Advances in Soil Moisture Mapping Techniques and Disaggregation Algorithms for Environmental and Agricultural Applications

Miriam Pablos[1], Gerard Portal[1,2], Adriano Camps[1,2,3], Mercè Vall-llossera[1,2] and Carlos López-Martínez[1,2]

[1]CommSensLab, Dept. of Signal Theory and Communications, Universitat Politècnica de Catalunya (UPC), 08034 Barcelona, Spain
[2]Institut d'Estudis Espacials de Catalunya (IEEC), 08034 Barcelona, Spain
[3]ASPIRE Visiting International Professor, UAE University, 15551 Al Ain, United Arab Emirates

Abstract

Soil moisture (SM) is a critical variable for understanding the water cycle, climate change, and agricultural management. This paper reviews advanced remote sensing techniques and disaggregation algorithms for high-resolution SM mapping, focusing on environmental and agricultural applications in North Africa and the UAE. Remote sensing methods, including optical sensors (e.g., Apparent Thermal Inertia, Temperature Vegetation Dryness Index), active microwave sensors (scatterometers, Synthetic Aperture Radar), and passive microwave radiometers (SMOS, SMAP), are evaluated for their ability to map SM at varying spatial and temporal scales. Despite advancements, coarse resolution remains a challenge for regional applications. To address this, two innovative downscaling algorithms are presented: the SMOS Semi-Empirical Method, which fuses SMOS data with ECMWF skin temperature and MODIS/Sentinel-3 NDVI to achieve 1 km and 300 m resolutions, and the Artificial Neural Network (ANN) Method, leveraging multi-sensor data to produce 60 m resolution SM maps. These algorithms have been validated across diverse environments, demonstrating RMSE values of 0.04–0.10 cm^3/cm^3. The case studies presented highlight their operational utility in flash flood monitoring (Algeria, Tunisia, UAE), ecosystem dynamics (Chott el Djerid, Tunisia), and precision agriculture (East Oweinat, Egypt). Future work includes the integration of multi-sensor data, to enhance machine learning models, and the improvement of SM measurements at deeper soil layers to support applications in arid regions.

Keywords: Soil moisture, remote sensing, disaggregation algorithms, spatial resolution, environmental monitoring.

1. Introduction

Soil moisture (SM) is a key environmental variable that plays a crucial role in understanding the water cycle, supporting climate change assessments, and enabling better agricultural and ecological management. Accurate soil moisture mapping is vital for monitoring drought, flood, and irrigation patterns, and it supports broader environmental and ecological research. This paper summarizes the state-of-the-art techniques for soil moisture mapping: first on the remote sensors and methods, and then on algorithms to enhance the spatial resolution of soil moisture maps. Examples of applications are provided in the North of Africa, and the UAE.

1.1 Remote Sensing Soil Moisture Mapping Techniques

Remote sensing technologies and techniques for soil moisture mapping have evolved significantly over the past several decades, representing a critical advancement in our ability to monitor one of the most important variables in the Earth's hydrological cycle. These technologies leverage multiple sensor types and platforms to overcome inherent challenges such as vegetation effects, atmospheric conditions including cloud cover, temporal sampling limitations, and spatial resolution constraints. The evolution from early experimental approaches to operational satellite missions has revolutionized our understanding of soil moisture dynamics at scales ranging from local agricultural fields to global climate monitoring systems.

An overview of the different remote sensing approaches for mapping soil moisture at different spatial and temporal scales is given below, with each technique offering unique advantages and facing specific limitations that must be carefully considered in application design:

1.1.1 Optical Sensors

Optical sensors measure reflected and emitted electromagnetic radiation from the Earth's surface across the visible, near-infrared, and thermal infrared portions of the spectrum, which can be used to estimate soil moisture indirectly through various physical relationships. These sensors have been among the earliest tools used for environmental monitoring and continue to play an important role in soil moisture estimation, particularly when integrated with other sensor types in multi-sensor approaches.

Two major techniques have emerged as particularly significant in optical-based soil moisture estimation:

- **Apparent Thermal Inertia (ATI)**

The Apparent Thermal Inertia (ATI) method estimates soil moisture by analyzing diurnal variations in land surface temperature, building on the fundamental principle that thermal inertia is strongly correlated with soil moisture content [1]. The physical basis of this approach lies in the fact that water has a high specific heat capacity and thermal conductivity compared to dry soil minerals, meaning that wet soils exhibit smaller temperature fluctuations throughout the day-night cycle than dry soils. The *ATI* is calculated using the relationship:

$$ATI = \frac{1-albedo}{\Delta T}, \quad (1)$$

where ΔT represents the diurnal temperature range and albedo represents the surface reflectance. This technique has been successfully applied using data from various thermal infrared sensors, including the Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), and Landsat Thermal Infrared Sensor (TIRS). However, the method requires clear-sky conditions for accurate temperature measurements and can be affected by variations in surface roughness, vegetation cover, and atmospheric conditions [2].

- **Temperature Vegetation Dryness Index (TVDI)**

The Temperature Vegetation Dryness Index (TVDI) represents a more sophisticated approach that uses the relationship between land surface temperature (LST) and vegetation health, typically represented by the Normalized Difference Vegetation Index (NDVI), to derive soil moisture estimates [3]. This method is based on the triangular or trapezoidal relationship observed in LST-NDVI feature space, where the distribution of pixels forms a characteristic pattern that reflects varying combinations of vegetation cover and moisture availability.

The TVDI is calculated as:

$$TVDI = \frac{LST-LST_{min}}{LST_{max}-LST_{min}}, \quad (2)$$

where LST_{min} and LST_{max} represent the minimum and maximum land surface temperatures for a given NDVI value, derived from the dry and wet edges of the LST-NDVI scatter plot. Values range from 0 (wet conditions) to 1 (dry conditions). This

https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-1139-2025

approach has been widely validated and applied using data from MODIS, AVHRR, and other optical sensors, with particular success in agricultural and semi-arid regions [4,5].

- **Limitations of Optical Sensors**

However, optical sensors face significant limitations that restrict their applicability in certain environments and conditions. The primary challenge is the inability to penetrate dense vegetation canopies, which means that in heavily vegetated areas, the signal primarily reflects canopy properties rather than underlying soil conditions. Additionally, cloud cover completely blocks optical observations, creating significant gaps in temporal coverage, particularly in tropical and temperate regions with frequent cloud cover. The indirect nature of soil moisture estimation through optical methods also introduces uncertainties, as the relationship between surface temperature, vegetation indices, and actual soil moisture can be influenced by factors such as atmospheric conditions, soil type, surface roughness, and vegetation phenology [6].

1.1.2 Active Microwave Sensors

Active microwave sensors, including scatterometers and Synthetic Aperture Radar (SAR) systems, represent a significant advancement in soil moisture remote sensing capabilities due to their ability to penetrate cloud cover and operate independently of solar illumination. These systems transmit microwave pulses and measure the backscattered energy, which is sensitive to the dielectric properties of the target surface.

- **Scatterometers**

Scatterometers, such as those aboard the European Remote Sensing (ERS) satellites and the Advanced Scatterometer (ASCAT) on MetOp satellites, provide global coverage with relatively coarse spatial resolution (typically 25-50 km). The backscatter coefficient measured by these instruments is related to soil moisture through the soil's dielectric constant, which increases significantly with water content. The relationship between backscatter and soil moisture has been extensively studied and forms the basis for operational soil moisture products [7,8]

The Vienna University of Technology (TU Wien) change detection method represents one of the most successful approaches for scatterometer-based soil moisture retrieval. This method uses the relative position of current backscatter observations between historically observed wet and dry reference values to estimate soil moisture as a degree of saturation [9].

- **Synthetic Aperture Radar (SAR)**

SAR systems, including those on Sentinel-1, RADARSAT, and ALOS PALSAR missions, offer much higher spatial resolution (typically 10-100 m) compared to scatterometers, making them valuable for regional and local applications. The relationship between SAR backscatter and soil moisture is complex and depends on multiple factors including radar frequency, polarization, incidence angle, surface roughness, and vegetation characteristics [10,11].

Different radar frequencies exhibit varying sensitivities to soil moisture: **L-band (1-2 GHz)** provides the deepest penetration into vegetation and soil, making it most suitable for soil moisture estimation beneath moderate vegetation cover; **C-band (4-8 GHz)** is commonly used in operational missions like Sentinel-1, offering a balance between vegetation penetration and sensitivity to surface conditions, and **X-band (8-12 GHz)** is highly sensitive to surface roughness and shallow soil properties**,** but limited vegetation penetration.

- **Challenges with Active Microwave Sensors**

Despite their advantages, active microwave sensors face several significant challenges. Speckle noise is inherent to all coherent radar systems and can significantly degrade measurement accuracy, requiring sophisticated filtering and processing techniques. The sensitivity to surface roughness can be both an advantage and a limitation, as it provides information about surface conditions but also introduces variability that must be accounted for in soil moisture retrieval algorithms. Additionally, while these systems can penetrate light to moderate vegetation, dense canopies still present challenges for accurate soil moisture estimation [12].

The temporal coverage limitation is another significant constraint, with most SAR systems providing revisit times of 6-12 days for full coverage, which may be insufficient for capturing rapid soil moisture dynamics associated with precipitation events or irrigation practices.

1.1.3 Microwave Radiometers

Microwave radiometers represent the current state-of-the-art for global soil moisture monitoring from space, offering direct sensitivity to soil moisture through measurement of naturally emitted microwave radiation. The physical principle underlying this approach is based on the strong contrast in dielectric properties between water and dry soil, which significantly affects the soil's microwave emissivity.

- **SMOS Mission**

The European Space Agency's Soil Moisture and Ocean Salinity (SMOS) mission was launched in 2009 and it was the first dedicated soil moisture satellite mission. SMOS carries the Microwave Imaging Radiometer using Aperture Synthesis (MIRAS), an L-band (1.4 GHz) interferometric radiometer that measures brightness temperature with global coverage every 2-3 days [13]. The L-band frequency was specifically chosen because it represents an optimal balance between sensitivity to soil moisture and minimal interference from vegetation and atmospheric effects.

The SMOS retrieval algorithm is based on the τ-ω model, which accounts for vegetation effects through the vegetation optical depth (τ) and single scattering albedo (ω) parameters. Despite its groundbreaking capabilities, SMOS faces challenges including radio frequency interference (RFI) from human activities, particularly in developed regions, and spatial resolution limitations [14].

- **SMAP Mission**

NASA's Soil Moisture Active Passive (SMAP) mission, launched in 2015, represents the most advanced soil moisture satellite currently in operation. SMAP was originally designed to combine L-band radiometer and radar measurements to achieve both high accuracy and improved spatial resolution. Although the radar component failed early in the mission, the radiometer continues to provide high-quality global soil moisture data with 2-3 day revisit time [15].

SMAP's radiometer operates at 1.41 GHz (L-band) with horizontal and vertical polarizations, measuring brightness temperature that is converted to soil moisture using sophisticated retrieval algorithms. The mission has achieved remarkable accuracy, with soil moisture estimates typically within 0.04 cm^3/cm^3 of ground-based measurements under optimal conditions [16].

1.2 Soil Moisture Disaggregation Algorithms to Enhance the Spatial Resolution

1.2.1 Soil Moisture Downscaling Algorithms: From Coarse Satellite Observations to High-Resolution Mapping

To address the fundamental limitations of the coarse spatial resolution inherent in current operational soil moisture satellite missions, novel disaggregation algorithms have been specifically designed and rigorously developed to downscale low-resolution satellite data into high-resolution soil moisture maps. These advanced methodologies are essential to bridge the gap between the capabilities of current spaceborne sensors and the detailed spatial information requirements of specific applications such as precision crop management, localized flood monitoring, drought forecasting at agricultural scales, irrigation scheduling, and ecosystem monitoring.

The challenge of spatial resolution enhancement in soil moisture remote sensing stems from the fundamental physics of microwave radiometry, where larger antenna apertures or interferometric techniques are required to achieve finer spatial resolution. Since physical constraints limit the practical size of spaceborne antennas, mathematical and algorithmic approaches to spatial disaggregation have become crucial for extracting maximum value from existing satellite observations. These downscaling techniques leverage the complementary strengths of multiple sensor systems and exploit the spatial relationships between soil moisture and various environmental variables that can be observed at higher spatial resolution.

1.2.2 Theoretical Foundation of Soil Moisture Downscaling

The theoretical framework underlying soil moisture downscaling is based on the assumption that, while coarse-resolution soil moisture observations provide accurate absolute values over large areas, soil moisture exhibits spatial patterns that are correlated with other observable environmental variables at finer spatial scales. These relationships can be exploited through various mathematical approaches, ranging from simple linear regressions to complex machine learning algorithms. The fundamental principle is that while coarse-resolution soil moisture observations provide accurate absolute values over large areas, the spatial variability within these areas can be estimated using auxiliary high-resolution data that correlate with soil moisture patterns.

The effectiveness of downscaling approaches depends on several critical factors: a) **Scale Relationships** refer to the degree to which soil moisture patterns at fine scales are predictable from coarse-scale observations and auxiliary variables, b) **Auxiliary Data Quality** in terms of spatial resolution, temporal consistency, and physical relevance of supporting datasets, c) **Environmental Homogeneity** refers to the spatial variability of soil properties, topography, and land cover within the coarse-resolution pixels, and the d) **Temporal Stability** refers to the consistency of relationships between soil moisture and auxiliary variables across different seasons and weather conditions

Two innovative algorithms developed by the research community, which are currently operational and widely used in scientific and operational applications, demonstrate different approaches to this challenge:

- **SMOS Semi-Empirical Downscaling Method**

The SMOS Semi-Empirical Method represents a sophisticated statistical approach that downscales soil moisture data from the native SMOS resolution of approximately 40-50 km (gridded at 25 km) to significantly finer resolutions of 1 km and, in recent implementations, down to 300 m. This method exemplifies the power of multi-sensor data fusion and has been continuously refined and validated since its initial development [16,17,18].

The algorithm combines data from multiple complementary sources, each contributing unique information to the downscaling process:

- **SMOS Brightness Temperature and Soil Moisture Data**: The foundation of the method relies on SMOS Level 1 brightness temperature observations and Level 2 soil moisture retrievals at their native resolution (~50 km, gridded at 25 km). The brightness temperature data provides the fundamental microwave emission measurements that are directly related to soil dielectric properties, while the Level 2 soil moisture products incorporate sophisticated retrieval algorithms that account for vegetation effects, surface roughness, and atmospheric corrections.
- **ECMWF Skin Temperature Data**: High-resolution skin temperature data from the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis provides crucial information about surface thermal conditions at spatial resolutions of approximately 9 km. Skin temperature serves as a proxy for surface moisture conditions and energy balance, exploiting the well-established relationship between surface temperature and soil moisture availability. This relationship is particularly strong in water-limited environments where evapotranspiration is constrained by soil moisture availability.
- **MODIS and Sentinel-3 NDVI Data**: The Normalized Difference Vegetation Index (NDVI) from both the Moderate Resolution Imaging Spectroradiometer (MODIS) at 250-1000 m resolution and Sentinel-3 Ocean and Land Colour Instrument (OLCI) at 300 m resolution provides high-resolution information about vegetation vigor and coverage. Vegetation indices serve as indicators of water stress and are strongly correlated with soil moisture conditions, particularly during the growing season. The integration of both MODIS and Sentinel-3 NDVI allows for improved temporal coverage and spatial consistency, with Sentinel-3's finer spatial resolution being particularly valuable for the 300 m downscaling implementation.

The SMOS Semi-Empirical Method employs a multi-step approach that combines linear regression models with spatial interpolation techniques to generate higher-resolution soil moisture maps. The core algorithm architecture consists of several key components:

The method establishes empirical relationships between coarse-resolution SMOS observations and the spatial patterns observed in auxiliary high-resolution datasets. These relationships are typically expressed as:

$$SM_{fine}(x,y) = f\big(SM_{coarse}(x,y), LST(x,y), NDVI(x,y), \text{auxiliary variables } (x,y)\big), \tag{3}$$

where SM_{fine} represents the high-resolution soil moisture estimate, SM_{coarse} is the coarse SMOS observation, and the auxiliary variables are evaluated at the target fine resolution. A critical innovation in the method is the implementation of spatial consistency constraints that ensure the downscaled high-resolution estimates, when aggregated back to the original coarse resolution, match the original SMOS observations. This "mass conservation" principle is essential to maintain the radiometric accuracy of the original satellite observations while adding spatial detail. The algorithm also incorporates temporal filtering and stability checks to ensure that the relationships between soil moisture and auxiliary variables remain consistent over time. This includes seasonal adjustments and detection of anomalous conditions that might invalidate the established regression relationships.

Recent implementations have incorporated an adaptive moving window technique that adjusts the spatial extent of the regression analysis based on local environmental conditions and data availability [17]. This approach improves the robustness of the method in heterogeneous landscapes and reduces artifacts at the boundaries between different land cover types.

The accuracy and reliability of the SMOS Semi-Empirical Method have been extensively validated across multiple European soil moisture networks, including sites from the International Soil Moisture Network (ISMN) and regional monitoring networks such as the Spanish REMEDHUS network, the French SMOSMANIA network, and various sites across central Europe. Validation studies have consistently demonstrated:

- Root Mean Square Error (RMSE) values typically ranging from 0.04 to 0.08 cm³/cm³ for 1 km resolution products, meeting or exceeding the accuracy requirements for most agricultural applications. The 300 m resolution products show slightly higher RMSE values (0.06-0.10 cm^3/cm^3) but still maintain acceptable accuracy for local-scale applications.

- High correlation coefficients (typically >0.7) between downscaled products and independent high-resolution soil moisture measurements, indicating good preservation of spatial patterns and gradients.
- Stable performance across different seasons and weather conditions, with particular strength during periods of moderate vegetation cover and clear-sky conditions.
- Successful application of the method across different European climatic zones, from Mediterranean to temperate continental conditions, demonstrating the robustness of the underlying physical relationships.

The SMOS Semi-Empirical Method has been successfully implemented in operational frameworks and is currently used in various applications, including agricultural decision support, hydrological modeling, climate monitoring, and environmental management.

- **Artificial Neural Network (ANN) Method**

The Artificial Neural Network (ANN) Method represents a paradigm shift toward machine learning-based approaches for soil moisture downscaling, leveraging the power of deep learning and advanced pattern recognition to generate exceptionally high-resolution soil moisture maps with spatial resolutions approaching 60 m. This technique demonstrates the potential of artificial intelligence in environmental remote sensing and has shown remarkable success in creating highly detailed, accurate soil moisture products that approach the spatial resolution requirements of field-scale agricultural applications.

The ANN method employs a sophisticated multi-layer neural network architecture specifically designed for spatial downscaling applications. The network architecture typically consists of: a) **input layer** designed to accommodate multiple input variables with different spatial and temporal characteristics, including both continuous variables (temperature, precipitation, spectral reflectances) and categorical variables (land cover, soil type), b) **hidden layers**: Multiple hidden layers with varying numbers of neurons, typically employing rectified linear unit (ReLU) activation functions to capture non-linear relationships between input variables and soil moisture. The number of hidden layers and neurons is optimized through systematic testing and cross-validation procedures. And c) **output layer**: a single neuron with linear activation function that produces the soil moisture estimate, with values constrained to physically realistic ranges (typically 0-0.5 cm^3/cm^3).

Regularization techniques include the implementation of dropout layers, batch normalization, and L2 regularization to prevent overfitting and improve generalization capabilities across different environmental conditions.

The ANN method distinguishes itself through the integration of a diverse range of data sources, each contributing unique information about the environmental conditions that influence soil moisture patterns:

- **ERA5-Land Precipitation Data**: High-resolution (9 km, hourly) precipitation data from the ERA5-Land reanalysis provides crucial information about water inputs to the soil system. The algorithm incorporates not only instantaneous precipitation values, but also accumulated precipitation over various time periods (1, 3, 7, and 30 days) to capture the temporal dynamics of soil moisture response to rainfall events.
- **MODIS Land Surface Temperature Data**: Daily land surface temperature observations from MODIS Terra and Aqua satellites at 1 km resolution provide information about surface energy balance and thermal conditions. The method incorporates both daytime and nighttime temperature observations, as well as derived metrics such as diurnal temperature range and thermal amplitude, which are related to surface moisture conditions through thermal inertia effects.

Sentinel-2 Multi-Spectral Reflectances: The method leverages the full spectral capability of Sentinel-2 MSI (Multispectral Instrument) observations, incorporating reflectance values from all relevant spectral bands at 10-20 m spatial resolution. This includes: a) **Visible bands** for surface composition analysis, b) **Near-infrared bands** for vegetation structure and vigor assessment, c) **Short-wave infrared bands** for moisture content estimation in vegetation and exposed soil, d) **Red-edge bands** for detailed vegetation stress and chlorophyll content analysis

Vegetation and Soil Indices: A comprehensive suite of spectral indices derived from Sentinel-2 data, including: a) **Vegetation Indices**: NDVI, Enhanced Vegetation Index (EVI), etc., b) **Water Content Indices**: Normalized Difference Water Index (NDWI), etc., c) **Soil Indices**: Bare Soil Index (BSI), Normalized Difference Soil Index (NDSI), e) **Topographic Data**: High-resolution digital elevation models (DEM) and derived topographic parameters that influence soil moisture patterns through their effects on drainage, solar radiation, and water accumulatio, such as elevation, slope, aspect, curvature... f) **Solar Radiation Indices,** g) **Soil Composition Data** (not always available)

The development and optimization of the ANN model involves sophisticated training procedures to maximize performance while ensuring robust generalization. The ANN method was initially developed and extensively validated over Spain's Central Plateau region, which provides an ideal testbed due to its diverse environmental conditions, ranging from agricultural areas to natural ecosystems, and varying topographic and climatic conditions. The validation process involved: a) **Ground truth data collection** through extensive field campaigns and permanent monitoring networks (e.g. REMEDHUS) providing high-quality soil moisture measurements at multiple depths and scales for model training and validation, b) **Performance metrics** including root mean square error (RMSE), mean absolute error (MAE), correlation coefficient, and bias, as well as spatial metrics assessing pattern fidelity and edge preservation, and c) **Seasonal and interannual validation**: Long-term validation studies demonstrating consistent performance across different years and seasons, including extreme events such as droughts and flood conditions.

The successful application of the ANN method to North African regions represents the demonstration of the technique's transferability and robustness across different climatic and environmental conditions.

2. Sample Applications of Advanced Soil Moisture Downscaling in North Africa: Case Studies in North Africa and the UAE and Operational Implementations

The disaggregation algorithms developed and refined since 2008 have been applied to several critical practical scenarios across North Africa and the Middle East, demonstrating their utility and operational value for a range of environmental monitoring, agricultural management, and disaster response applications. These real-world implementations serve as proof-of-concept demonstrations that bridge the gap between advanced remote sensing research and practical societal benefits, while highlighting the transformative potential of high-resolution soil moisture information for addressing pressing challenges in water-limited environments.

The selection of North African study sites was motivated by several factors: the region's vulnerability to extreme weather events, water scarcity challenges, the presence of unique ecosystems under environmental stress, and ambitious agricultural development projects in arid lands. These applications collectively demonstrate the versatility and robustness of the downscaling algorithms across diverse environmental conditions, from coastal Mediterranean climates to hyperarid desert environments, and across various temporal scales from rapid flood events to seasonal ecosystem dynamics.

2.1 Flash Flood Monitoring and Emergency Response Systems

2.1.1 Flash Flood Events in Algeria and Tunisia (May 2021)

The catastrophic flash flood events that occurred in May 2021 across northern Algeria and Tunisia provided a critical opportunity to evaluate the operational potential of high-resolution soil moisture data for disaster response and emergency management applications (Fig. 1). These events, characterized by intense rainfall rates exceeding 50 mm/hour over periods of 2-6 hours, resulted in significant economic damages, infrastructure destruction, and unfortunately, loss of life across multiple urban and rural areas.

The disaggregation algorithms were rapidly deployed to process SMOS observations and generate 1 km resolution soil moisture maps covering the affected regions during the pre-flood, flood, and post-flood periods. The enhanced spatial resolution proved crucial for several aspects of the emergency response:

The high-resolution maps revealed that antecedent soil moisture conditions varied significantly across the landscape, with some areas showing saturation levels approaching 0.3-0.4 m^3/m^3 due to earlier spring rainfall, while others remained relatively dry (<0.1 m^3/m^3). This spatial variability in initial conditions was invisible in coarse-resolution products, but is critical to understand flood susceptibility patterns.

During the flood events, algorithms identified areas experiencing rapid soil moisture increases, with maximum detected values reaching 0.5 m^3/m^3 in valley bottoms and urban areas with poor drainage. The 1 km spatial resolution allowed the identification of specific areas at high risk.

Following the flood events, the continued monitoring revealed the spatial patterns and temporal dynamics of soil moisture recession, providing valuable information for assessing ongoing landslide risks, planning reconstruction activities, and understanding the hydrological impacts on local water resources.

2.1.2 United Arab Emirates Flash Flood Monitoring (July 2022)

The flash flood events that occurred during July 27-29, 2022, in the eastern Emirates of Fujairah and the Kalba region provided an additional validation opportunity in a different climatic and topographic setting (Fig. 2). These events were particularly significant due to their occurrence in typically hyperarid environments where annual rainfall averages less than 100 mm, making the region highly vulnerable to flash flooding when intense precipitation does occur.

The application of the downscaling algorithms in this context revealed several unique insights:

- **Desert Soil Response Characteristics**: The high-resolution soil moisture maps revealed that desert soils in the UAE exhibit extremely rapid response to precipitation inputs, with soil moisture levels increasing from near-zero baseline conditions (<0.02 m^3/m^3) to saturation levels (>0.4 m^3/m^3) within hours of rainfall initiation. This rapid response time has critical implications for flood warning systems in arid regions.
- **Topography Controls on Soil Moisture Distribution**: The 1 km resolution maps clearly delineated the strong topographic controls on soil moisture distribution, with dry riverbed systems showing the highest moisture accumulation and longest retention times.
- **Urban-Rural Differences**: The enhanced spatial resolution allowed for clear differentiation between urban and rural soil moisture responses, due to impermeable urban surfaces, while agricultural areas showed more complex patterns.
- **Identification of critical infrastructure** elements (roads, telecommunications, power systems) in areas of high soil moisture accumulation, supporting post-event damage assessment and future resilience planning efforts.

2.2 Ecosystem Monitoring and Environmental Conservation

2.2.1 Chott el Djerid Ecosystem Dynamics

Chott el Djerid, Tunisia's largest salt lake and one of the most distinctive ecosystems in the Sahara Desert, represents a unique environmental monitoring challenge due to its extreme temporal variability, harsh environmental conditions, and ecological significance. This ephemeral salt lake system, covering approximately 7,000 km^2 at maximum extent, exhibits dramatic seasonal and interannual fluctuations in water levels, salinity, and biological activity that are closely coupled to regional climate patterns and groundwater dynamics.

The application of 300 m resolution soil moisture mapping to Chott el Djerid monitoring (Fig. 3) represents a significant advancement in understanding the complex hydro-ecological processes governing this unique ecosystem:

- **Seasonal Water Balance Dynamics**: The high-resolution soil moisture maps revealed seasonal spatial patterns, micro-topographic controls on water retention, revealing that small variations in elevation influence local hydrology and ecosystem structure.
- **Evaporation Process Characterization**: During the intense summer evaporation period (June-September), soil moisture maps documented the spatial progression of desiccation across the lake bed. The maps revealed that evaporation rates vary significantly across the lake surface due to variations in salt crust thickness, substrate composition, and micro-meteorological conditions.
- **Groundwater-Surface Water Interactions**: The continuous monitoring capability provided by the downscaling algorithms enabled the detection of groundwater discharge zones around the lake periphery, where slightly elevated soil moisture levels persist even during dry periods. These zones are habitat areas for specialized halophytic vegetation communities and serve as refugia for wildlife during extreme dry periods.
- **Ecological Habitat Mapping**: The detailed soil moisture information, combined with optical satellite data, enabled mapping of distinct ecological zones within the Chott el Djerid system: permanent brine pools, seasonal wetlands, salt flats and **t**ransition zones.
- **Climate Change Impact Assessment** revealing trends toward longer dry periods, more intense, but briefer wet periods, and shifts in the spatial patterns of water retention that have implications for ecosystem resilience.
- **Conservation Management Applications**: The detailed ecosystem monitoring data supports several critical conservation management applications.Broader Ecosystem Monitoring Applications.

2.3 Agricultural Resource Management and Food Security

2.3.1 East Oweinat Agricultural Development Project

The East Oweinat region of Egypt represents one of the most ambitious agricultural land reclamation projects in the world, involving the transformation of over 200,000 hectares of hyperarid desert land into productive agricultural areas through groundwater irrigation from the Nubian Sandstone Aquifer. This project, initiated in the 1980s and continuing today, presents unique challenges for water resource management due to the extreme aridity (annual rainfall <5 mm), high evapotranspiration rates (>2000 mm/year), and the finite nature of the groundwater resource.

The application of 60 m resolution soil moisture maps generated by the ANN method has provided insights into agricultural water management practices and has become an integral component of precision agriculture implementation in this challenging environment (Fig. 4):

- **Irrigation System Optimization**: The ultra-high spatial resolution of the soil moisture maps enables monitoring of individual irrigation pivots (typically 50-125 hectares each) and detection of within-field variability that was previously invisible to farm managers. Key applications include the detection of mechanical problems in center pivot irrigation systems through identification of under-irrigated sectors, assessment of irrigation uniformity, identification of areas with different soil hydraulic properties that require modified irrigation management.
- **Crop Water Stress Monitoring**: The combination of high-resolution soil moisture data with vegetation indices enables early detection of crop water stress conditions.
- **Water Use Efficiency Analysis** for the analysis of agricultural water use efficiency, and **Soil Salinity Management.**
- **Precision Agriculture Implementation**: The 60 m resolution soil moisture maps will enable precision agriculture applications such as variable rate irrigation, precision fertilizer application, or harvest planning. Economic and Environmental Impact Assessment

3. Conclusion and Future Directions

The importance of combining innovative remote sensing technologies and data analytics to improve soil moisture monitoring has been presented. Advanced remote sensing techniques such as microwave radiometry provide nowadays valuable soil moisture data at the global scale. In a near future, possibly GNSS-R will be a gap filler between current ESA SMOS and NASA SMAP, and future ESA CMIR missions. However, limitations such as coarse resolution remain a challenge for regional applications. These limitations can be overcome by using disaggregation algorithms to downscale low-resolution satellite data into high-resolution soil moisture maps. These algorithms have significant implications for agriculture, flood management, and environmental monitoring, where high-resolution data can support more precise decision-making.

Looking ahead, the integration of multiple sensor types, improved machine learning models, and better regional calibration will be essential for advancing soil moisture mapping capabilities.

Future developments will likely focus on enhancing the accuracy of soil moisture measurements at deeper soil layers, improving the resolution of global datasets, and refining the tools needed to apply these technologies in real-world applications, particularly in arid and semi-arid regions.

Acknowledgments

This research was supported by the Spanish Ministry of Science, Innovation and Universities (MCIN/AEI/10.13039/501100011033) through projects INTERACT (PID2020-114623RB-C32) and GENESIS (PID2021-126436OB-C21).

References

[1] J. C. Price, "On the analysis of thermal infrared imagery: The limited utility of apparent thermal inertia," Remote Sens. Environ., vol. 18, no. 1, pp. 59–73, Aug. 1985, doi: 10.1016/0034-4257(85)90038-0.
[2] I. Sandholt et al., "A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status," Remote Sens. Environ., vol. 79, no. 2–3, pp. 213–224, Feb. 2002, doi: 10.1016/S0034-4257(01)00274-7.
[3] M. E. Holzman et al., "Estimating soil moisture and the relationship with crop yields using surface temperature and vegetation index," Int. J. Appl. Earth Observ. Geoinf., vol. 28, pp. 181–192, May 2014, doi: 10.1016/j.jag.2013.12.006.
[4] P. Rahimzadeh-Bajgiran et al., "Comparative evaluation of the vegetation dryness index (VDI), the temperature vegetation dryness index (TVDI) and the improved TVDI (iTVDI) for water stress detection in semi-arid regions of Iran," ISPRS J. Photogramm. Remote Sens., vol. 78, pp. 21–28, Apr. 2013, doi: 10.1016/j.isprsjprs.2012.12.006.
[5] G. Petropoulos et al., "A review of Ts/VI remote sensing based methods for the retrieval of land surface energy fluxes and soil surface moisture," Prog. Phys. Geogr., vol. 33, no. 2, pp. 224–250, Apr. 2009, doi: 10.1177/0309133309338997.
[6] V. Naeimi et al., "An improved soil moisture retrieval algorithm for ERS and METOP scatterometer observations," IEEE Trans. Geosci. Remote Sens., vol. 47, no. 7, pp. 1999–2013, Jul. 2009, doi: 10.1109/TGRS.2008.2011617.
[7] W. Wagner et al., "The ASCAT soil moisture product: A review of its specifications, validation results, and emerging applications," Meteorol. Z., vol. 22, no. 1, pp. 5–33, Feb. 2013, doi: 10.1127/0941-2948/2013/0380.
[8] W. Wagner et al., "A study of vegetation cover effects on ERS scatterometer data," IEEE Trans. Geosci. Remote Sens., vol. 37, no. 2, pp. 938–948, Mar. 1999, doi: 10.1109/36.752212.
[9] S. Paloscia et al., "Soil moisture mapping using Sentinel-1 images: Algorithm and preliminary validation," Remote Sens. Environ., vol. 134, pp. 234–248, Jul. 2013, doi: 10.1016/j.rse.2013.02.027.
[11] M. C. Dobson and F. T. Ulaby, "Active microwave soil moisture research," IEEE Trans. Geosci. Remote Sens., vol. 24, no. 1, pp. 23–36, Jan. 1986, doi: 10.1109/TGRS.1986.289585.
[12] Y. H. Kerr et al., "The SMOS mission: New tool for monitoring key elements of the global water cycle," Proc. IEEE, vol. 98, no. 5, pp. 666–687, May 2010, doi: 10.1109/JPROC.2010.2043032.
[13] Y. H. Kerr et al., "Overview of SMOS performance in terms of global soil moisture monitoring after six years in operation," Remote Sens. Environ., vol. 180, pp. 40–63, Jul. 2016, doi: 10.1016/j.rse.2016.02.042.
[14] D. Entekhabi et al., "The Soil Moisture Active Passive (SMAP) mission," Proc. IEEE, vol. 98, no. 5, pp. 704–716, May 2010, doi: 10.1109/JPROC.2010.2043918.
[15] S. K. Chan et al., "Assessment of the SMAP passive soil moisture product," IEEE Trans. Geosci. Remote Sens., vol. 54, no. 8, pp. 4994–5007, Aug. 2016, doi: 10.1109/TGRS.2016.2566662.
[16] M. Piles et al., "Downscaling SMOS-derived soil moisture using MODIS visible/infrared data," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 9, pp. 3156–3166, Sep. 2011, doi: 10.1109/TGRS.2011.2120615.
[17] G. Portal et al., "A spatially consistent downscaling approach for SMOS using an adaptive moving window," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 11, no. 6, pp. 1883–1894, Jun. 2018, doi: 10.1109/JSTARS.2018.2832447.
[18] M. Pablos et al., "A modified downscaling approach to estimate SMOS soil moisture at high resolution (300 m) using

Copernicus Sentinel-3 NDVI," in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), 2023, pp. 1–4, doi: 10.1109/IGARSS.2023.9876543.
[10] F. T. Ulaby, R. K. Moore, and A. K. Fung, Microwave Remote Sensing: Active and Passive. Norwood, MA, USA: Artech House, 1996.

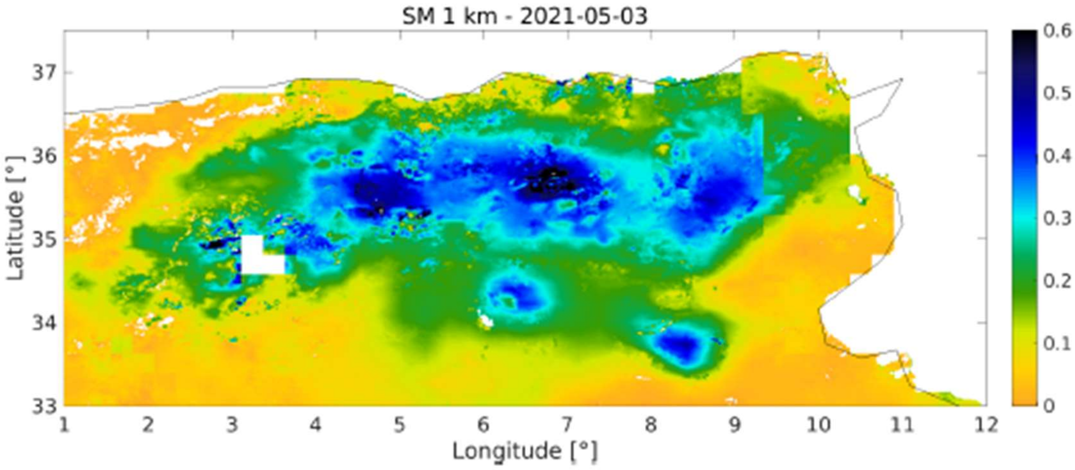

Figure 1. 1 km 3-day SMOS SM over the Chott el Djerid lake.

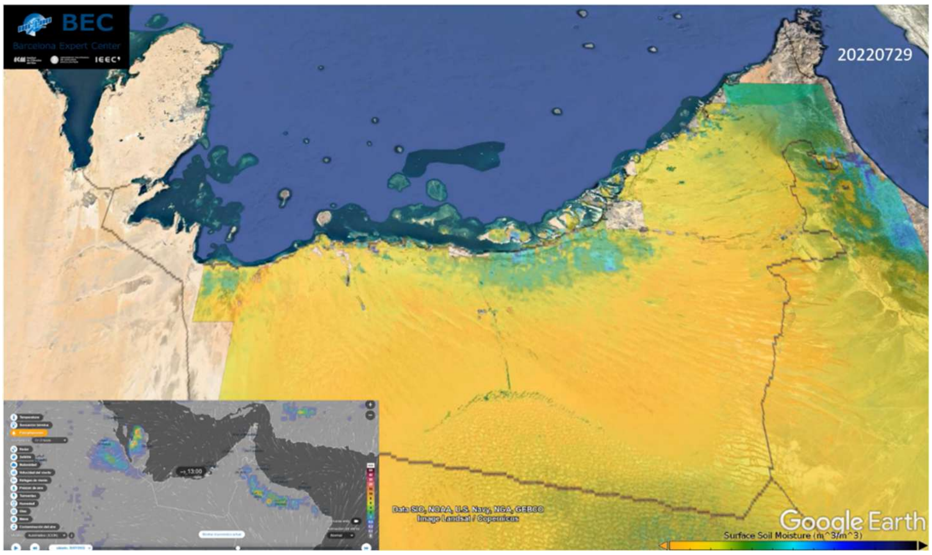

Figure 2. Rain rate and 1 km 3-day SMOS SM over the UAE.

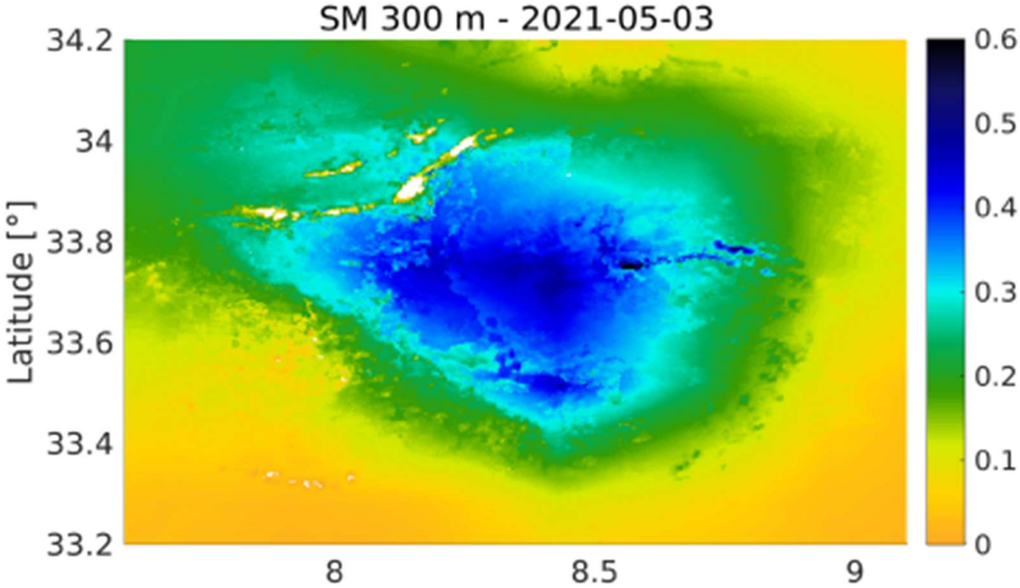

Figure 3. 300 m 3-day SMOS SM over the Chott el Djerid lake.

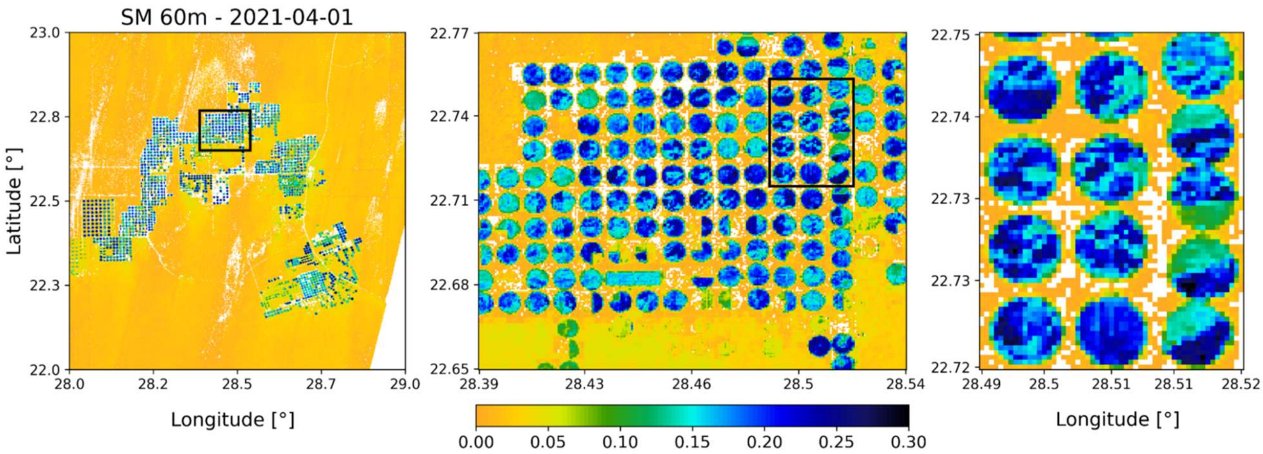

Figure 4. (left) CCI SM at 60 m over East Oweinat, (b) and (c) successive zooms over a specific region on April 1, 2021