ERA5-Land: soil moisture dry-downs detection over the Argentine Pampas

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Abstract

Soil moisture (SM) in the profile is the main reservoir of water available for vegetation. Therefore, monitoring SM during dry-down periods is crucial for understanding vegetation water status, among other applications. Datasets derived from Land Surface Models, such as the ERA5-Land dataset, provide SM estimates at different depths. The aim of this study was to evaluate the ability of ERA5-Land SM data to detect dry-down periods and to test whether its drying time scale aligns with field measurements at three sites in the Argentine Pampas. The analysis was carried out across the three standard soil layers used by ERA5-Land: layer 1 (L1, 0-7 cm), layer 2 (L2, 7-28 cm), and layer 3 (L3, 28-100 cm). First, the evaluation of the ERA5-Land SM data showed a moderate agreement with field data, although it exhibited a high overestimation (bias > |0.09| m^3/m^3) in the SM estimates. On the other hand, dry-down periods analysis indicated that ERA5-Land SM data was able to detect a similar number of dry-down periods and drying time scales as observed in the field for L1 and L2. In contrast, at L3, both the number of detected periods and the estimated drying time scale were lower. ERA5-Land SM data showed a consistent and expected pattern of faster drying in the shallower layers, demonstrating its potential for monitoring SM dynamics within the profile.

1. INTRODUCTION

Soil moisture (SM) plays a fundamental role in land-atmosphere interactions and is the main reservoir of water available for vegetation. As an integrative variable, SM in the soil profile is crucial for monitoring drought periods or even flash droughts (Holzman et al., 2025). Short periods of water deficit (e.g., 10-30 days) can have a key effect on vegetation water status and productivity. Thus, SM datasets should have a suitable temporal coverage to monitor those periods and also a certain accuracy level, especially to reflect values near thresholds where vegetation is harmed (e.g., wilting point).

Using observations from the Monte Buey Core Validation Site (Thibeault et al., 2015; Niclos et al., 2016), Cappelletti et al. (2020) have shown that ESA's SMOS mission was able to detect surface dry-down periods consistently with in situ measurements, although with a faster soil drying. Moreover, Ruscica et al. (2020), focusing on the Argentine Pampas, have identified the temporal sampling frequency (such as 2-3 days) as a main source of uncertainty in dry-down periods of surface SM from both satellite observations and Land Surface Models (LSMs). Despite this, these datasets provide valuable information for drought monitoring and soil-vegetation interaction studies. However, surface SM dynamics are not always coupled with subsurface, especially under dry soil conditions (Degano et al., 2025). This is especially relevant in croplands, where most plant water uptake occurs below 30 cm depth (Feldman et al., 2023; Olivera Rodríguez et al., 2024). Therefore, the evaluation of SM throughout the soil profile and field data comparison remains a critical and crucial gap.

Particularly, the ERA5-Land dataset, which provides daily estimates of SM at different depths (Muñoz-Sabater et al., 2021), is commonly used for drought monitoring (Zhang et al., 2021; Liu et al., 2025), being scarcely evaluated in the Argentine Pampas. This information shows promise for capturing SM dynamics within the soil profile in agricultural systems, which is key to understanding the vegetation water status (Holzman et al., 2021). Consequently, the aim of this study was to analyze the capacity of the ERA5-Land dataset to detect SM dry-down periods compared to field data, testing both their occurrence and drying time scale at different depths (0-7 cm, 7-28 cm, 28-100 cm).

2. STUDY AREA

The study area is located in the Argentine Pampas, one of the most extensive and productive agricultural plains in the world, with an approximate area of 520000 km² (Degano et al., 2021). Three study sites with different climatic and soil textural conditions were selected: Anguil (ANG), Villegas (VIL), and Tandil (TAN) (Figure 1 and Table 1). In terms of land cover, all study sites are predominantly classified as croplands, with at least 60% of cultivable surface (Friedl and Sulla-Menashe, 2022). The main crops in the region are barley and wheat during the winter period, and soybean, corn, and sunflower during the summer period (Olivera Rodríguez et al., 2024).

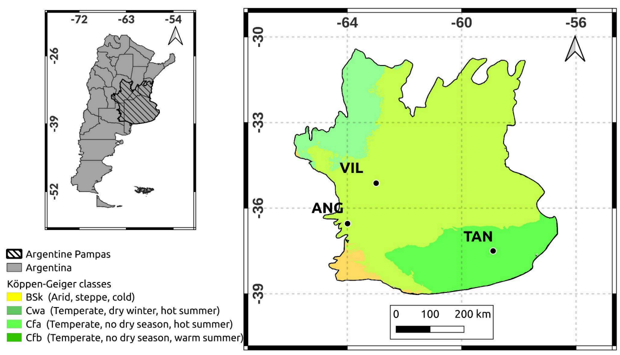

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Figure 1. Location of the three study sites in the Argentine Pampas and their corresponding Köppen climate classifications (Beck et al., 2023).

The dominant soil order across the study sites is Mollisols, with some variations in their morphological and textural characteristics (INTA, 2025). At the VIL site, the soil corresponds to a Thapto Argic Hapludoll, featuring a sandy loam texture, suggesting good permeability and moderate water retention capacity. At the ANG site, the soil type is an Entic Haplustoll, characterized by a sandy loam texture throughout the profile and excessive drainage. Finally, the TAN site presents a Typic Argiudoll, with a clay loam texture, indicating good drainage and high water retention.

Site	ANG	VIL	TAN
Temperature	16 ºC	16 ºC	14 ºC
Relative humidity	64 %	74 %	75 %
annual precipitation	754 mm	941 mm	913 mm
soil textures at profile	sandy loam	sandy loam	clay loam

Table 1: Annual climatic and soil characteristics at each study site (SMN, 2025; INTA, 2025).

3. DATA

3.1 ERA5-Land Data

ERA5-Land is a global land surface reanalysis fifth-generation dataset developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), providing hourly estimates of water and energy cycle variables at a spatial resolution of ~9 km. It is produced by assimilating satellite observations and atmospheric forcing data into a LSM. SM (m^3/m^3) is modeled using the Hydrology-Tiled ECMWF Scheme for Surface Exchanges over Land (HTESSEL), which numerically solves the coupled water and energy balance at the soil-atmosphere interface. ERA5-Land discretizes the soil profile into four layers: 0-7 cm (layer 1, L1), 7–28 cm (layer 2, L2), 28–100 cm (layer 3, L3), and 100–289 cm (layer 4, L4) (Muñoz-Sabater, 2019; Muñoz-Sabater et al., 2021).

A main feature of ERA5-Land SM data is its revised soil hydrology scheme, which includes enhanced parameterizations based on soil texture. However, a current limitation is that ERA5-Land assumes a fixed land cover throughout the complete reanalysis period, and both the leaf area index (LAI) and albedo are based on a static monthly climatology. This static representation may not capture short-term vegetation dynamics, potentially affecting the accuracy of SM estimations through changes in evapotranspiration and plant water uptake in the root zone (Muñoz-Sabater et al., 2021).

For this study, the daily aggregated version of ERA5-Land SM was obtained from Google Earth Engine (GEE), specifically from the collection "ECMWF/ERA5_LAND/DAILY_AGGR" (Muñoz-Sabater, 2019). Although the dataset documentation reports a delay of 2-3 months with respect to acquisition date, in GEE this daily aggregated version is available with only a 7-day delay. SM data from layers L1, L2, and L3 were used, while L4 was excluded due to the absence of field measurements at those depths.

3.2 Field Data

The Telemetric Network of Soil Moisture of the SAOCOM Mission, by the Comisión Nacional de Actividades Espaciales (CONAE), acquires SM data at different sites across the Argentine Pampas region. These measurements are used for the validation and calibration of SM data from the SAOCOM mission as well as other soil moisture satellite missions (Niclos et al., 2016; Colliander et al., 2022). These data consist of hourly SM measurements in surface and subsurface layers, obtained using Hydra Probe II sensors installed at field stations surrounded by crop fields (Thibeault et al., 2015). For this study, SM field data were used from the ANG and VIL sites. At the ANG site, sensors record SM at depths of 5, 10, and 50 cm, which approximately represent the 0-10 cm (L1), 5–15 cm (L2), and 45–55 cm (L3) (ERA5-Land) soil layers, respectively. At the VIL site, sensors are located at depths of 5 cm and 30 cm, corresponding approximately to the 0–10 cm (L1) and 25–35 cm (L2) layers, respectively. The deepest field SM was at a depth of up to 50 cm and was considered representative of the ERA5-Land L3, given that the main variability in the study area occurs at these measured depths. Similar approaches have been applied in the evaluation of root-zone SM datasets, both in different regions of the Argentine Pampas and globally (Spennemann et al., 2020; Muñoz-Sabater et al., 2021). The measurement period covers 2014 to 2024, including diverse climatic conditions (dry, normal, and wet years). Although there are some data gaps at both sites, the overall time series remains representative of SM interannual variability.

On the other hand, SM data from the TAN site were collected during two wheat and three soybean campaigns between 2020 and 2024 by the Instituto de Hidrología de Llanuras (IHLLA). Measurements were recorded every 10 minutes using the SoilVUE™10 sensor (Campbell Scientific Inc.), which includes probes installed at depths ranging from 5 cm to 50 cm (Olivera Rodríguez et al., 2024). For this study, daily 5 cm measurement was used to represent the 0–10 cm layer (L1), average of the 10 and 20 cm measurements approximates the 5–25 cm depth range (L2), and mean of the 30 and 50 cm corresponds to the 25–55 cm layer (L3).

4. METHODOLOGY

ERA5-Land SM data were first evaluated against field data at each study site to ensure their suitability for the subsequent detection and analysis of SM dry-down periods. All data processing and analysis were performed in Python.

4.1 ERA5-Land Evaluation

A sparse network analysis was carried out for layers L1, L2, and L3 to evaluate the performance of the ERA5-Land SM at study sites. The daily aggregated ERA5-Land SM data were compared against daily field data using the Pearson correlation coefficient (r), the bias, and the unbiased root mean square difference (ubRMSD) (Gruber et al., 2020). The entire data series for the three stations were considered.

4.2 Dry-down Periods

4.2.1 Detection

For each depth layer, dry-down periods in both field and ERA5-Land data were identified as sequences of consecutive days with decreasing SM ($SM_t < SM_{t-1}$), allowing thresholds of up to 0.003 m³/m³ for the field data and 0.015 m³/m³ for the ERA5-Land data (below the observed ubRMSD, see subsection 5.1). These thresholds were set to minimize the detection of spurious periods due to sensor noise or model uncertainty.

A minimum duration of 9 consecutive days was defined to consider a valid period, while the maximum duration was limited to 90 days (not exceeding the length of a season). This time window was selected to consider significant dry-down periods and to avoid short periods due to noise in the data. In addition, if gaps between observations exceeded 4 days, dry-down periods longer than 9 days were truncated, whereas those shorter than 9 days were discarded.

4.2.2 Modelling

Several previous studies have modeled surface SM dynamics during dry-down periods using a decreasing exponential model, as shown in Equation 1 (McColl et al., 2017; Ruscica et al., 2020).

$$SM(t) = A\,exp\left(-\,t * \tau^{-1}\right) + SM_f \quad (1)$$

A (m³/m³) represents the amplitude of the dry-down period, t is the number of days since the period start, τ (days) is the time scale of the dry-down period, and SM_f (m³/m³) denotes the equilibrium (asymptotic) value, which has to be lower than the minimum SM observed during the period. In this study, special focus was given to the parameter τ, which is interpreted as an indicator of the rate of SM decreases of each dry-down period: higher τ values indicate slower soil drying, whereas lower values reflect faster drying periods.

For each identified dry-down period, a nonlinear curve fitting procedure was applied to the SM data using the exponential model described in Equation 1. This fitting was performed using the SciPy library in Python, which estimates the model parameters by minimizing the sum of the squared residuals between the observed data and the model (Virtanen et al., 2020). The procedure was carried out independently for each of the three soil layers (L1, L2, and L3) and both field and ERA5-Land data. Only fits with a coefficient of determination (R^2) greater than 0.6 were considered to ensure reliable estimates of the τ parameter.

5. RESULTS AND DISCUSSION

5.1 ERA5-Land Evaluation

Table 2 shows the statistical metrics of the three analyzed layers (L1, L2, and L3) at TAN, ANG, and VIL sites. r values ranging from 0.52 to 0.76 indicated a moderate agreement between the field data and the ERA5-Land SM in all layers, with VIL exhibiting the best performance.

The ubRMSD values were between 0.03 and 0.08 m³/m³ in all layers, with higher values observed at TAN. These results are similar to values reported for the Argentine Pampas using ERA5-Land, ERA5-Interim, and other satellite and reanalysis-based SM datasets (Lal et al., 2022; Spennemann et al., 2020; Colliander et al., 2022; Degano et al., 2024). However, ERA5-Land SM generally overestimated field data, with significant bias values ranging from -0.08 to -0.18 m³/m³ across all sites and layers. In particular, the lowest bias was observed at L3 TAN, suggesting that ERA5-Land SM values at this depth were more closely centered around the field data mean.

Based on the standard deviations (std), it was observed that at ANG, field SM exhibited lower variability (std ≈ 0.04 m³/m³) compared to ERA5-Land (std ≈ 0.07 m³/m³), particularly in L1 and L2. In layer L3, the difference in std between field data and ERA5-Land was less than 0.01 m³/m³, suggesting that ERA5 captured similar SM variability to that observed in the field.

A different pattern was observed at TAN and VIL, where SM field data consistently showed higher variability than ERA5-Land data across all layers. At TAN, std values remained similar across layers (≈ 0.09 m³/m³), whereas ERA5-Land SM variability decreased with depth (from 0.06 to 0.02 m³/m³). At VIL, SM field variability was also higher than ERA5-Land in both L1 and L2 (0.08 m³/m³ vs. 0.06 m³/m³, and 0.06 m³/m³ vs. 0.05 m³/m³, respectively).

Layer	Region	n	r	bias (m3/m3)	ubRMSD (m3/m3)
L1	TAN	576	0.53	-0.14	0.08
	ANG	621	0.59	-0.18	0.06
	VIL	1103	0.76	-0.16	0.05
L2	TAN	576	0.55	-0.08	0.07
	ANG	1538	0.69	-0.17	0.05
	VIL	1103	0.68	-0.09	0.05
L3	TAN	576	0.52	-0.001	0.08
	ANG	1534	0.66	-0.13	0.03

Table 2. Statistical metrics for the comparison between field and ERA5-Land SM data at L1, L2, and L3 for TAN, ANG, and VIL. Number of data (n), Pearson correlation coefficient (r), bias (field data – estimation), and unbiased root-mean-square difference (ubRMSD).

5.2 Field and ERA5-Land Dry-down Periods

Figure 2 shows time series examples of SM for layers L1, L2, and L3, comparing field data with ERA5-Land estimates. As mentioned above, ERA5-Land tended to overestimate the field data, except during certain periods in the L3 layer at TAN. This is consistent with the lower bias observed for this layer (see Table 2).

In general, SM temporal fluctuations decreased with increasing depth. Layers L1 and L2 in both field and ERA5-Land data exhibited similar temporal patterns, with L1 showing greater fluctuations, as expected due to its stronger interaction with atmospheric processes (e.g., evapotranspiration). As shown in Figure 2, some dry-down periods were not identified in the analysis, either because the variations did not meet the established thresholds or their duration was shorter than the minimum required (9 days). However, ERA5-Land SM data demonstrates remarkable sensitivity in these shallow layers, detecting quick and less intense dry-down periods.

In layer L3, SM fluctuations were slower due to the reduced interaction with atmospheric processes and are primarily regulated by the water demand of vegetation and the dynamics of the shallow soil layers. However, these fluctuations were even less noticeable in the ERA5-Land data. This pattern is particularly evident during specific periods at the TAN site, as shown in Figure 2, where ERA5-Land SM remained nearly constant while field data exhibited significant variations. Notably, these changes coincided with the critical growth stage of soybean (20 January to 12 March), a period characterized by increased water uptake from deeper soil layers (Olivera Rodríguez et al., 2024).

Regarding differences between ERA5-Land and field data, ERA5-Land tended to detect multiple dry-down periods that corresponded to a single period observed in the field data, as shown for L1 at ANG (Figure 2). This discrepancy may be partly attributed to the spatial resolution of the ERA5-Land product, where temporal variations at the pixel level, such as scattered and non-generalized rainfall, may have occurred but were not captured by point-based field measurements.

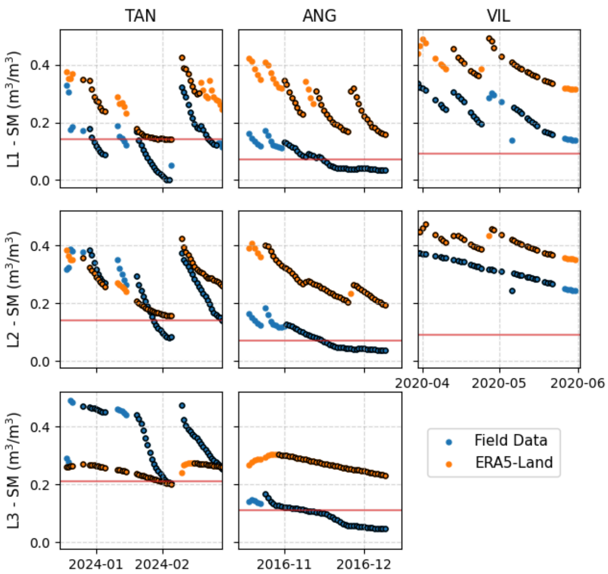
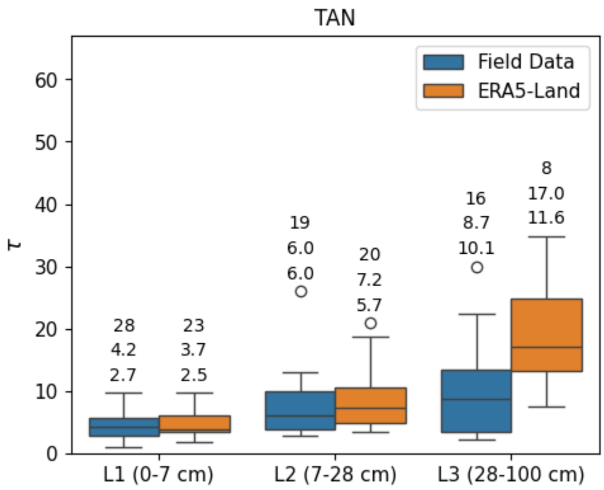


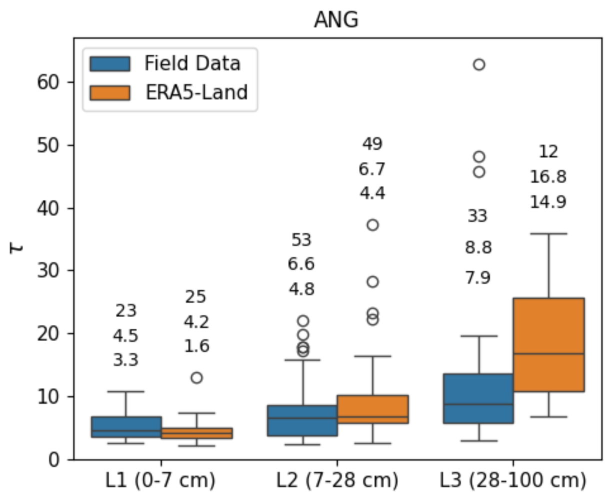
Figure 2. Field and ERA5-Land SM time series examples for layers L1 (0-7 cm), L2 (7-28cm), and L3 (28-100 cm) at TAN, ANG, and VIL sites. Black edge markers indicate detected dry-down periods, and red lines represent estimated wilting points.

Figure 3 shows τ distributions corresponding to the time scale of the analyzed dry-down periods, for layers L1, L2, and L3 at each study site. It is important to highlight that the VIL site does not include data for L3 due to the lack of field data. The number of detected dry-down periods at L1 and L2 was relatively similar between the field and ERA5-Land data (Figure 3). Whereas, ERA5-Land detected nearly 50% fewer dry-down periods than field data for L3 at TAN and ANG sites. This discrepancy suggests a lower ERA5-Land product sensitivity in capturing SM dynamics in the deepest layer (28–100 cm). This layer is important, as generally the upper 40 cm depth contributes approximately 70% of the water uptake by vegetation, especially in croplands (Feldman et al., 2023; Olivera Rodríguez et al., 2024).

Dry-down periods tended to occur faster in the upper layers at all sites, following the expected pattern: $\tau_{L1} < \tau_{L2} < \tau_{L3}$ (Figure 3). This trend, observed in both field and ERA5-Land data, reflects the typical vertical dynamics of SM within the soil profile. On average, the median τ values across all sites were around 4 days (4 days) for L1 and 6 days (6.5 days) for L2 in the field (ERA5-Land) data, with no significant differences observed between datasets for these two layers. For L3, median values averaged approximately 10 days in the field and 17 days in ERA5-Land, indicating a slower drying time scale in the deeper soil layer. Despite the difference between the number of detected dry-down periods in this layer, this discrepancy may be partly due to the static representation of the vegetation cover in the ERA5-Land model. Consequently, plant water uptake from deeper soil layers during periods of higher vegetation demand, such as during crop reproductive stages, may be underestimated, resulting in an overestimation of SM.



(a)



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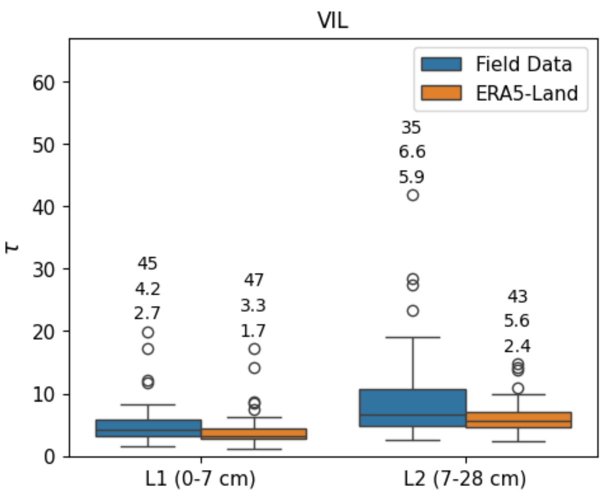

(c)

Figure 3. τ distributions a) TAN, b) ANG, and c) VIL. Numbers above each box plot (from top to bottom): number of detected dry-down periods, percentile 50 (median), and interquartile range (IQR)

The variability of τ was analyzed using interquartile ranges (IQR) in all layers for both field and ERA5-Land data at each site (from boxplots in Figure 3). At ANG, ERA5-Land data showed lower τ variability at L1, with an IQR 1.5 days lower than that of the field data. At L2, IQR values were similar between datasets, whereas at L3, ERA5-Land showed approximately twice the τ variability observed in the field. This discrepancy in L3 may be related to the non-comparable number of dry-down periods detected. In VIL, ERA5-Land showed a lower IQR in L1 (approximately 1 day shorter), and an even larger difference in L2, where its IQR was almost three times lower than the τ variability of the field data. This suggests that the durations of ERA5-Land SM dry-down periods are more tightly distributed than those observed in the field. In contrast, in TAN, τ IQR values were comparable between field and ERA5-Land data in all layers

Part of the discrepancies in τ variability, most evident in VIL, may be attributed to generalized or low-resolution of input variables to the ERA5-Land soil hydrology scheme, such as soil texture (about 10 km, textural class medium for TAN and ANG), that affect the water retention properties of the soil profile. In addition, mismatches in spatial resolution and differences in vertical discretization of the soil profile between ERA5-Land and field data likely contribute to these discrepancies, as this is often a potential source of commonly noted uncertainties when comparing LSMs and field data (Spennemann et al., 2020).

6. CONCLUSIONS

Despite some possible discrepancies between the field and medium resolution SM analyzed data, statistical metrics indicate that the ERA5-Land SM dataset performs similarly to other SM datasets previously evaluated in the Argentine Pampas region ($0.5 < r > 0.8$ and $0.03 < ubRMSD > 0.08$ m³/m³). However, a general tendency of ERA5-Land to overestimate SM was observed in all the study sites, with significant biases across all layers (-0.08 to -0.18 m³/m³). This overestimation should be considered carefully, especially during key periods, as in advanced stages of a drying process, where the estimated SM can be higher than the wilting point. In this context, bias correction procedures could help improve the reliability of the product, particularly during dry periods when accurate SM estimates are critical for assessing vegetation stress. This is especially relevant in deep soil layers, which can sustain vegetation under non-stress conditions even when surface moisture is limited. However, when performing these procedures, the moderate correlation values observed between the data sets must be considered.

The number of detected dry-down periods in ERA5-Land and field data was comparable in the shallow soil layers (L1 and L2), supporting the potential of the ERA5-Land SM product to capture drying processes. At L3 (deepest layer), ERA5-Land detected nearly 50% fewer dry periods than those observed in the field, which may reflect a lower sensitivity to SM dynamics at this depth. Despite these discrepancies, ERA5-Land SM captured consistent and coherent drying patterns in all layers at all study sites: typical slower drying at greater depths.

Taking into account the expected variations of SM in agricultural areas, daily data from the ERA5-Land product should be suitable for monitoring the potential impact on crops. However, to improve its applicability in operational agricultural drought monitoring, it is important to consider the observed overestimation and possible limitations reflecting SM variabilities in the deepest horizons. Another issue to consider is the delay in data availability, which reduces its usefulness for near real-time applications. In addition, future studies can consider the role of specific model inputs in this area, such as static land cover, soil texture, and evapotranspiration, to better estimate deep SM.

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