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Optical Trapezoid Model (OPTRAM) model-based plot-level soil moisture mapping using Sentinel-2 imagery

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ABSTRACT

The Optical Trapezoid Model (OPTRAM) utilizes remotely sensed data to accurately determine soil moisture by analysing the relationship between the Normalized Difference Vegetation Index (NDVI) and transformed short-wave infrared (STR) values. The main goal was a plot-scale OPTRAM validation, demonstrating the applicability of the model on various soils at the resolution of Sentinel-2. First, in the spring of 2020, more than 1,400 in situ measurements were carried out with Spectrum FieldScout TDR 350 instrument on ground surfaces at the same time as Sentinel-2 satellite image acquisitions. The correlation coefficient (r) between in situ measured and OPTRAM estimated soil moisture shows high values ($r = 0.70$ – 0.80), particularly on bare soil surfaces. As a second element of the investigation, in the fall of 2023, Sentinel-2 time-series data were compared with in situ data from three soil moisture monitoring stations, resulting in a strong correlation ($r = 0.80$ – 0.85). The OPTRAM-based methodology demonstrates significant potential for remote sensing-based soil moisture determination and illustrates well time-series variation, improving the scalability and accuracy of drought while emphasizing the need for integrating soil properties context to enhance accuracy in plot-level analyses.

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Soil moisture; OPTRAM;
Sentinel-2; plot-level

1. Introduction

Drought presents a serious threat and is intensified by climate change in the Pannonian Basin; accurate soil moisture is a critical parameter here for water management (Fiala et al. 2018). Remote sensing detects moisture in the top 5 cm of soil, but cloud cover limits the multispectral imagery. Active sensors, such as those in the ESA Soil Moisture and Ocean Salinity mission, bypass cloud interference (Wigneron et al. 2017); however, their coarse spatial resolution restricts field-level analyses. Downscaling can improve resolution, but requires calculations, expert knowledge, and ancillary data (Yang, Wang, and Liu 2024). The spatial, spectral, and temporal resolutions of optical satellites determine consistency in soil moisture monitoring (Bertalan et al. 2022, eoPortal 2026; Kogan, Adamenko, and Guo 2012).

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Indices are used for estimation of early drought detection; vegetation indices are simpler, while drought indices like the Vegetation Drought Response Index integrate broader spectral data, making them less directly applicable to soil moisture analysis (Brown et al. 2008). Triangle and trapezoid space-based modelling approaches have been shown to improve soil moisture estimation by exploiting the relationship between vegetation cover and soil reflectance. Zhao, Sánchez, and Li (2018) demonstrated that triangle space methods integrating in situ measurements with optical and thermal infrared data can provide reliable soil moisture estimates. The Optical Trapezoid Model (OPTRAM) further advances this concept by enabling soil moisture estimation using optical data alone, without the need for thermal information (Babaeian et al. 2018; Sadeghi et al. 2017). Satellites support it, but parcel-level use remains limited (Ma, Johansen, and McCabe 2022). Recent developments divide the parameter determination methods into linear (Du et al. 2024; Sadeghi et al. 2023) and nonlinear (Ambrosone et al. 2020; Ma, Johansen, and McCabe 2022) approaches, which OPTRAM estimates align closely with field data, though they often neglect soil structure, surface heterogeneity limiting accuracy.

This study applies Sentinel-2 multispectral imagery and two sets of in situ measurements to produce high-resolution soil moisture maps in different soil and surface conditions. Evaluation of water deficits can support both precision agriculture and broader regional strategies. The method incorporates surface and soil type classifications along with time-series analysis, advancing sustainable farming practices.

2. Materials and methods

In situ soil moisture measurements were carried out on the Great Hungarian Plain in 2020 and 2023 in four study areas: Deszk, Rösztke, Sándorfalva, and Szeged (Figure 1).

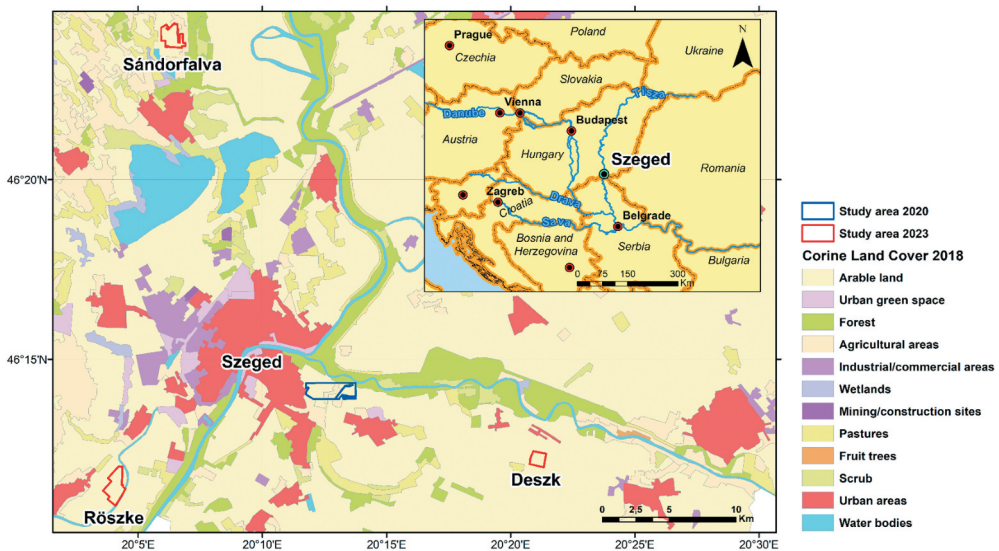


Figure 1. Study areas for soil moisture measurements on the Great Hungarian Plain at the boundary of Szeged and at monitoring stations in Deszk, Rösztke, and Sándorfalva.

2.1. In situ soil moisture measurements

In situ soil moisture measurements were performed on 5 March 2020 and 6 April 2020 in agricultural plots near Szeged (Figure 2). In the 30 days without frost before 5 March, the average temperature was 5.4°C, increasing to 7.8°C in the last 5 days, with 34.8 mm of precipitation falling on meadow soils with a clay content of 50–60%. Of this, 9.3 mm fell between 29 February 2020 and 4 March 2020 (WMO (World Meteorological Organization), 2024; Drought Monitoring Station; DOSoReMI, 2024). Compared to long-term February and March averages, the weather in early 2020 was typical for the region (HungaroMet, 2024). Based on the Hungarian Drought Index (HDI, Fiala et al. 2018), conditions were drought-free and improved in early March.

Before 6 April 2020, the monthly average temperature was 6.5°C, rising to 7.9°C by 5 April 2020. Between 7 March 2020 and 5 April 2020, 30.6 mm of rain fell, though none in the 10 days before sampling. The HDI values indicated that there was no drought during this period.

Each in situ soil moisture value represented the average of 3–5 individual Spectrum FieldScout TDR 350 ($\pm 3\%$ accuracy) taken within a radius of 5 m to minimize local heterogeneity. This footprint corresponds to a single Sentinel-2 pixel (10×10 m), ensuring that the ground measurements are spatially comparable with the OPTRAM results. More than 1,400 data points were collected on 205 ha, including 8 agricultural plots totalling 90 ha (Figure 2). Cloud-free Sentinel-2 Level-2 imagery was available for both dates, allowing precise integration of ground and satellite data. This setup supports high-resolution comparison with OPTRAM estimates and allows classification by land cover and soil type (rough cultivated bare soil, smooth-flat cultivated soil and sparse vegetation), similar to the approach of Basu et al. (2024).

We previously analysed the relationship between soil moisture in situ and spectral indices (Bare Soil Index, Normalized Difference Wetness Index, Visible Atmospherically Resistant Index, Normalized Difference Vegetation Index), but it showed low values in

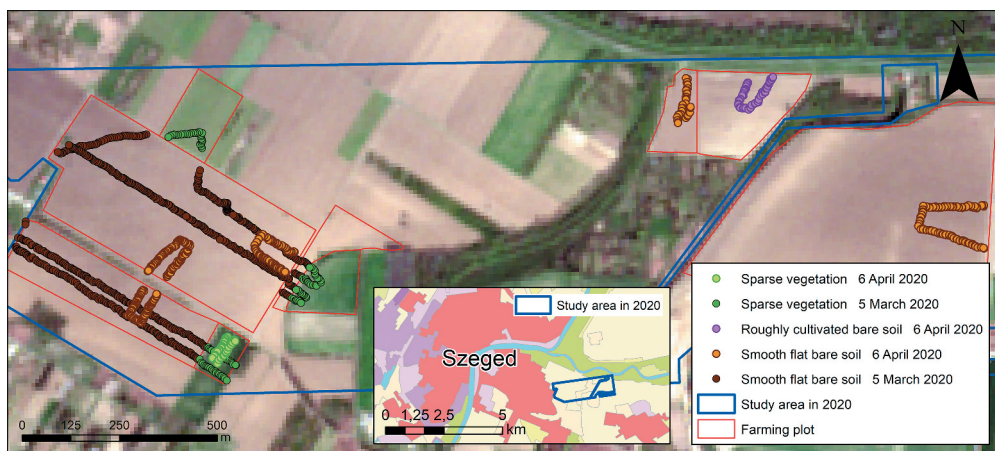


Figure 2. Soil moisture measurements in Szeged on 5 March 2020 and 6 April 2020 and Spectrum FieldScout TDR 350 measurement on smooth-flat cultivated soil.

maximum Pearson correlation coefficient ($r_{max} \approx 0.30$). Due to nonlinear relationships, bands exhibit differing sensitivities, necessitating their appropriate combination for reliable moisture results (Foroughi et al. 2020; McGuirk and Cairns 2024). Remote sensing may correlate better with root zone moisture of vegetated areas (Santos et al. 2014), observing the strongest correlation at 60 cm depth.

2.2. Sample sites for the new drought monitoring station and the Sentinel-2 survey

In autumn 2023, tests were carried out at three monitoring stations and their surrounding plots (Figures 1 and 3). Measurements were taken using Decagon 5TM sensors at depths ranging from 10 to 75 cm, providing Volumetric Water Content (VWC%) (0–50%) based on dielectric conductivity, with an accuracy of $\pm 2\%$. The stations also recorded hourly meteorological data sets calibrated to local soil types (Fiala et al. 2018); however, each station monitors only a single fenced location, which may not fully represent the heterogeneity of the surrounding land cover.

For temporal analysis, sites were selected based on the occurrence of at least one significant rainfall event during the study period (Figure 3). The monitored areas range from 80 to 190 ha, each with distinct hydrological characteristics of the soil, aligning with the spatial requirements of the OPTRAM model. Detailed modelling focused on areas directly adjacent to the stations, consisting of contiguous agricultural parcels free from buildings, roads, or water bodies. Vegetated areas were specifically selected to support the later calibration of model constants. In each plot, 10 sampling points with homogeneous surface cover were identified, resulting in 30 evaluated Sentinel-2 pixels per station. Six cloud-free Level-2 Sentinel-2 images (radiometrically and atmospherically corrected) covering the T34TDS tile were processed for the period 1 September 2023–12 November 2023. Due to path overlap, a total of 16 usable images were available for the Deszk station, enhancing temporal resolution.

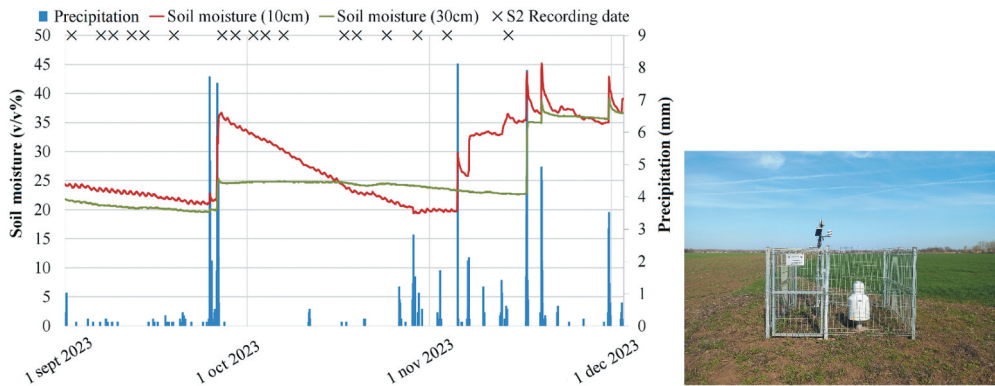


Figure 3. Soil moisture and precipitation values measured at the Deszk station and the monitoring station (Deszk: chernozem meadow soil, clay in the upper 30 cm; Röszke: meadow soil, clay loam in the upper 30 cm; Sándorfalva: humic sandy soil, loamy sand on the upper 30 cm).

2.3. Optical trapezoid model

The Thermal-Optical Trapezoidal Model (TOTRAM) (Wang and Qu 2009) estimates soil moisture by relating surface temperature to vegetation indices. Thermal infrared (TIR) data limit its usability due to low spatial resolution and data availability. Landsat OLI offers 100 m resolution data every 8 days, constraining plot-level applications.

Since the spectral indices and bands tested proved inadequate, our research focused on OPTRAM – an enhanced version of TOTRAM by Sadeghi et al. (2017). OPTRAM uses a physics-based two-flux radiative transfer model and replaces the TIR with transformed short-wave infrared (STR) data, allowing more accurate soil moisture estimation and finer spatial resolution using multispectral imagery (Figure 4).

Although machine learning models, such as neural networks that integrate radar and optical data, may yield higher accuracy, they require substantial computational power and large training datasets. In contrast, OPTRAM offers a simpler and more efficient alternative with good spatial resolution, making it well suited for field-scale applications (Lee et al. 2023). It represents a step forward in indirect soil moisture estimation, offering improved accuracy and broader applicability for environmental monitoring. Soil moisture (W) is calculated using the following:

$$W = \frac{\theta - \theta_d}{\theta_w - \theta_d} = \frac{STR - STR_d}{STR_w - STR_d} \quad (1)$$

where θ : surface soil moisture, θ_d and θ_w denote the soil moisture at the dry and wet edges; STR: transformed Short-Wave Infrared (SWIR) reflectance, derived as:

$$STR = \frac{(1 - \rho_{SWIR})^2}{2\rho_{SWIR}} \quad (2)$$

The SWIR reflectance is derived from the Landsat SWIR band (2.21 μm), which has proven suitable for the model (Sadeghi et al. 2017). OPTRAM is based on a trapezoidal STR–NDVI feature space, where dry and wet edges are fitted to define model parameters. The dry edge, following minimum STR values, is more distinct, whereas the wet edge varies with vegetation and soil conditions. The model constants (i_d and i_w are the

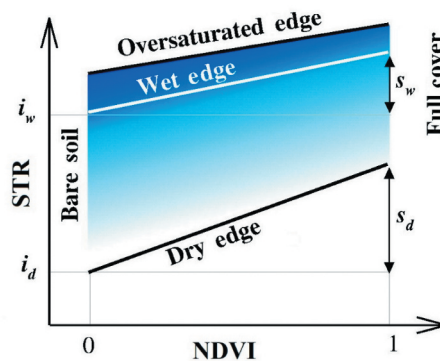


Figure 4. Parameters of OPTRAM; it is parametrized by pixel distributions in the STR-NDVI space (Sadeghi et al. 2017).

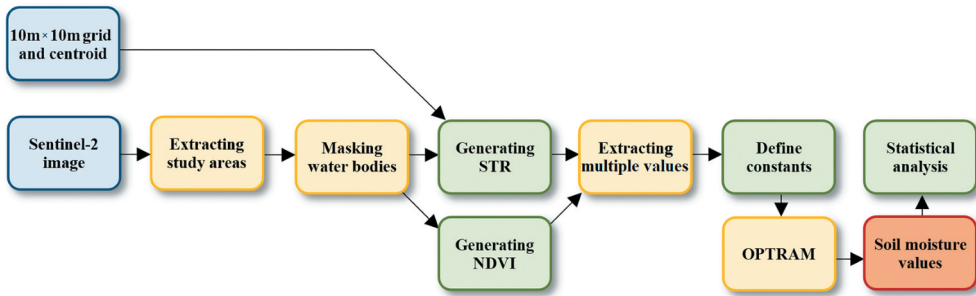


Figure 5. OPTRAM application flowchart.

intercepts, and S_d and S_w are the slopes of the dry and wet edges in the STR–NDVI space) are extracted from scatter plots, forming the equation:

$$W = \frac{i_d + S_d \times \text{NDVI} - \text{STR}}{i_d - i_w + (S_d - S_w) \times \text{NDVI}} \quad (3)$$

The variability of NDVI and STR between crops and growth stages influences the edge parameters. The model may overestimate soil moisture at medium to high content and underestimate it under dry conditions (Ambrosone et al. 2020). It is less accurate in oversaturated conditions because excess water does not reflect changes in soil moisture.

Sentinel-2 images were acquired from the Copernicus browser (Copernicus Browser, 2024). NDVI and STR maps were generated, and a 10×10 m grid was used to extract the values of the STR–NDVI plots, which defined constants for the estimation of soil moisture. Each Sentinel-2 pixel (10×10 m) was matched with the nearest TDR measurement point. When multiple readings occurred within one pixel, their average value was used to represent that pixel. This ensured that field measurements and satellite data were spatially comparable during OPTRAM calibration and validation (Figure 5).

3. Results and discussion

3.1. Application and results of the OPTRAM model

To determine OPTRAM constants, three linear methods were tested. They were manually defined for each sample area and date, which may introduce uncertainty (Stanczyk et al. 2023). The original linear method was chosen as it showed minimal differences compared to alternatives (Ma, Johansen, and McCabe 2022). Constants for three wet-edge scenarios, underestimation (W_1), ideal (W_2), and overestimation (W_3) are shown in Figure 6, in the example of April 2020. Based on differences of 5,000 STR–NDVI points (March and April 2020), statistics W_2 were used for analysis. Only remotely detected values closest to the in situ data were adjusted under the W_2 scenario, without altering the correlation.

The scenarios produced different spatial moisture patterns, but the relative differences remained consistent (Figure 7). Validation by selected field measurements confirmed the reliability of the remotely sensed estimates. In particular, significant variability was found, especially in the southeast due to an old riverbed visible through its curved shape.

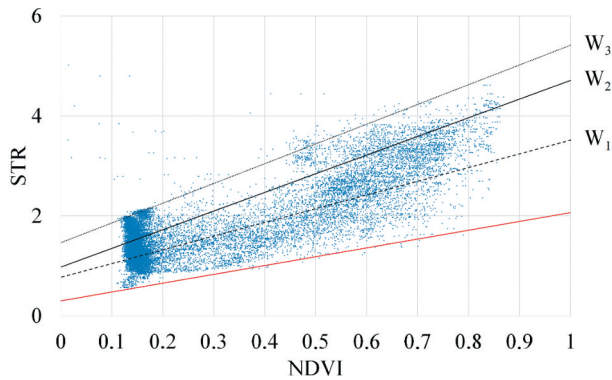


Figure 6. Scatter plot STR and NDVI derived from Sentinel-2 imagery on 6 April 2020. Each point represents a 10 m × 10 m pixel. Black lines: W_1 –underestimate, W_2 –ideal scenario, W_3 –overestimate of the wet edge. Red line: the dry edge.

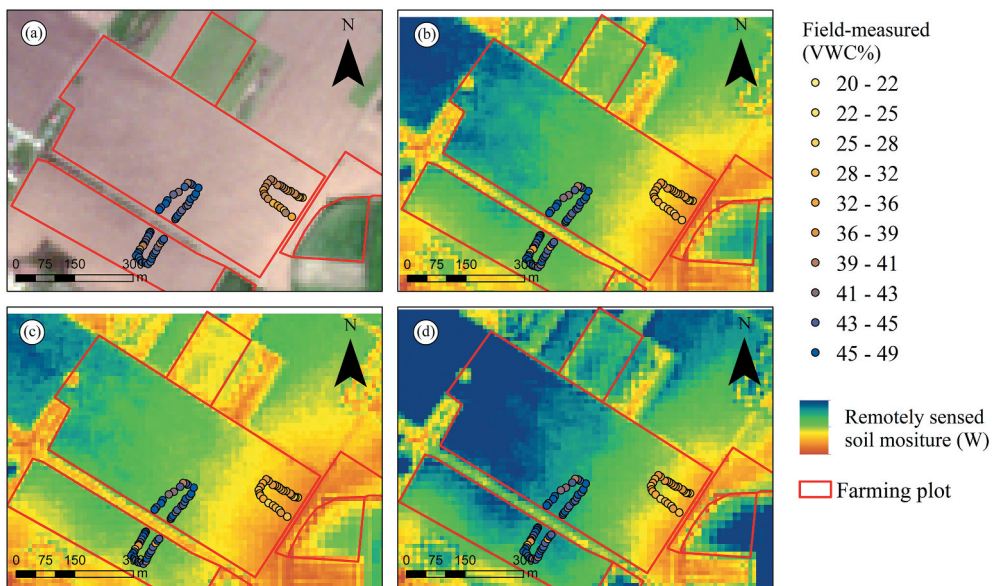


Figure 7. Modelled soil moisture values under different scenarios on 6 April 2020 in the Szeged study area (with selected field measurements). a: Sentinel-2 RGB composite, b: W_2 -ideal scenario, c: W_3 -overestimation, d: W_1 -underestimation of constants.

The relative soil moisture values and in situ point measurements were compared using Pearson’s correlation (Table 1). The model results vary depending on the measurements on the two dates; similar surface cover gives different correlation coefficients. The difference between the values for the two dates is smaller than that between the different scenarios. The correlation between soil moisture and spectral data varied with surface conditions and survey date. On smooth-flat soils, the data for March showed a weak negative correlation (~ -0.30), but a strongly positive correlation in April (~ 0.73). In contrast, the rough bare soils in April exhibited

Table 1. Correlation relationship between in situ and modelled results on two dates: 5 March 2020/ 6 April 2020 on different surface coverages. Bold: strong correlation (>0.50); NA: unavailable data (no rough cultivated soil in March).

| | | W_1 | W_1 | W_2 | W_2 | W_3 | W_3 |
|-----------------------------|----------------|------------------|------------------|------------------|------------------|------------------|------------------|
| | | Average | Median | Average | Median | Average | Median |
| Smooth-flat cultivated soil | In situ | -0.30/ | -0.30/ | -0.30/ | -0.30/ | -0.30/ | -0.30/ |
| | Average | 0.73 | 0.73 | 0.73 | 0.73 | 0.73 | 0.73 |
| | In situ Median | -0.53/ | -0.23/ | -0.24/ | -0.23/ | -0.24/ | -0.23/ |
| | | 0.71 | 0.72 | 0.71 | 0.71 | 0.71 | 0.71 |
| Rough cultivated bare soil | In situ | NA/0.04 | NA/-0.07 | NA/-0.05 | NA/-0.05 | NA/0.02 | NA/0.02 |
| | Average | | | | | | |
| Sparse vegetation | In situ Median | NA/-0.41 | NA/-0.38 | NA/-0.42 | NA/-0.39 | NA/-0.45 | NA/-0.42 |
| | In situ | 0.57/0.48 | 0.62/0.47 | 0.53/0.48 | 0.59/0.46 | 0.51/0.47 | 0.57/0.46 |
| | Average | | | | | | |
| | In situ Median | 0.57/0.38 | 0.60/0.37 | 0.52/0.38 | 0.57/0.36 | 0.49/0.37 | 0.56/0.36 |

a negative correlation (-0.40). Sparse vegetation produced more stable results in March (0.50–0.60), but lower correlations in April (0.35–0.47). The inconsistencies probably stem from limited pixel availability and unknown tillage practices between dates, with no significant rainfall recorded. The model, like field instruments, struggles under such conditions, particularly when sandy and clay soils dry at different rates. To reduce uncertainty, the analysis was extended with new areas and time-series data from drought monitoring stations (Fiala et al. 2018), improving the reliability of the estimation.

3.2. OPTRAM model results in a time series study

Pearson's correlation analysis was conducted between Sentinel-2-based soil moisture estimates and drought monitoring station data using the 10 nearest aligned pixels per plot (Table 2). Each station was surrounded by three parcels, and soil moisture values were also examined at depths of 20 cm and 30 cm.

The strongest correlations were found at the Sándorfalva station, particularly on smooth and humus-rich sandy soils, where soil moisture at 20 cm and 30 cm depths correlated at 0.83 and 0.86, respectively. Sparse vegetation also produced high correlations across all depths. At Rösztke, although sparse vegetation showed statistically significant correlations, meadow soils had the weakest overall correlation. The rough cultivated soils showed correlations above 0.70 only at Deszk, where a higher

Table 2. Correlation coefficients for drought monitoring samples at the plot level. Bold: significant correlation (>0.50), *calibrated data are identical to original data.

| Study area | Surface coverage | Depth | | | |
|-------------|-------------------------------|-------------|--------------------|-------------|-------------|
| | | 10 cm | 10 cm (calibrated) | 20 cm | 30 cm |
| Deszk | Smooth-flat cultivated soil | 0.06 | 0.08 | -0.60 | -0.60 |
| | Rough cultivated bare soil 1. | 0.80 | 0.79 | 0.71 | 0.76 |
| | Rough cultivated bare soil 2. | 0.80 | 0.80 | 0.45 | 0.45 |
| Sándorfalva | Smooth-flat cultivated soil | 0.77 | 0.76 | 0.86 | 0.83 |
| | Rough cultivated bare soil | 0.09 | 0.07 | 0.30 | 0.61 |
| | Sparse vegetation | 0.75 | 0.75 | 0.80 | 0.74 |
| Rösztke | Smooth-flat cultivated soil | -0.49 | -0.49* | 0.30 | 0.77 |
| | Rough cultivated bare soil | -0.65 | -0.65* | -0.85 | 0.09 |
| | Sparse vegetation | 0.69 | 0.69* | 0.21 | -0.66 |

clay content was present. In general, smooth bare soils showed strong correlations, although statistical significance was observed mainly at sandy soil sites. Sparse vegetation consistently showed significant correlations across sandy and loamy soils.

Rough and clay-rich soils tend to retain water longer, which affects the SWIR reflectance, altering the STR–NDVI relationship. Smooth-flat cultivated bare soils dry faster, resulting in sharper spectral responses and stronger correlations with in situ moisture values. It also highlights that both soil physical characteristics and surface coverage play a significant role in shaping OPTRAM performance.

In the Deszk study area, the analysis was expanded to more Sentinel-2 images and additional data from November. It revealed a decrease in the previously observed higher correlation values on rough, cultivated soil surfaces, which is due to the significant influence of agricultural operations, such as the turning of the soil carried out during this period. These results highlight the importance of incorporating farm management records into plot-level analyses to better account for the effects of agronomic practices on soil moisture dynamics, as reflected by the low coefficient of determination ($R^2 = 0.11$) for the extended Deszk time series.

Using the W_2 (ideal) constant determination method, the remotely sensed soil moisture data at six time points showed a good match with the surface soil moisture values recorded by the monitoring station (Figure 8), reflecting the variations by depth (Ladányi et al. 2021). A notable increase in soil moisture was observed in late September, after a significant rain event of 19.6 mm recorded at the Sándorfalva station between 23 and 25 September. Although the units differ, the timing and magnitude of changes in the remote sensing and in situ data are clearly related. This underscores the potential to incorporate soil porosity parameters and distinguish between soil types in future OPTRAM-based assessments.

Root Mean Square Error (RMSE) was used as the primary metric to evaluate the agreement between OPTRAM estimates and soil moisture measurements in situ. Model performance varied substantially between sites. The best agreement was observed at Sándorfalva (RMSE = 5.85 VWC%, Spearman correlation (ρ) = 0.55, bias = -0.96 VWC%), while Deszk showed moderate precision (RMSE = 6.41 VWC%, $\rho = 0.31$, bias = -2.70 VWC%). In contrast, the results at Rösztke were weak (RMSE = 11.65 VWC%, negative correlations), indicating a pronounced site dependence (Figure 9).

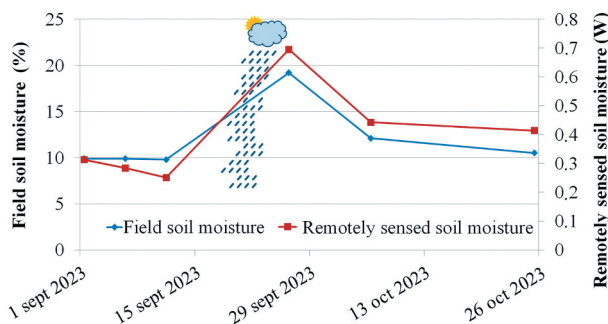


Figure 8. Variation of modelled soil moisture values and in situ data in Sándorfalva with sparse vegetation surface coverage at a depth of 0–10 cm (1 September 2023–26 October 2023).

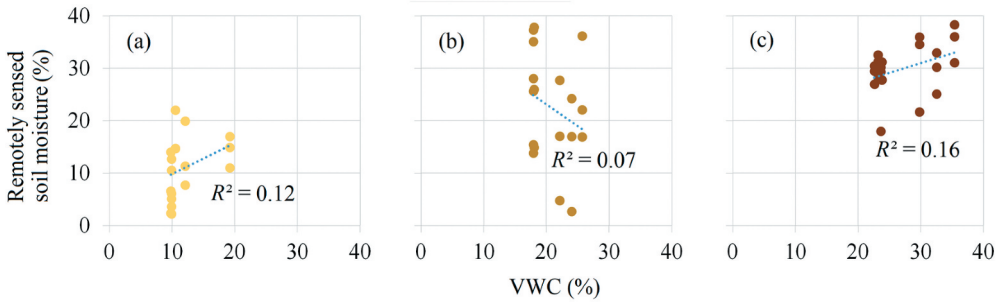


Figure 9. Comparison of remote sensed and field soil moisture values at different stations based on plot averages (a: Sándorfalva, b: Röszke, c: Deszk).

Surface cover exerted a stronger control over accuracy than site location alone. When grouped in across the study area, the lowest errors and strongest correlations were obtained under sparse vegetation (RMSE = 4.75 VWC%, $\rho = 0.83$), followed by rough bare soil (RMSE = 7.05 VWC%, $\rho = 0.72$), while smooth bare surfaces showed the highest deviations (RMSE = 10.20 VWC%, $\rho = 0.40$). Bias patterns revealed systematic surface-dependent behaviour, with underestimation over smooth soil and overestimation over rough surfaces. OPTRAM captures temporal dynamics more reliably than absolute moisture levels and requires surface-aware calibration (Figure 10).

Previous studies reported OPTRAM performance with RMSE values between 0.05 and 0.09 m³ m⁻³ and R^2 between 0.43 and 0.65 (Ma, Johansen, and McCabe 2022). Stanczyk et al. (2023) similarly observed (R^2 0.67) stronger correlations under sparse vegetation. Sadeghi et al. (2023) reported comparable results using Landsat-8 ($R^2 = 0.47$ – 0.67) and Ambrosone et al. (2020) in agricultural environments (RMSE = 0.08; Mean Average Error (MAE) = 0.06).

Although direct numerical comparison is limited by scaling differences, relative performance patterns are consistent. Automated wet–dry edge detection is therefore recommended to reduce uncertainty in future applications.

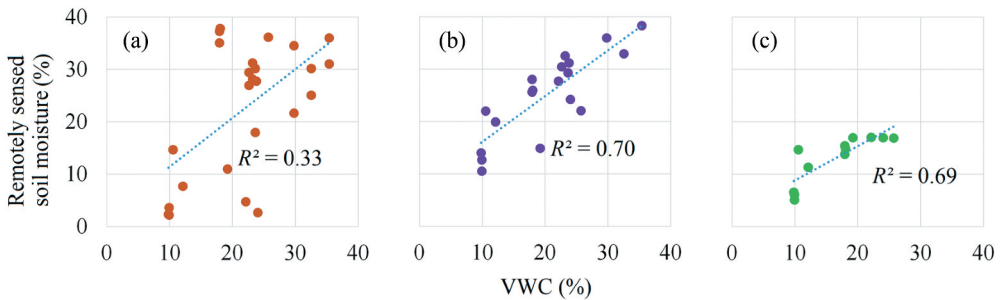


Figure 10. Comparison of remote sensed and field soil moisture values on different coverages based on plot averages (a: smooth-flat cultivated soil; b: rough cultivated soil; c: sparse vegetation).

4. Conclusions

This study demonstrated the potential of parcel-scale satellite-based soil moisture mapping using Sentinel-2 data and the OPTRAM model, with strong determination coefficient ($R^2 = 0.73$) between modelled and in situ measurements. High accuracy was achieved in various soil textures, tillage practices, and surface covers, underscoring the ability of the OPTRAM to capture the interactions between porosity and soil moisture dynamics.

The results highlight the importance of considering genetic soil types and grain composition of the upper soil layers, which influence infiltration and retention. Differences between field and satellite data were observed due to spatial resolution, surface cover, and soil layering, yet Pearson's correlations over 0.80 were reached in some cases. This supports the robustness of the model, especially when integrated with local agronomic records, such as tillage and rotation practices.

During 3 months, Sentinel-2 imagery effectively captured temporal changes in soil moisture. These results confirm the utility of OPTRAM for high-resolution monitoring and reinforce the need to incorporate site-specific factors and automated parameterization to reduce uncertainty and improve model reliability.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data used are available free on the Copernicus Browser and from the Hungarian Operational Drought and Water Scarcity System. Field measurements collected during this research can be provided by the corresponding author upon reasonable request.

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