its increase is influenced by multiple factors and does not typically follow precipitation patterns directly (Ljutic et al., 2024). Despite considerable research on rainfall-soil moisture interactions, significant uncertainty remains regarding the depth-dependent response of soil moisture to individual precipitation events and the relative influence of event characteristics and antecedent conditions. Previous research in Slovenia has primarily focused on agricultural drought and water deficits in crops rather than on how water moves through the soil during rainy periods. Therefore, this study's main objective was to identify how rainfall intensity, antecedent precipitation, and prior soil moisture conditions at different depths influence the onset and magnitude of soil moisture increase.

2. Materials and methods

2.1 Study site and measurements

Data were collected in a small urban park in central Ljubljana, Slovenia (Figure 1), near the Department of Environmental Civil Engineering building (46.04° N, 14.49° E, 292 m ASL). The site has a sub-alpine climate with well-defined seasons. The long-term (1991–2021) yearly average rainfall amount is 1377 mm, ranging between 70 mm on average in January and 163 mm on average in September (ARSO, 2025). The air temperature is highest during the summer months, at 21.2 ºC on average, and the lowest during the winter months, on average equal to 1.8 ºC (ARSO, 2024).

The experimental site covers an area of 600 m² and is characterized by flat terrain. The western part of the site is covered by trees, whereas the eastern part is covered by regularly mowed grass. Detailed information on the plot and tree characteristics is provided by Radulović et al. (2023) and Zabret and Šraj (2018).

Following landscaping activities carried out after 1945, the wider area was levelled and raised using predominantly alluvial material with minor amounts of construction debris, resulting in the development of urban (anthropogenic) soils. According to the Slovenian soil classification system (Vrščaj et al., 2019), the upper soil layer is a humus-accumulative horizon (A), extending to depths of approximately 25–30 cm in the open area, 22 cm beneath the pine tree, and 33 cm beneath the birch tree. The underlying layers are classified as urban horizons (U), containing anthropogenic inclusions such as brick and concrete fragments. The soil is moderately alkaline, with pH values ranging from 7.85 to 8.50, and is classified as eutric, medium-heavy soil. Most soil horizons at all three monitoring locations are characterized as loam (L) or silt loam (SL).

Soil physical properties were determined in the laboratory using undisturbed soil samples collected with Kopecky cylinders at depths where sampling was feasible. In the upper soil layers, saturated volumetric water content (VWC) averaged 0.55 ± 0.01 m³/m³ in the open area and beneath the birch tree (5-10 cm depth), whereas a lower average value of 0.45 ± 0.003 m³/m³ was measured beneath the pine tree (10-15 cm depth). The corresponding dry bulk densities were 1.14, 1.26, and 1.32 g/cm³, while field capacity was 0.359, 0.324, and 0.347 m³/m³ in the open area, beneath the birch tree, and beneath the pine tree, respectively. Since soil bulk density is closely related to pore space and water movement, higher bulk density values generally indicate lower infiltration capacity.

Measurements of precipitation and volumetric water content (VWC) were taken in the open part of the plot, which is covered with grass (Figure 1). Gross precipitation (P) was measured on the clearing at the experimental site, approximately 10 m from the nearest tree, using a tipping bucket (0.2 mm/tip) rain gauge (Onset RG2-M) with an automatic data logger (Onset HOBO Event). Events with snow precipitation and the possibility of freezing were excluded from the analysis. Soil moisture values were measured using TEROS 10 soil moisture sensors (METER Group), calibrated for mineral soils, with a single sensor deployed at each of the three monitored depths (16, 51, and 74 cm). The time resolution of the data was 20 minutes. Accordingly, the precipitation data were also aggregated to 20-minute intervals.

The analysis includes data measured in years 2022 and 2023. Seasons were defined as follows: winter (December–January), spring (March–May), summer (June–August), and autumn (September–November). However, to calculate some indices that take into account the previous condition, data measured in December 2021 were also used.

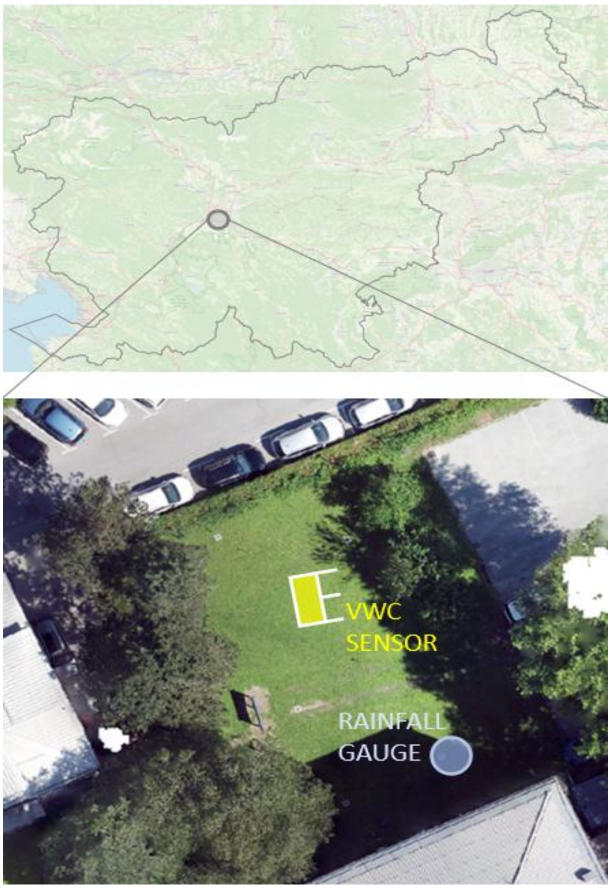

***Figure 1:** Study site.*

***Slika 1:** Raziskovalna ploskev.*

2.2 Influential indices

Different rainfall and soil moisture indices were calculated to determine the influence of antecedent hydrological conditions on the increase in soil moisture value and the degree of its dynamics (Table 1). In particular, the amount of precipitation over different time steps (24 h/48 h/5 days/7 days/10 days/20 days) before the change in VWC slope was considered. This corresponds to the sum of precipitation over these time steps. The second index used is the average relative VWC value (Zabret et al., 2023):

$$VWC_{rel} = \frac{VWC - VWC_{mean}}{VWC_{mean}} \quad (1)$$

The average relative VWC was calculated for different time steps (12 h/24 h/48 h/5 days/7 days/10 days) before the considered point at the time of the measurements. The last index used is the maximum precipitation intensity over 20 minutes for different time steps (2 h/6 h/12 h/24 h) before the observation.

***Table 1:** Indices considered in the analysis of the influence on the increase of soil moisture value.*

***Preglednica 1:** Kazalniki, upoštevani v analizi vpliva na povečanje vsebnosti vode v tleh.*

Index	Description
P24h	Amount of precipitation for 24 hours [mm]
P48h	Amount of precipitation for 48 hours [mm]
P5d	Amount of precipitation for 5 days [mm]
P7d	Amount of precipitation for 7 days [mm]
P10d	Amount of precipitation for 10 days [mm]
P20d	Amount of precipitation for 20 days [mm]
VWC24h	Average relative VWC value for 24 hours [m^3/m^3]
VWC48h	Average relative VWC value for 48 hours [m^3/m^3]
VWC5d	Average relative VWC value for 5 days [m^3/m^3]
VWC7d	Average relative VWC value for 7 days [m^3/m^3]
VWC10d	Average relative VWC value for 10 days [m^3/m^3]
VWC20d	Average relative VWC value for 20 days [m^3/m^3]
MaxI2h	Maximum 20-minute rainfall intensity 2 h before the change [mm/20 min]
MaxI6h	Maximum 20-minute rainfall intensity 6 h before the change [mm/20 min]
MaxI12h	Maximum 20-minute rainfall intensity 12 h before the change [mm/20 min]
MaxI24h	Maximum 20-minute rainfall intensity 24 h before the change [mm/20 min]

2.3 Determining the trend of soil moisture

To be able to determine the increasing and decreasing trend of soil moisture, we calculated the angle of the tangents at each point of the soil moisture measurements, forming the curve as a function of time. The value of the tangent angle at a measurement point corresponds to the arctangent of the line’s slope at that point. With these values, it is possible to detect a change in the soil moisture trend. When the angle becomes positive, the soil moisture trend increases, and vice versa. This allows for the precise detection of the soil moisture response to a rainfall input.

The tangents' angles were calculated using Python. First, we computed the numerical derivatives of time and soil moisture (dx and dy) using the numpy.gradient() python function. From these, the local slopes can be inferred, which is the ratio of the numerical derivatives (dx/dy). Finally, the angle at each point was calculated by finding the arctangent of the slope at each point using the `numpy.arctan()` function.

A decision tree model was used to define the threshold values of the tangent angles that would adequately indicate a change in the trend. The measurement time points were attributed with "yes" and "no" options, indicating the change in soil moisture dynamics, which was dependent on the tangent's angle value. This attribute was the model's target value, while influencing variables were the angle of the tangent and rainfall indices (Table 1).

Decision tree models and random forests are machine learning models used for both regression and classification tasks. They are both based on the concept of decision trees, where the data is recursively split according to certain criteria to make predictions (Brown, 2021). A decision tree is a simple yet powerful model that splits the data into branches based on feature values, making a series of decisions to predict an outcome. A random forest is an ensemble method that combines multiple decision trees to improve prediction accuracy and control over-fitting. It builds several trees using different subsets of the data and features, and then aggregates their results (Brown, 2021).

The decision tree shows a clear and decisive classification where allow the instances on each branch meet the condition set by the value of the tangent (Figure 2). To describe the significant positive change (increase of soil moisture value), for the first and the second depth the following threshold values were set: the angle is greater than 0.1 degrees, the difference between the previous angle and the current angle is positive, and the difference between the next angle and the current angle is negative. As the VWC at the third depth responds less intensively to rainfall input, an angle greater than 0.03 degrees was used.

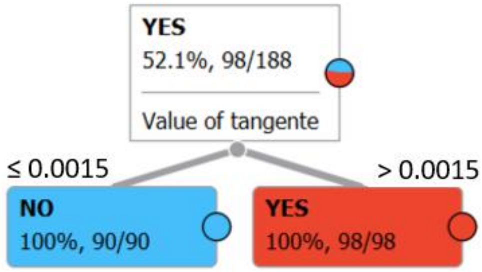

Figure 2: *Example of a decision tree for determining the threshold value of the tangent slope.*

Slika 2: *Primer odločitvenega drevesa za določitev mejne vrednosti naklona tangente.*

This result confirms that the selected threshold values of the tangents' angles are appropriate for determining the change in soil moisture dynamics. Based on this, the data sets consisting of the target variable (the angle of the tangent, calculated for selected measurement time points) and the influencing variables (the corresponding rainfall indices, Table 1) were prepared for every VWC measurement depth. From a complete two-year data set, there were 140 data points included in the analysis for the first depth (16 cm), 70 data points for the second (51 cm), and 52 for the third depth (74 cm).

2.4 Influence of the indices on the increase of the soil moisture

When building and evaluating decision trees and random forest models, several parameters are crucial for optimizing performance. For each model (decision trees and random forest models for all three VWC measurement depths), the best values of parameters were set according to the performance of the models, which was evaluated taking into account the coefficient of determination (R^2) and root mean square error (RMSE). The training (75%) and test (25%) sets of the data were used, with the following parameters considered:

- Max Depth: Controls the maximum depth of the individual trees. Deeper trees can capture more complex patterns but may overfit the data.
- Min Samples Split: The minimum number of samples required to split an internal node. This

helps prevent the model from learning noise in the data.

- Min Samples Leaf: The minimum number of samples required to be at a leaf node.
- Number of Estimators (for Random Forest): The number of trees in the forest. More trees usually improve performance but increase computation time.
- Max Features: The number of features to consider when looking for the best split. It controls the randomness of the model and can help in improving accuracy and reducing overfitting.

The software used to build the models is Orange, which is an open-source data exploration software (Demšar et al., 2013). The models were established for two cases. First, only the decision tree model was trained, for which the target variable was the descriptive value, indicating the degree of change in the soil moisture dynamics. This was to prove that, among all of the selected indices (Table 1), the value of the tangent angle is the relevant indicator of soil moisture change (Figure 2). Secondly, the decision tree and random forest models were trained, for which the target variable was the angle of tangent and influencing variables were all the other indices (Table 1).

3. Results and discussion

3.1. Rainfall and soil moisture

The total amount of rainfall measured over the years 2022 and 2023 was 3058.8 mm. Compared to the long-term yearly average rainfall amount of 1377 mm (ARSO, 2025), the year 2022 was similar, delivering 1321.4 mm of rainfall, while 2023 was wetter, delivering 1737.4 mm of rainfall in total. The spring and summer of 2022 were characterized by dry conditions, receiving only 212.2 mm and 198.8 mm of precipitation, respectively, which corresponds to 66% and 57% of the long-term seasonal averages. Conversely, the summer of 2023 was exceptionally wet, with a cumulative rainfall amount of 757.8 mm, approximately double the long-term summer average (Figure 3).

During both observed years, the VWC was on average the lowest at the upper depth (0.258 m³/m³), followed by the second (0.327 m³/m³) and the third depth (0.330 m³/m³) (Figure 4). The largest variation in the values was observed at the first depth, ranging between 0.157 m³/m³ in summer 2022 and 0.403 m³/m³ in September 2022. The VWC values at the second layer ranged between 0.222 m³/m³ and 0.406 m³/m³, while at the third depth they were between 0.259 m³/m³ and 0.366 m³/m³. The VWC at all three layers was the lowest during the summer of 2022, corresponding to a longer dry period, which started already in winter of 2022 (Figures 3 and 4).

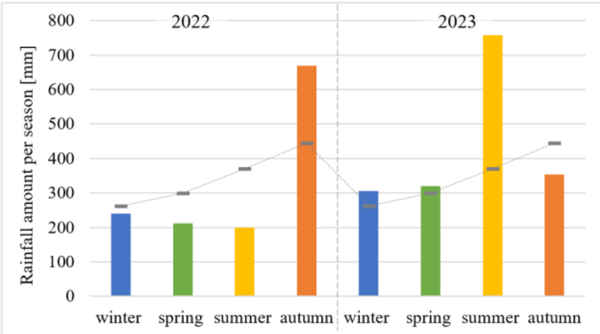

Figure 3: *Rainfall amount per season during the considered measurement period (the long-term average is shown by the grey line).*

Slika 3: *Količina padavin v posamezni sezoni upoštevanega obdobja meritev (s sivo črto je prikazano dolgoletno povprečje).*

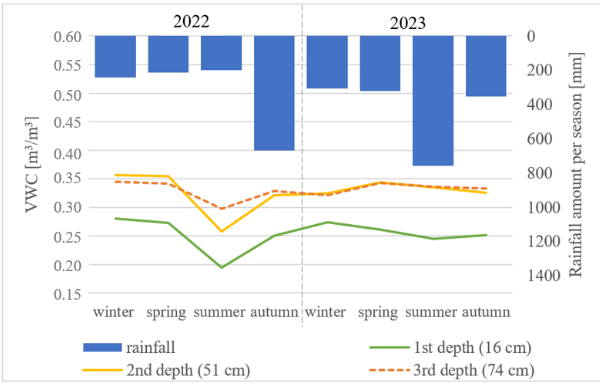

Figure 4: *Average VWC values per measurement depth and corresponding total rainfall amount per season.*

Slika 4: *Povprečne vrednosti VWC glede na globino meritev in pripadajoče količine padavin v posamezni sezoni.*

3.2. Influential indices

Based on rainfall and soil moisture data, several rainfall indices were calculated to describe the pre-event conditions and their relation to the increase in volumetric water content values (Table 1). First, the total amount of rainfall delivered in a selected time period before the observed VWC value was calculated. This index is similar to the antecedent precipitation index, often used to explain or estimate soil moisture conditions (Li et al., 2021; Moraes et al., 2024). The index's average value during the complete measurement period is the lowest for the shortest selected time period of 24 h (4.2 mm), increasing with the increase of the time period up to 20 days (83.2 mm) (Figure 5). The largest values observed for 48 hours, 5 days, and 7 days are similar (290.6 mm, 296.2 mm, and 298.4 mm, respectively), while for longer periods of 20 days these values reach up to 497.8 mm.

To describe the pre-existing soil wetness conditions, the average relative VWC values (Zabret et al., 2023) were calculated for the same time periods as the total amount of rainfall. The average values are similar among themselves, as is expected, given that these are the relative values (Figure 6). However, the average values between the seasons are significantly different ($p<0.05$), with averages ranging between 0.28 m^3/m^3 in winter and 0.22 m^3/m^3 in summer.

Additional rainfall event properties were included, taking into account the maximum 20-minute intensity, which occurred in a selected time period before the observed VWC value. During the entire measurement period of two years, the maximal 20-minute intensity observed was equal to 21.4 mm/20 min. The average values of 20-minute maximal intensity increase with an increase in the length of the period considered, resulting in 0.16 mm/20 min 2 hours before the measurement and 0.82 mm/20 min 24 hours before (Figure 7, upper). In the complete dataset, the majority of values for 2 hours and 6 hours (87% and 80% of the values, respectively) are equal to zero. There are no such observations included in the subsets of data with an observed significant increase in the VWC values according to the tangent angle (Figure 7, lower).

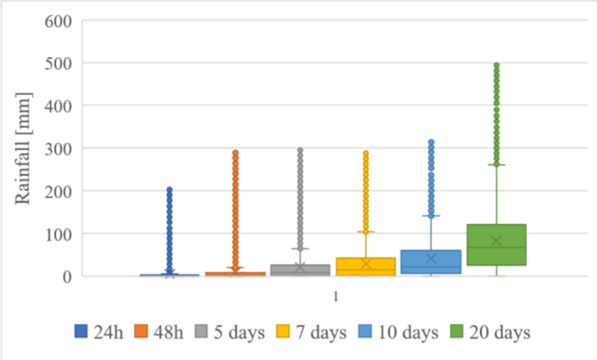

Figure 5: *The total amount of rainfall delivered in the selected time period before the observation.*

Slika 5: *Skupna količina padavin, ki je padla v določenem časovnem obdobju pred meritvijo.*

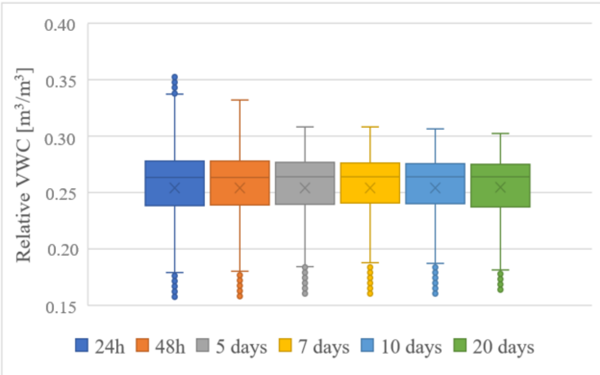

Figure 6: *Relative VWC value for selected time period before the observation.*

Slika 6: *Vsebnost vode v tleh v določenem časovnem obdobju pred meritvijo.*

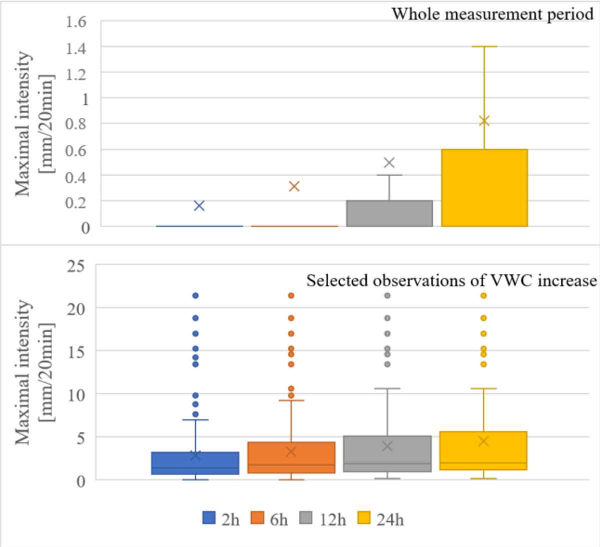

Figure 7: *Maximum rainfall intensity in a selected time period before the observation for the complete measurement period of 2 years (upper) and for the selected observations of VWC increase (lower).*

Slika 7: *Največja 20-minutna intenziteta padavin v določenem časovnem obdobju pred meritvijo v celotnem obdobju (zgoraj) in za posamezne izbrane meritve naraščanja vlage v tleh (spodaj).*

3.3. Influence on increase of soil moisture

Regression tree and random forest models were used to determine the variables influencing the increase of soil moisture values. The target variable of the models was the angle of the tangent, calculated for selected measurement time points, while the influencing variables were the corresponding rainfall indices (Table 1). To construct the model, only data points that met the selected criteria for a significant increase according to the angle of the tangent were used.

For the regression tree model, the top three splitting variables were selected as those with the strongest influence. For the case of the VWC in the first depth, the most influential variable is the maximum 20-minute precipitation intensity, observed 6 hours before the slope of VWC significantly changes (Figure 8). If the rainfall intensity exceeds 6 mm/20 min in the period of 6 hours before, the increase in VWC equals 0.05 m^3/m^3 in 2 hours on average and is further dependent on the average relative soil moisture during the previous 5 days. If the maximum 20-min rainfall intensity is lower, the average soil moisture increase is equal to 0.003 m^3/m^3 in 2 hours and is further influenced by the threshold of 2.6 mm of rainfall within 24 hours.

Similar to the 16 cm depth, the VWC response at a depth of 51 cm is also most influenced by the maximum 20-minute precipitation intensity observed 6 hours before the slope of VWC significantly changes (Figure 9). However, for the second depth, the intensity inducing the significant change of 0.02 m^3/m^3 in 2 hours is set at 8.8 mm/20 minutes. This index was also recognized as the second-most influential at a value of 3.6 mm/20 min, indicating an average increase in VWC equal to 0.01 m^3/m^3 in 2 hours for intensity values in between.

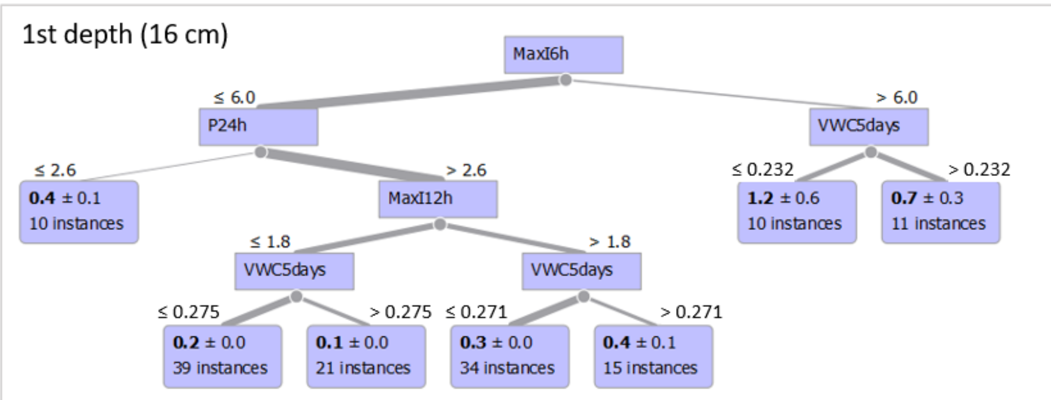

Figure 8: *Regression tree, showing the influencing indices for soil moisture increase at first depth.*

Slika 8: *Regresijsko drevo vplivnih indeksov povečanja vsebnosti vode v tleh na prvi globini.*

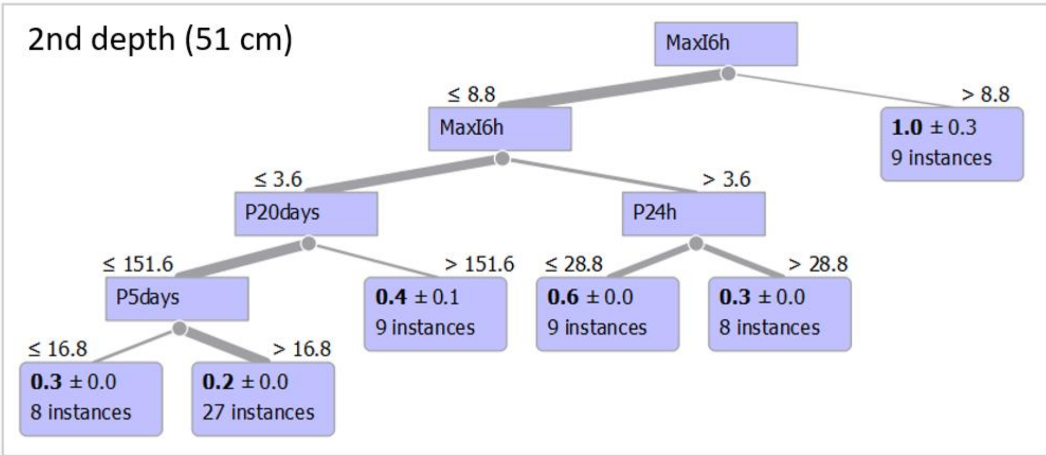

Figure 9: *Regression tree, showing the influencing indices for soil moisture increase at second depth.*

Slika 9: *Regresijsko drevo vplivnih indeksov povečanja vsebnosti vode v tleh na drugi globini.*

The increase in soil moisture values at the third depth is most influenced by the prior rainfall conditions (Figure 10). According to the regression tree, the total amount of rainfall one week (7 days) before the increase has the strongest influence, ensuring an average increase equal to 0.001 m^3/m^3 in 2 hours when more than 79 mm of rainfall was delivered in this period, while hardly any increase in the period of 2 hours is observed for lower rainfall amounts. Additionally, prior soil moisture conditions also influence the increase of soil moisture at this depth.

The random forest model was also used to estimate the influential variables on the soil moisture trend. However, in this case, the variables' influence is expressed by the relative influence estimated for each variable (Zabret et al., 2018). The influencing indices are similar for the first two depths, with six and four indices indicated as significantly influential (contributing at least 70% of influence), respectively, while for the third depth, the influential indices are completely different and have lower relative influence (Figure 11). For the first and second depths, the maximum 20-minute intensities 6 and 2 hours before the change have the strongest influence on the soil moisture trend. For the deepest layer, it is rather the average relative VWC before the change in soil moisture that produces the strongest response in soil moisture, especially for the values observed 48 hours in advance.

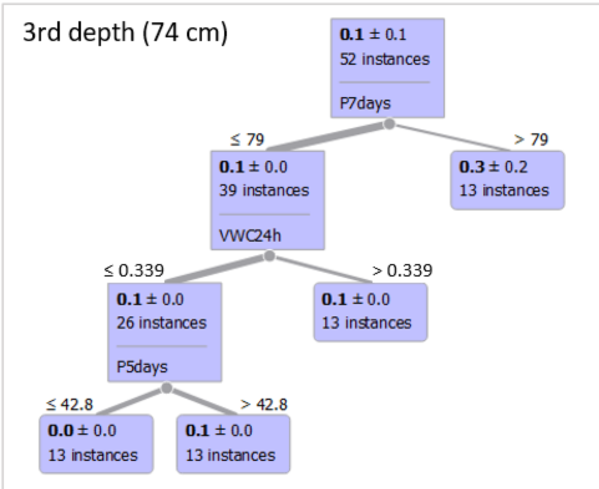

Figure 10: *Regression tree, showing the influential indices for soil moisture increase at third depth.*

Slika 10: *Regresijsko drevo vplivnih indeksov povečanja vsebnosti vode v tleh na tretji globini.*

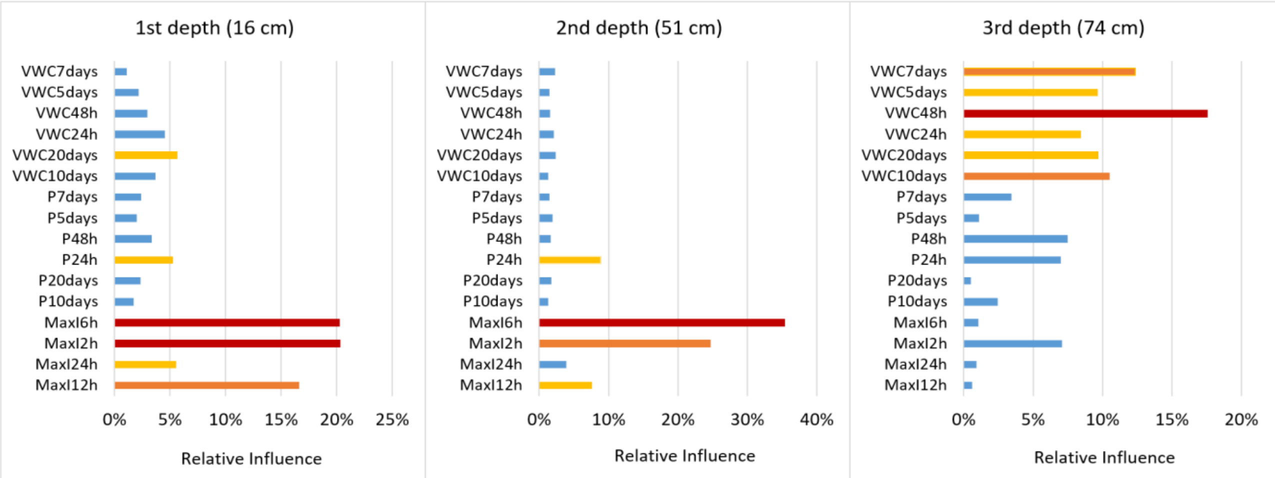

Figure 11: *Relative influence of indices on soil moisture increase per depth according to random forest modelling.*

Slika 11: *Relativni vpliv indeksov na povečanje vsebnosti vode v tleh v različnih globinah glede na rezultate modela naključnega gozda.*

Indices influencing the response of soil moisture change with the depth of the soil profile. In addition to the greater distance from the surface where precipitation enters the soil, this may also be due to higher and more stable soil moisture conditions (Figure 4). An increase in soil moisture values correlating to an increase in depth was also reported by Gruchot et al. (2022) in their controlled lab experiment, as well as by Zabret et al. (2023) for an open site area. However, the presence of trees can significantly alter such a pattern (Zabret et al., 2023).

In their global analysis of influencing factors on soil moisture conditions, Peng et al. (2023) determined precipitation as the main influence for Slovenia. The results of both models used directly connected responses in upper levels to rainfall indices. The maximal 20-minute rainfall intensity within a 6-hour period (MaxI6h) showed the strongest influence on soil moisture response (Table 2). On average, soil moisture increases were observed when MaxI6h reached 3.3 mm/20 min in the first layer and 4.1 mm/20 min in the second layer. These values are also dependent on the seasons, increasing from winter to summer, when the average MaxIh6 is the highest, resulting also in the highest increase of soil moisture values. For example, 24 hours after the observed increase in soil moisture, its values on average increased by 0.028 m^3/m^3 in summer and by 0.014 m^3/m^3 in winter. The significant influence of seasonality on soil moisture values has also been confirmed by other studies (Hui et al., 2025; Liu et al., 2024; Stahl and McColl, 2022; Zabret et al., 2023).

For the upper two layers also maximal 20-minute intensity observed 2 hours before the increase was indicated by the BRT model, which is probably related to the highest correlation between MaxI6h and MaxI2h among intensity indices.

For the soil moisture response in the third depth, each model indicated different indices; however, they both highlight the longer period of time required to record an increase in soil moisture (Table 2). This is, however, expected, as it was reported that differences in soil moisture storage decrease with depth (Liu et al., 2024), that the response of VWC to rainfall event is delayed (Zabret et al., 2023), and that soil moisture values in deeper layers maintain certain differences from values in higher layers, especially in seasons with average and below-average precipitation (Koehn et al., 2021) The root splitting variable for the tree model was the 7-day precipitation amount, while the second variable was related to antecedent soil moisture values during 24 hours. However, the BRT model assigned the strongest relative influence only to antecedent soil moisture conditions with even longer extent (48 hours, 7 and 10 days).

Table 2: *Comparison of two model's results.*

Preglednica 2: *Primerjava rezultatov obeh modelov.*

Soil depth	Model	1st variable	2nd variable	3rd variable
1st depth (16 cm)	Tree	MaxI6h	P24h, VWC5d	MaxI12h
	RF	MaxI6h	MaxI2h	MaxI12h
2nd depth (51 cm)	Tree	MaxI6h	MaxI6h	P20d, P24h
	RF	MaxI6h	MaxI2h	P24h
3rd depth (74 cm)	Tree	P7d	VWC24h	P5d
	RF	VWC48h	VWC7d	VWC10d

4. Conclusions

Soil moisture is an important factor influencing the distribution of precipitation between runoff and infiltration, providing optimal conditions for plant growth, as well as regulating temperature and soil erosion. Different processes require different optimal conditions; however, soil moisture dynamics depend primarily on precipitation and other meteorological conditions (e.g. air temperature, solar radiation, relative humidity), land cover, slope, soil water-retention properties, and soil type. The influence of rainfall and antecedent soil moisture conditions on the increase in soil moisture values was evaluated using two different tree models. Results showed that an approach using the tangent angle is appropriate for determining changes in soil moisture dynamics. In the upper soil layers above 51 cm, the soil moisture increase depends mainly on the duration and amount of precipitation, which is expressed by intensity. However, in deeper soil layers, the antecedent soil moisture conditions play the most important role in determining the rate of soil moisture values increase. Based on the results of the analysis presented, it would be useful to modify the set of indices considered in further studies to include other meteorological factors such as air temperature, solar radiation, vapor pressure deficit and wind speed, and the influence of seasonality, with an emphasis on extremely dry and wet conditions.

CRediT authorship contribution statement

EV – Data curation, Formal analysis; Investigation; Visualization; Writing – original draft; KZ – Conceptualization, Methodology; Supervision; Validation; Writing – review & editing

Data availability

The data can be accessed via the following link: https://repozitorij.uni-lj.si/IzpisGradiva.php?id=185681

Declaration of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

ARSO (2024). Arhiv meteoroloških meritev/ Meteorological measurements archive. Dostopno na: http://www.meteo.si/met/sl/archive/ (pridobljeno 13. 8. 2024).

Brown, D. (2021). How do Decision Trees and Random Forests Work? Towards data science. Dostopno na: https://towardsdatascience.com/how-do-decision-trees-and-random-forests-work-66a1094e6c5d/ (pridobljeno 6. 5. 2025).

Demšar, J., Curk, T., Erjavec, A., Gorup, Č., Hočevar, T., Milutinović, M., Možina, M., Polajnar, M., Toplak, M., Starič, A., Štajdohar, M., Umek, L., Žagar, L., Žbontar, J., Žitnik, M., Zupan, B. (2013). Orange: Data Mining Toolbox in Python. Journal of Machine Learning Research 14, 2349–2353.

Dong, J., Ochsner, T. E. (2018). Soil Texture Often Exerts a Stronger Influence Than Precipitation on Mesoscale Soil Moisture Patterns. Water Resources Research 54(3), 2199–2211. https://doi.org/10.1002/2017WR021692.

Gimbel, K. F., Puhlmann, H., Weiler, M. (2016). Does drought alter hydrological functions in forest soils? Hydrology and Earth System Sciences 20(3), 1301–1317. https://doi.org/10.5194/hess-20-1301-2016.

Gruchot, A., Zydroń, T., Wałęga, A., Pařílková, J., Stanisz, J. (2022). Influence of Rainfall Events and Surface Inclination on Overland and Subsurface Runoff Formation on Low-Permeable Soil. Sustainability 14(9), 4962. https://doi.org/10.3390/su14094962.

Haiyan, D. A. I., Haimei, W. A. N. G. (2021). Influence of rainfall events on soil moisture in a typical steppe of Xilingol. Physics and Chemistry of the Earth 121, 102964. https://doi.org/10.1016/j.pce.2020.102964.

Hui, S., Guo, L., Liu, H., Wu, X., Lan, P., Boyer, E. W., Mello, C. R., Li, H. (2025). Spatiotemporal dynamics of soil moisture and the occurrence of hysteresis during seasonal transitions in a headwater catchment. Geoderma 454, 117169. https://doi.org/10.1016/j.geoderma.2025.117169.

Koehn, C. R., Petrie, M. D., Bradford, J. B., Litvak, M. E., Strachan, S. (2021). Seasonal Precipitation and Soil Moisture Relationships Across Forests and Woodlands in the Southwestern United States. Journal of Geophysical Research: Biogeosciences 126(4), e2020JG005986. https://doi.org/10.1029/2020JG005986.

Li, X., Wei, Y., Li, F. (2021). Optimality of antecedent precipitation index and its application. Journal of Hydrology 595, 126027. https://doi.org/10.1016/j.jhydrol.2021.126027.

Liu, S., Van Meerveld, I., Zhao, Y., Wang, Y., Kirchner, J. W. (2024). Seasonal dynamics and spatial patterns of soil moisture in a loess catchment. Hydrology and Earth System Sciences 28(1), 205–216. https://doi.org/10.5194/hess-28-205-2024.

Marchi, L., Borga, M., Preciso, E., Gaume, E. (2010). Characterisation of selected extreme flash floods in Europe and implications for flood risk management. Journal of Hydrology 397, 118-133. https://doi.org/10.1016/j.jhydrol.2010.07.017.

Moraes, M. A. E. D., Filho, W. M. M., Mendes, R. M., Bortolozo, C. A., Metodiev, D., Andrade, M. R. M. D., Egas, H. M., Mendes, T. S. G., Pampuch, L. A. (2024). Antecedent Precipitation Index to Estimate Soil Moisture and Correlate as a Triggering Process in the Occurrence of Landslides. International Journal of Geosciences 15(01), 70–86. https://doi.org/10.4236/ijg.2024.151006.

Ljutic, A., Moore, J., Ali, G., Van Eerd, L., Macrae, M. L., Wagner-Riddle, C. (2024). Variable soil moisture responses to rainfall events in fields under different management practices. Hydrological Processes 38, e15242. https://doi.org/10.1002/hyp.15242.

Nielsen, M., Cook, B. I., Marvel, K., Ting, M., Smerdon, J. E. (2024). The Changing Influence of Precipitation on Soil Moisture Drought With Warming in the Mediterranean and Western North America. Earth's Future 12(5), e2023EF003987. https://doi.org/10.1029/2023EF003987.

Ochsner, T.E., Cosh, M.H., Cuenca, R.H., Dorigo, W.A., Draper, C.S., Hagimoto, Y., Kerr, Y.H., Larson, K.M., Njoku, E.G., Small, E.E., Zreda, M. (2013). State of the Art in Large-Scale Soil Moisture Monitoring. Soil Science Society of America Journal 77, 1888-1919. https://doi.org/10.2136/sssaj2013.03.0093.

Peng, C., Zeng, J., Chen, K.-S., Li, Z., Ma, H., Zhang, X., Shi, P., Wang, T., Yi, L., Bi, H. (2023). Global spatiotemporal trend of satellite-based soil moisture and its influencing factors in the early 21st century. Remote Sensing of Environment 291, 113569. https://doi.org/10.1016/j.rse.2023.113569.

Radulović, L., Bezak, N., Šraj, M. (2023). The influence of vegetation on the microstructure and erosivity of precipitation. Acta hydrotechnica 57–79. https://doi.org/10.15292/acta.hydro.2023.04.

Stahl, M. O., McColl, K. A. (2022). The Seasonal Cycle of Surface Soil Moisture. Journal of Climate 35(15), 4997–5012.

Sušnik, A., Pogačar, T., Gregorič, G., Roškar, J., Ceglar, A. (2010). Establishment of agricultural drought monitoring at different spatial scales in southeastern Europe. Acta Agriculturae Slovenica 95, 231–243. https://doi.org/10.14720/aas.2010.95.3.14768.

Vrščaj, B., Grčman, H., Kralj, T. (2019). Klasifikacija tal Slovenije 2019: sistem za opisovanje in poimenovanje tal Slovenije (in Slovenian). 156 p.

https://www.gov.si/assets/ministrstva/MOPE/Okolje/Tla/Klasifikacija_tal_Slovenije.pdf.

Whiteley, J.S., Chambers, J.E., Uhlemann, S., Wilkinson, P.B., Kendall, J.M. (2019). Geophysical Monitoring of Moisture-Induced Landslides: A Review. Reviews of Geophysics 57, 106–145. https://doi.org/10.1029/2018RG000603.

Zabret, K., Lebar, K., Šraj, M. (2023). Temporal response of urban soil water content in relation to the rainfall and throughfall dynamics in the open and below the trees. Journal of Hydrology and Hydromechanics 71(2), 210–220. https://doi.org/10.2478/johh-2023-0007.

Zabret, K., Rakovec, J., Šraj, M. (2018). Influence of meteorological variables on rainfall partitioning for deciduous and coniferous tree species in urban area. Journal of Hydrology 558, 29–41. https://doi.org/10.1016/j.jhydrol.2018.01.025.

Zabret, K., Šraj, M. (2018). Spatial variability of throughfall under single birch and pine tree canopies / Prostorska spremenljivost prepuščenih padavin pod krošnjama breze in bora. Acta hydrotechnica 31(54), 1–20.

Zhu, P., Jia, X., Zhao, C., Shao, M. (2022). Long-term soil moisture evolution and its driving factors across China's agroecosystems. Agricultural Water Management 269, 107735. https://doi.org/10.1016/j.agwat.2022.107735.