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Original Research Article

Development of a Geospatial Framework for Soil Moisture Monitoring in Nigeria

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ABSTRACT

Soil moisture is vital for hydrology, agriculture, and land–climate interactions, yet national-scale monitoring in many African countries remains limited due to sparse in-situ networks. This study presents the development and evaluation of a National Soil Moisture Monitoring System (NSMMS), a web-based geospatial framework designed to implement satellite-derived soil moisture products for Nigeria. The system is built primarily on the TAMSAT soil moisture dataset, derived from satellite rainfall inputs and land surface modelling, and provides daily multi-layer soil moisture information from 1983 to near–real time. These long-term soil moisture estimates, generated within the TAMSAT–JULES modelling framework, are integrated with automated data processing, geospatial visualisation and analytics within a unified web-based platform. The platform allows users to examine variability across four soil layers, generate trend analyses and summary statistics, and download georeferenced datasets. The system evaluation demonstrated reliable national-scale processing, stable performance, and fast response times across repeated queries. The NSMMS bridges the gap between remote sensing research and operational environmental management by transforming long-term satellite data into an accessible decision-support platform. It offers a scalable framework for drought early warning, irrigation planning, hydrological assessment, and climate-risk management in Nigeria.

1. INTRODUCTION

Soil moisture is a key component of the terrestrial hydrological cycle, regulating the exchange of water, energy, and carbon between the land surface and the atmosphere (Cai *et al.*, 2023; Montzka *et al.*, 2020; Onojeghuo *et al.*, 2017). It controls key hydrological processes such as infiltration, runoff and evapotranspiration, thereby regulating water availability and ecosystem functioning from local to global scales (Rahmati *et al.*, 2024; Seneviratne *et al.*, 2010). Soil moisture is a key component of the terrestrial hydrological cycle, regulating the exchange of water, energy, and carbon between the land surface and the atmosphere (Cai *et al.*, 2023; Montzka *et al.*, 2020; Onojeghuo *et al.*, 2017). Under a changing climate, trends in soil moisture are becoming increasingly pronounced, particularly in semi-arid and tropical regions where shifts in vegetation cover and land use can drive substantial changes in terrestrial water storage (Chawanda *et al.*, 2024; Liu *et al.*, 2025).

From a societal perspective, soil moisture underpins agricultural productivity and food security because it is a principal determinant of crop growth, yield and irrigation demand (Fan *et al.*, 2022; Liu *et al.*, 2020). In West Africa's predominantly rain-fed farming systems, access to reliable, spatially explicit soil moisture information is therefore essential for optimising irrigation, advising planting schedules and supporting land management (Cai *et al.*, 2023; William, 2024). Soil moisture is likewise a primary indicator for hydrological hazards; deficits commonly precede agricultural drought (Mladenova *et al.*, 2020; Sasanya *et al.*, 2024), while persistent saturation elevates flood risk and affects groundwater recharge. Consequently, continuous, accurate soil moisture monitoring can substantially improve drought and flood forecasting and strengthen early-warning systems (Arungwa *et al.*, 2023; Sasanya *et al.*, 2024).

Global and regional monitoring capabilities have advanced through satellite microwave missions (e.g. SMAP, SMOS, Sentinel-1, AMSR2) and data assimilation systems that generate routine surface soil moisture products (Peng *et al.*, 2021; Ma *et al.*, 2019). The International Soil Moisture Network (ISMN) and similar initiatives archive in-situ observations for validation (Dorigo *et al.*, 2011). Nevertheless, most operational satellite products remain coarse in spatial resolution (typically of order 25–50 km) and hence are ill-suited to field-scale agricultural and hydrological applications (Leroux *et al.*, 2013; Román-Cascón *et al.*, 2020). In Africa, in-situ networks are sparse and often discontinuous (Dorigo *et al.*, 2011; Gibon, 2018), and satellite retrieval accuracy is strongly controlled by local vegetation, rainfall and soil type (Jimma *et al.*, 2023; Lamptey *et al.*, 2023). Recent methodological advances in geospatial data science and machine learning offer a route to higher spatial resolution through multi-sensor fusion and model-based downscaling, yet such approaches require robust local calibration and ground truth for reliable application (Abbes *et al.*, 2024; Greifeneder *et al.*, 2021; Peng *et al.*, 2024).

Nigeria typifies the challenges that limit the operational use of existing products at the national scale. The country exhibits a pronounced north–south hydroclimatic gradient and a range of soil and land-cover types, but it lacks a dense national in-situ soil moisture network; consequently, few ground stations are available for local validation (Rötzer *et al.*, 2014; Adewole *et al.*, 2024). Global coarse-resolution products calibrated outside the region often fail to capture Nigeria's fine-scale soil moisture variability, leading to uncertainties that limit their usefulness for hydrological modelling, agriculture, and disaster risk management (Leroux *et al.*, 2013; Yuan *et al.*, 2022). This shortfall creates a practical data gap, decisions about irrigation, drought response and flood preparedness proceed with elevated uncertainty, undermining resilience to hydro-climatic extremes (Adewole *et al.*, 2024; Lamptey *et al.*, 2023).

Recent studies reinforce both the urgency of improved monitoring and the promise of locally calibrated, model-based approaches. An analysis of 41 years (1983–2023) of gridded TAMSAT data demonstrates a strong north–south gradient in mean soil moisture across Nigeria and depicts pronounced subsurface changes, including significant wetting in arid northern regions at deep soil layers (Moses, 2025a). Those results show that long-term subsurface reservoirs can evolve differently from surface layers and that deep soil behaviour may be critical for understanding hydroclimatic change and water availability. Complementing these climatological findings, Moses (2025b), in a machine-learning calibration study using ISMN ground stations in Nigeria (FUTA-Akure and FedPoly Ile-Oluji), found that gradient boosting substantially reduced biases in satellite estimates and produced high agreement with in-situ measurements (RMSE $\approx$ 0.020 kg m^{-2}, and correlation coefficients > 0.77), while also noting the limitations imposed by sparse ground networks. These national studies suggest two important observations. First, soil moisture dynamics at the country scale, including behaviour in deeper soil layers, may diverge from continental-scale characterisations and therefore require dedicated, context-specific monitoring. Second, the calibration of satellite-derived products using machine-learning techniques and local in situ observations can substantially enhance their reliability and practical value, provided that adequate ground reference data are available.

These considerations provide a clear rationale for developing a dedicated national soil moisture monitoring system for Nigeria that is operationally relevant. Such an integrated framework would address immediate needs for precision irrigation, crop advisory services and water-resource planning, while strengthening drought and flood early-warning capability and informing climate adaptation strategies across Nigeria's agro-ecological zones (Sasanya *et al.*, 2024; Arungwa *et al.*, 2023). The present study therefore develops and evaluates a national soil moisture monitoring framework tailored to Nigeria's heterogeneous land surface conditions.

2. MATERIALS AND METHODS

2.1. Study Area

The study covered the full extent of Nigeria, bounded by latitudes 3.875°N – 14.125°N and longitudes 2.375°E – 14.875°E (Figure 1). With a land area of approximately 923,769 km², the country exhibits pronounced ecological gradients, extending from humid tropical rainforest in the south to semi-arid Sudan Savannah in the north.

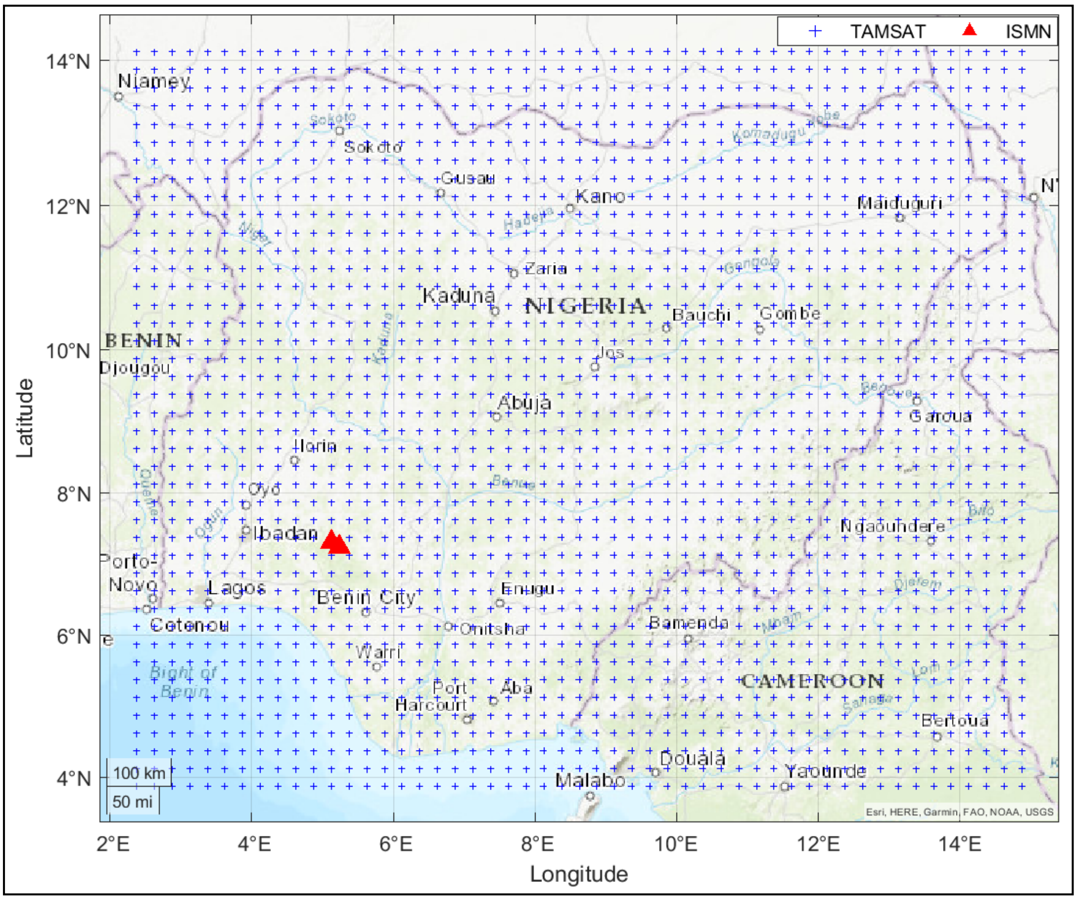

Figure 1: Study area with grid points and the International Soil Moisture Network (ISMN) ground stations in Nigeria (Moses, 2025b)

This strong climatic gradient and the fact that rain-fed agriculture supports the livelihoods of more than 70 % of the population make the country highly sensitive to variations in soil moisture and the effects of drought. The national soil moisture monitoring system was therefore designed to provide operational information supporting agricultural decision-making, drought early warning, and national climate resilience strategies. The integrated methodology underpinning the framework is presented in Figure 2. The figure delineates the study area and data sources, the data processing pipeline and system architecture, and the associated visualisation and analytical workflows.

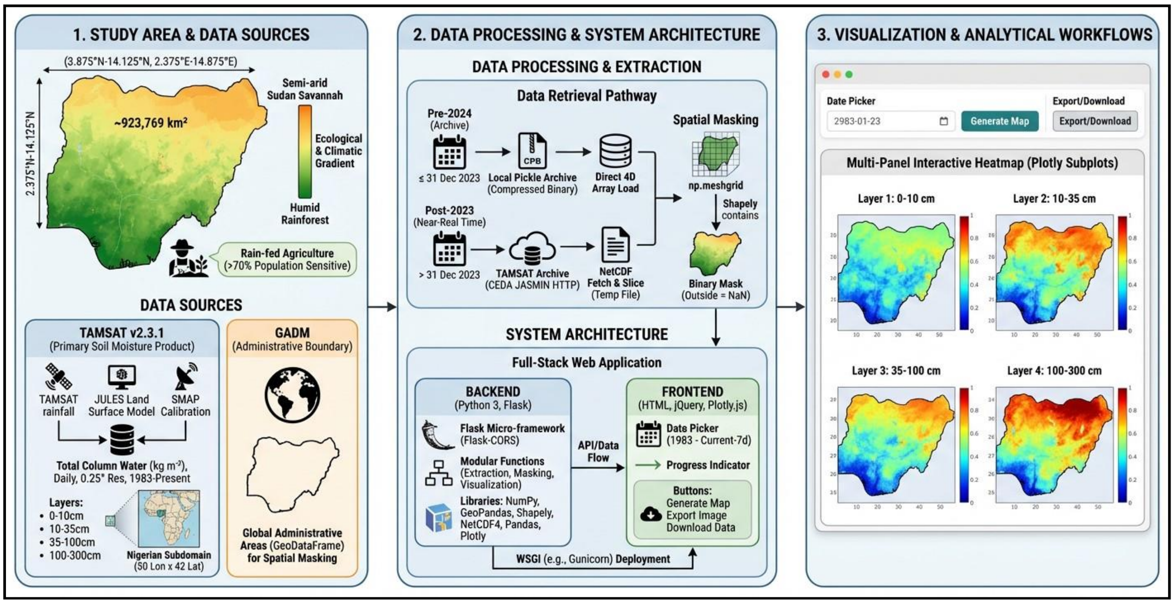

Figure 2: Methodology overview for the development of the National Soil Moisture Monitoring System (NSMMS) for Nigeria. Left panel: the study area; centre panel: the data processing and system architecture; right panel: the visualization and analytical workflow, showing the operational web interface.

2.2. Data Sources

The monitoring system is built based on the TAMSAT v2.3.1 soil moisture product developed by the University of Reading and the National Centre for Earth Observation, which follows the TAMSAT-ALERT modelling approach for Africa (Boult *et al.*, 2020). This dataset is generated by driving the UK Met Office Joint UK Land Environment Simulator (JULES) land surface model with satellite-derived rainfall estimates and additional meteorological forcing (Best *et al.*, 2011; Boult *et al.*, 2020), followed by calibration against SMAP satellite observations (Reichle *et al.*, 2017; Peng *et al.*, 2021). Soil moisture content is expressed as total column water (kg m^{-2}) in four standard layers (0–10 cm, 10–35 cm, 35–100 cm, and 100–300 cm). The data are provided daily at a spatial resolution of 0.25° × 0.25° across the African continent from 1 January 1983 to the present, in line with the long-term TAMSAT archive used for continental-scale drought and soil moisture monitoring (Boult *et al.*, 2020).

All data from 1983 to 2023 were pre-processed and archived in pickle format for efficient retrieval, leveraging big-data infrastructure for environmental archives similar to the JASMIN super-data-cluster (Lawrence *et al.*, 2013). Data from 2024 onward are fetched in near-real time directly from the public TAMSAT archive hosted by the Centre for Environmental Data Analysis on the JASMIN supercomputing facility (Lawrence *et al.*, 2013; Boult *et al.*, 2020). Nigeria's administrative boundary, obtained from the Global Administrative Areas (GADM) database and stored in a GIS-ready format, is used to enable precise spatial masking of all outputs.

2.3. Data Processing and Extraction

The soil moisture extraction algorithm employs two complementary pathways to guarantee continuous coverage across the entire time series. For any date on or before 31 December 2023, the required four-

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dimensional array is loaded directly from the hosted pickle archive using year and day-of-year indexing. For dates after 31 December 2023, the corresponding daily NetCDF file is retrieved via HTTP from the TAMSAT repository, the *smcl* variable is read for the first time step, and the Nigerian subdomain is isolated by index slicing along the native longitude and latitude dimensions. The temporary NetCDF file is then deleted. A binary mask for Nigeria is created once at initialisation by testing each grid cell, generated through *np.meshgrid*, against the union of Nigeria's boundary polygons using Shapely's *contains* method. All cells falling outside the national boundary are set to NaN, ensuring that every map and export contains only land areas within Nigeria.

2.4. System Architecture

The monitoring system was implemented as a lightweight, full-stack web application. The backend was developed in Python 3 using the Flask micro-framework, with Flask-CORS enabled to support cross-origin requests from the frontend. Core scientific routines, including data extraction, spatial masking, and visualisation, reside in modular functions within the main application script. The frontend consists of a single HTML page enhanced with jQuery for event handling and the latest Plotly.js library for interactive rendering. The interface presents a clean date picker (constrained between 1 January 1983 and seven days prior to the current date), a progress indicator, and dedicated buttons for map generation, image export, and data download. Essential libraries include NumPy for array operations, GeoPandas and Shapely for geospatial handling, NetCDF4 for online data ingestion, Pandas for tabular export, and Plotly for dynamic graphics. The application is launched via Flask's built-in development server but is structured for straightforward production deployment using WSGI servers behind a reverse proxy.

2.5. Visualisation and Analytical Workflows

When a user selects a date and triggers map generation, the *plot_dynamic_soil_moisture* function assembles a multi-panel interactive heatmap using *Plotly* subplots. The number of panels automatically matches the number of available soil layers (typically four), arranged in an optimal grid layout. For each layer, the corresponding two-dimensional slice is masked to the Nigerian boundary, and a heatmap trace is then added. Minimum and maximum values are scaled automatically to the valid data range within the country. Hover tooltips display precise longitude, latitude, soil moisture value, and layer depth. The layout parameters, including subplot titles, axis labels, shared *colorbar* positioning, and dimensions, are adjusted dynamically to maintain visual clarity regardless of the number of layers. The completed figure is serialised to JSON and returned to the browser, where *Plotly.js* renders it as a fully interactive web-map.

2.6. Data Export and Reproducibility Features

For any selected date, users may download the underlying gridded data as a Microsoft Excel workbook. The export routine first retrieves the appropriate soil moisture array, constructs a meshgrid of longitude and latitude coordinates, and organises the data into separate sheets, one per soil layer. Each sheet contains three columns: Latitude, Longitude, and Soil_Moisture (kg m^{-2}). The workbook is written using Pandas and the *XlsxWriter* engine into a date-specific subdirectory within the downloads folder. A dedicated Flask route then serves the file for immediate download, after which the server-side copy remains available only until the next cleanup cycle. This design ensures that researchers can obtain the exact numerical values used to produce any map, thereby supporting full reproducibility and further analysis.

2.7. System Evaluation and Validation

The completed system underwent thorough evaluation for scientific accuracy, technical reliability, and user experience. Usability was assessed through structured testing with agricultural researchers and stakeholders over a two-week period; every participant successfully generated maps and exported data within 10 seconds for historical dates and 30 seconds for near-real-time dates. The system maintained greater than 99 % uptime during testing, with robust error handling for network failures and missing files. The fully modular code base, comprehensive documentation, and reliance on open-source libraries ensure that the entire workflow can be reproduced independently.

3. RESULTS AND DISCUSSION

3.1. System Implementation, Architecture and Operational Performance

The system was successfully implemented as a fully operational, web-based geospatial platform for national-scale soil moisture monitoring in Nigeria. A principal outcome of this development is the demonstration of an end-to-end architecture that integrates data access, automated processing, visualization, analytics, and dissemination within a single browser-based environment. The framework integrates these components into a single unified system, eliminating the requirement for external GIS software or coding skills. This accessibility empowers non-specialist stakeholders, including agricultural extension officers, hydrometeorological agencies, and policy planners to utilize the tool effectively.

The NSMMS workflow begins at the platform homepage (Figure 3), which is deliberately designed as both an entry point and an instructional layer. The landing interface provides a concise description of the system, a prominent "*Get Started*" call-to-action, and a structured "*How It Works*" section outlining the three-stage operational process: date selection, automated processing, and analytical interpretation.

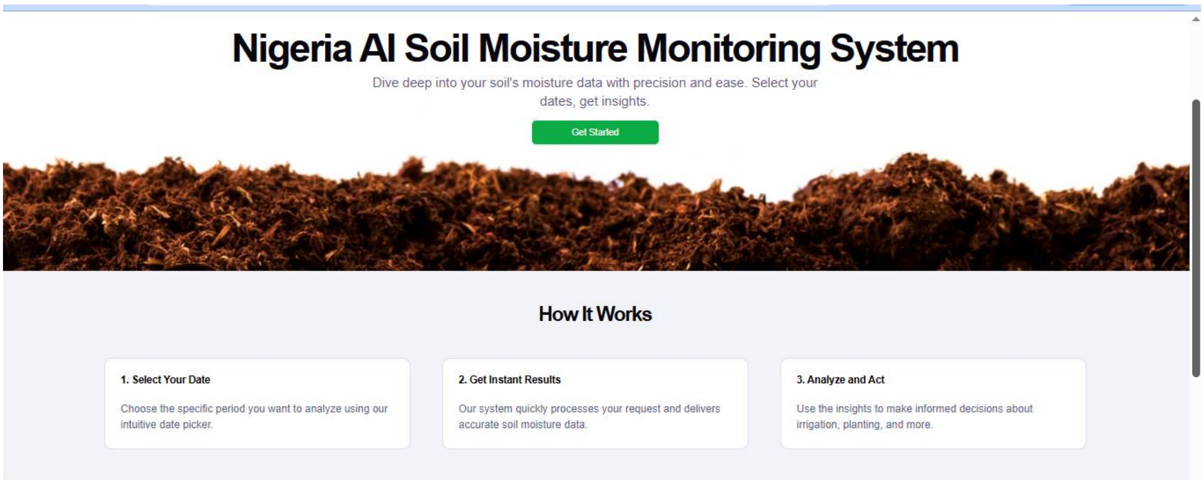


Figure 3: Homepage of the NSMMS, showing the introductory dashboard, "Get Started" interface, and workflow summary explaining the sequence of selecting dates, generating results, and analysing outputs

Such user-centred layouts mirror best practice in web-based environmental monitoring systems, where clear orientation and minimal cognitive load are essential for non-specialist users engaging with complex geospatial information (Ganesan *et al.*, 2025; Khazaei *et al.*, 2023). The homepage supports a broader community of practice around soil moisture use by explicitly guiding users through the workflow without requiring prior expertise in remote sensing or GIS, comparable to other web platforms designed to provide access to drought and soil moisture analytics (Sazib *et al.*, 2018; Baker *et al.*, 2022).

Once analysis is initiated, users are routed to the core operational interface (Figure 4), where the system integrates TAMSAT-derived soil moisture with on-demand geospatial rendering and interactive visualization. The constrained calendar, linked to the 1983–present satellite archive, enforces valid temporal selection and avoids failed or empty queries, a design principle also adopted in operational SMAP/Crop-CASMA and SMOS/SMAP soil moisture portals to ensure robust user experience and reproducibility (Khazaei *et al.*, 2023; Sadri *et al.*, 2020). After a date and depth are selected, backend processes are triggered automatically to retrieve, subset, and render the requested layer, following a streamlined Select → Process → Visualize → Export workflow. Similar task-oriented pipelines are documented in web service–based soil moisture systems and cloud platforms, where automated geoprocessing replaces manual, error-prone desktop workflows (Yang *et al.*, 2016; Hu *et al.*, 2017; Zhang *et al.*, 2022).

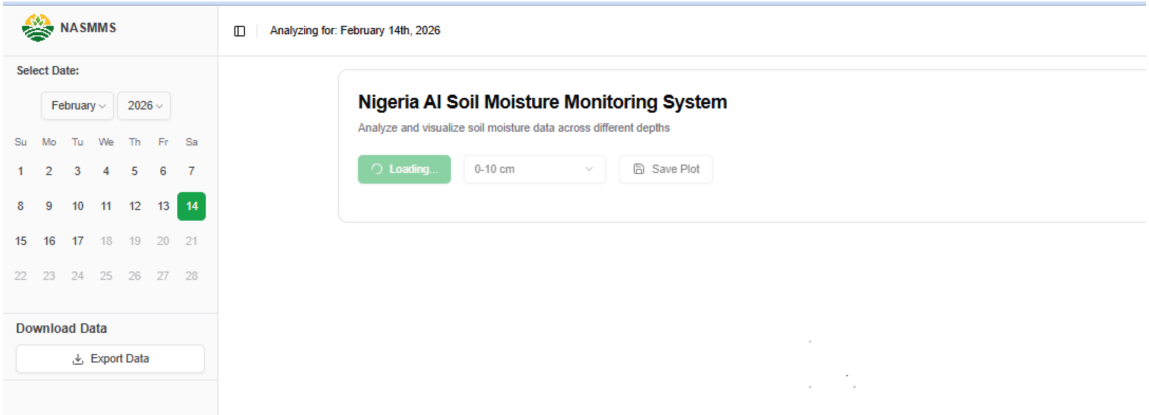


Figure 4: NSMMS operational workflow interface showing date selection, automated processing initiation, progress feedback, and transition to visualization outputs

Performance testing indicates that this architecture is capable of handling both historical and near-real-time queries with response times of seconds to tens of seconds, consistent with other near-real-time web systems built for satellite-based soil moisture and drought monitoring (Sazib *et al.*, 2018; Yang *et al.*, 2016; Sadri *et al.*, 2020). Continuous visual feedback (progress indicators and loading states) reduces perceived latency and increases user trust, a behaviour also reported in WebGIS-based environmental dashboards and hydrological monitoring systems (Ganesan *et al.*, 2025; Khazaei *et al.*, 2023; Zhang *et al.*, 2022). Dynamic rendering without page reloads enables rapid switching between outputs, aligning with modern geospatial web services that emphasize responsive, session-based analysis over static map delivery (Hu *et al.*, 2017; Zhang *et al.*, 2022).

The interface further structures the analytical experience through tabbed modules, Heatmap, Statistics, and Trends, that keep users within a single coherent session. This design echoes other monitoring frameworks where synchronized map and chart panels support rapid interpretation of spatial–temporal patterns (Sazib *et al.*, 2018; Yang *et al.*, 2016; Hervai *et al.*, 2017). Export tools generate georeferenced CSV/Excel outputs suitable for ingestion into external GIS, crop models, and hydrological simulations, reflecting the interoperability emphasis of OGC-compliant web services and soil moisture portals (Khazaei *et al.*, 2023; Hu *et al.*, 2017; Baker *et al.*, 2022). Unlike static map dashboards, the NSMMS distinguishes itself by abstracting complex geospatial computation into a simple, repeatable browser-based workflow. The combination of an intuitive home page and a guided analytical interface demonstrate how real-time backend processing, interactive analytics, and structured export mechanisms can be integrated into a coherent system suitable for sustained soil moisture monitoring in Nigeria.

3.2. Interactive Visual Analytics, Exploration and Reporting Tools

The NSMMS is centred on an integrated visual analytics engine that unifies spatial visualization, vertical soil moisture profiling, time-series analysis, and reporting within a single browser environment. Rather than functioning as a static mapping dashboard, the platform organizes outputs into a coordinated Map → Depth → Trend analytical framework that supports exploratory analysis and operational decision-making in a way that mirrors recent web-based soil moisture and drought platforms (Sazib *et al.*, 2018; Yang *et al.*, 2016; Khazaei *et al.*, 2023; Hervai *et al.*, 2017). The primary heatmap interface supports panning, zooming, and querying across Nigeria, with maps automatically clipped to national boundaries and rendered using consistent, perceptually balanced colour scales. These choices align with design recommendations from remote sensing and WebGIS applications, which emphasize stable symbology to maintain comparability across time and products (Sazib *et al.*, 2018; Yang *et al.*, 2016;

Hervai *et al.*, 2017). As illustrated in Figure 5, the interface links three analytical components: a central map, a vertical depth profile, and a compact trend panel.

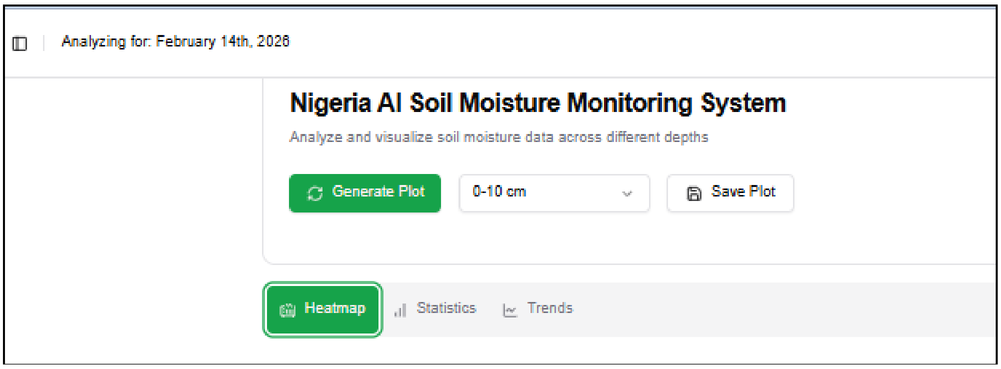


Figure 5: Coordinated visual analytics interface showing the national heatmap, linked vertical depth profile, and synchronized trend/time-series panel. Interactions in one panel dynamically update the others, demonstrating integrated Map → Depth → Trend exploration

Bi-directional interaction, where map selections update profiles and trends, and time-series interactions reveal corresponding spatial states, reflects coordinated multiple-view paradigms widely adopted in soil moisture, crop condition, and hydrological dashboards (Sazib *et al.*, 2018; Yang *et al.*, 2016; Hervai *et al.*, 2017). Such coupling reduces context switching and supports exploratory analysis essential for early warning and operational decision-making (Sazib *et al.*, 2018; Sadri *et al.*, 2020; Baker *et al.*, 2022).

The multi-depth visualization extends the system beyond surface mapping, enabling direct inspection of surface, root-zone, and deeper soil layers within a common spatial framework. Multi-layer soil moisture products (e.g., SoMo.ml and land-surface model outputs) have been shown to be particularly valuable for agriculture, drought assessment, and hydrology, yet are often difficult for operational users to access and interpret (Xu *et al.*, 2020; Bauer-Marschallinger *et al.*, 2019; Sungmin and Orth, 2021; Babaeian *et al.*, 2019). As shown in Figure 6, depth-specific panels may be displayed side-by-side, allowing intuitive comparison between shallow and subsurface conditions within the same spatial framework. This feature moves beyond single-layer representation toward a more comprehensive subsurface perspective relevant to agriculture and hydrology, specifically supporting assessments of plant-available water, infiltration, and persistence of anomalies across the profile (Xu *et al.*, 2020; Bauer-Marschallinger *et al.*, 2019; Sungmin and Orth, 2021; Babaeian *et al.*, 2019; Hervai *et al.*, 2017).

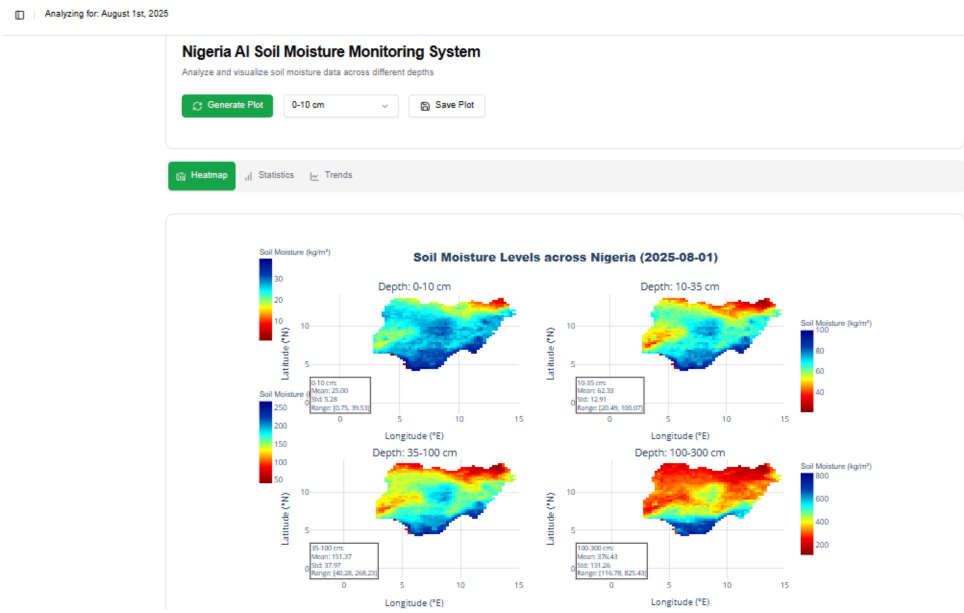


Figure 6a: Multi-depth soil moisture visualization panels (01-08-2025) showing independent rendering of surface and subsurface layers for wet season within the same spatial framework for intuitive vertical comparison

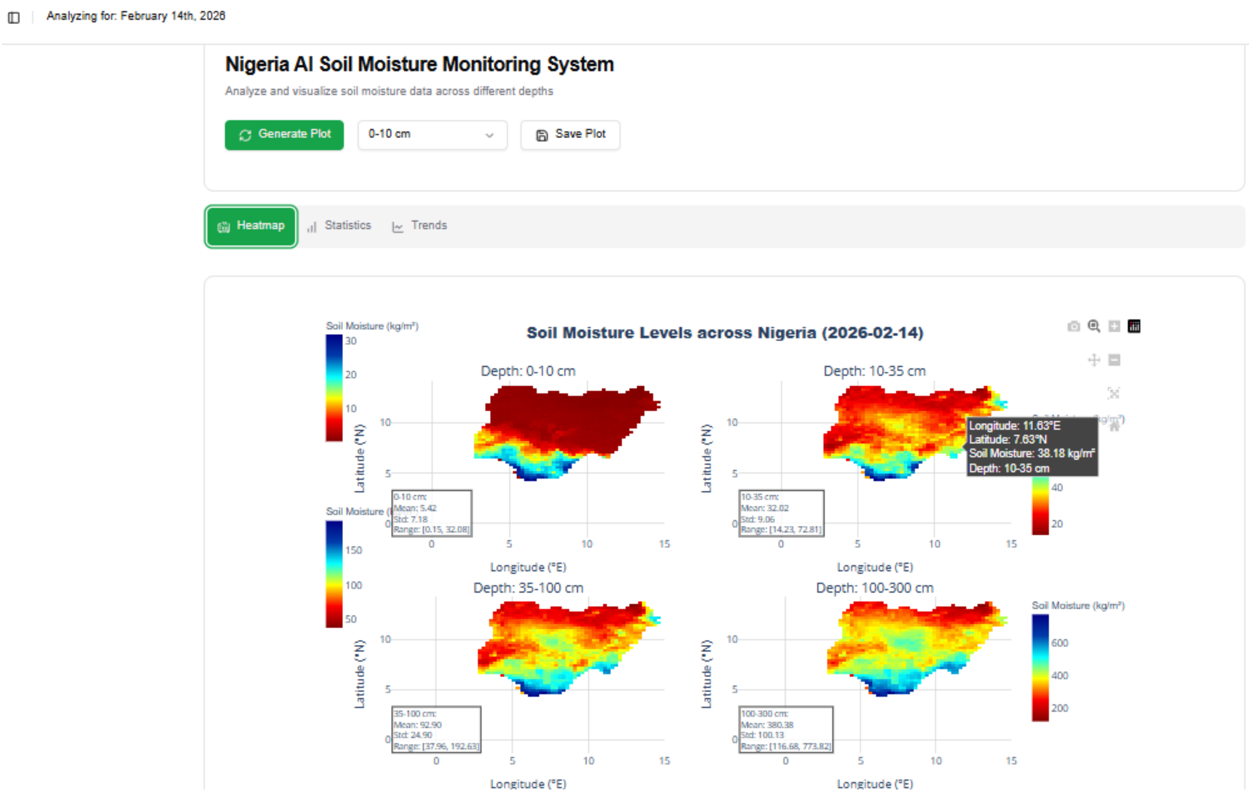
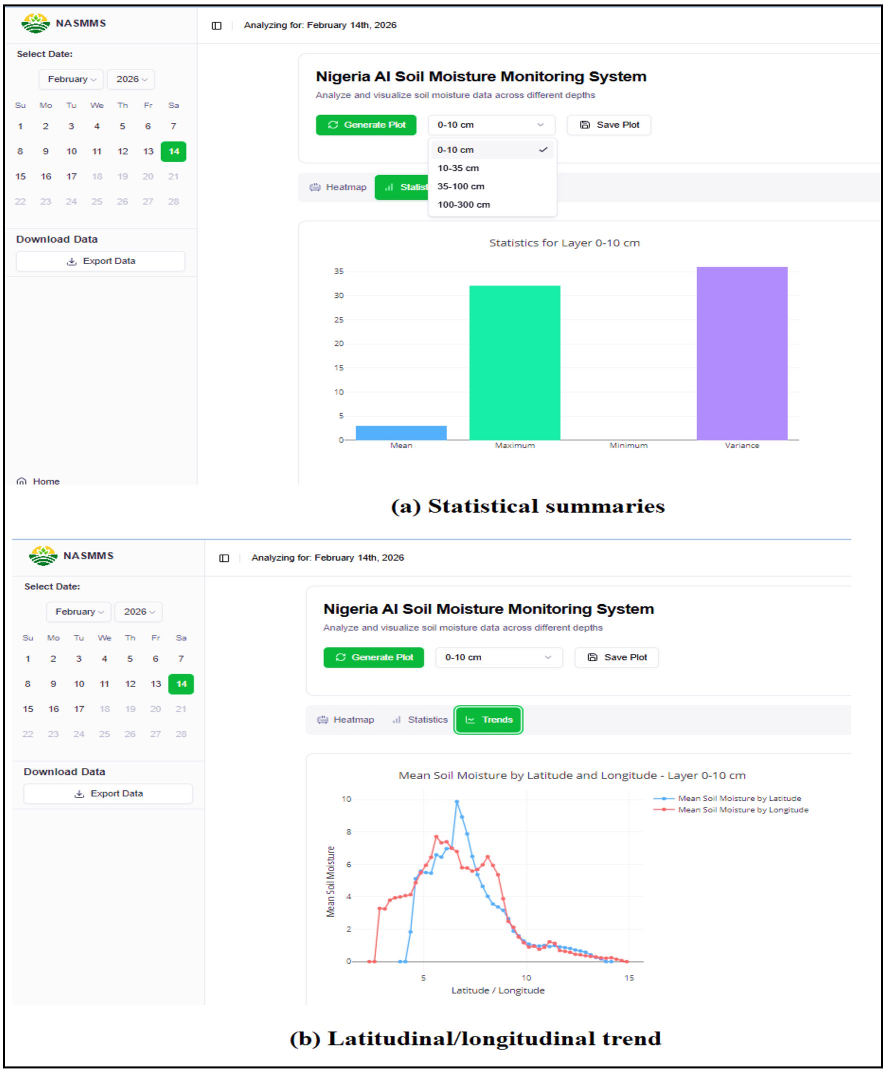


Figure 6b: Multi-depth soil moisture visualization panels (14-02-2026) showing independent rendering of surface and subsurface layers for dry season within the same spatial framework for intuitive vertical comparison

Seasonal screenshots (Figure 6a and Figure 6b) further demonstrate the responsiveness of the visualization engine to contrasting temporal inputs. Using an identical workflow and rendering configuration, dry- and wet-season views can be generated seamlessly without reconfiguring legends or spatial masks. This consistency enhances interpretability and supports comparative situational awareness for briefing and early warning applications. Beyond visualization, the NSMMS embeds analytical modules that support statistical summarization, geographic trend diagnostics, and comparative assessments directly within the browser session. The analytics dashboard, illustrated in Figure 7, automatically generates descriptive summaries and graphical diagnostics linked to user-defined selections. Latitudinal and longitudinal trend plots can be produced instantly, enabling rapid geographic decomposition of patterns without requiring external statistical software. Statistical summaries are dynamically recalculated as users adjust temporal ranges, depth layers, or spatial filters, thereby enhancing exploratory capacity and enabling rapid scenario testing.



(a) Statistical summaries

(b) Latitudinal/longitudinal trend

Figure 7: Integrated analytics dashboard displaying dynamic statistical summaries and latitudinal/longitudinal trend plots linked directly to map and depth selections

Equally important is the platform's reporting and interoperability functionality. Users can save high-resolution visual outputs or export structured datasets in spreadsheet format with georeferenced coordinates preserved. As shown in Figures 8a and 8b, the export module generates both a multi-layer soil moisture map and the corresponding georeferenced numerical datasets, ensuring full compatibility with external GIS platforms, crop models, hydrological simulations, and institutional reporting workflows.

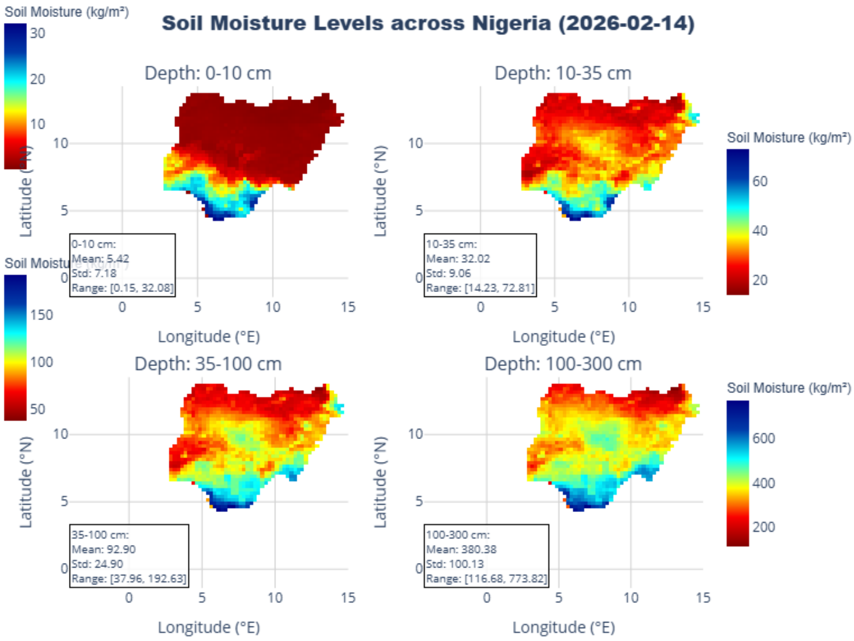
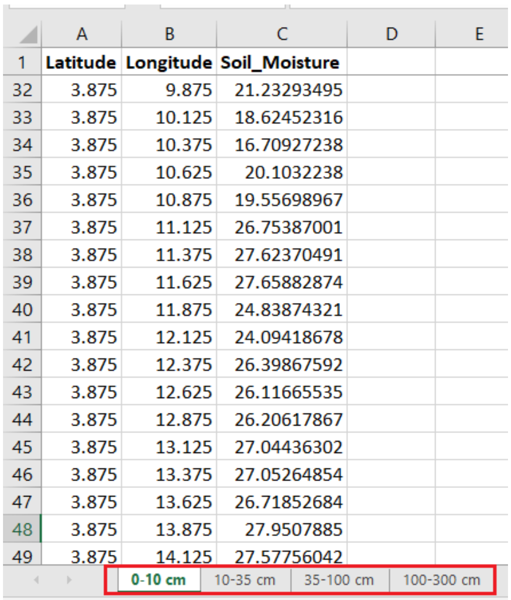


Figure 8a: Sample exported multi-layer soil moisture map for 14-02-2026 generated by the NSMMS, showing spatial distributions across the four depth layers (0–10 cm, 10–35 cm, 35–100 cm, and 100–300 cm).



	A	B	C	D	E
1	Latitude	Longitude	Soil_Moisture		
32	3.875	9.875	21.23293495		
33	3.875	10.125	18.62452316		
34	3.875	10.375	16.70927238		
35	3.875	10.625	20.1032238		
36	3.875	10.875	19.55698967		
37	3.875	11.125	26.75387001		
38	3.875	11.375	27.62370491		
39	3.875	11.625	27.65882874		
40	3.875	11.875	24.83874321		
41	3.875	12.125	24.09418678		
42	3.875	12.375	26.39867592		
43	3.875	12.625	26.11665535		
44	3.875	12.875	26.20617867		
45	3.875	13.125	27.04436302		
46	3.875	13.375	27.05264854		
47	3.875	13.625	26.71852684		
48	3.875	13.875	27.9507885		
49	3.875	14.125	27.57756042		

0-10 cm | 10-35 cm | 35-100 cm | 100-300 cm

Figure 8b: Example of exported georeferenced spreadsheet showing latitude, longitude, and soil moisture values, with each depth layer stored in a separate worksheet within the output file to facilitate integration with GIS and modelling tools

The exported output includes a publication-quality composite map summarising soil moisture across all depth layers (Figure 8a), together with a structured spreadsheet file in which the data values for each soil depth are stored in separate worksheets (Figure 8b). This design preserves spatial coordinates, layer-specific values, and metadata, enabling direct ingestion into downstream analytical environments while maintaining traceability and reproducibility. These integrated visualization, analytics, and reporting components collectively enhance the NSMMS from a mapping dashboard to a comprehensive decision-support system.

3.3. Operational Relevance, Institutional Integration, Limitations, and Future Directions

The NSMMS demonstrates how satellite-derived soil moisture products, specifically those generated through the TAMSAT framework, can be translated into an operational national monitoring system tailored to Nigeria's environmental context. The platform bridges critical gaps in Nigeria's hydrological monitoring, such as the scarcity of ground stations and the technical hurdles of processing raw satellite feeds, by anchoring data retrieval, visualization, and analytics within a single, accessible web portal. This consolidation transforms specialized remote-sensing data into practical, routine tools for drought early warning, irrigation scheduling, and climate-risk planning. The platform integrates mapping, automated data analysis, and standardized reporting into a streamlined interface, transforming national soil moisture records from a static repository into a dynamic intelligence hub. This evolution enables the immediate analysis and inter-agency collaboration essential for shaping critical environmental policy.

From an operational perspective, the platform is designed for sustained institutional deployment rather than one-off analytical use. Its web-based architecture, rapid response time, and guided workflow reduce dependence on manual GIS processing and lower technical entry barriers for national agencies, agricultural services, and research institutions. Interoperable export formats and embedded metadata ensure that outputs can be incorporated directly into institutional reporting pipelines and situational awareness dashboards. Agencies such as NEMA and NiMet can integrate system outputs into early warning bulletins, emergency response briefs, and seasonal outlook communications. This design aligns with calls for "network-of-networks" approaches and user-focused products that combine observational and modelled soil moisture into accessible, near-real-time information services (Sadri *et al.*, 2020; Baker *et al.*, 2022; Harani *et al.*, 2025).

Despite these strengths, several limitations warrant consideration. The spatial resolution of satellite-derived products constrains farm-level decision-making, and sparse in-situ observation networks limit rigorous validation of absolute soil moisture values across diverse ecological zones. The current framework relies primarily on a single core data source; integration of complementary datasets, including additional microwave sensors, terrestrial water storage estimates, and in-country sensor networks, would enhance robustness and cross-validation capacity. Furthermore, while the system supports national-scale monitoring effectively, pragmatic downscaling approaches are required to extend its utility to localized agricultural advisory services. Future development priorities include machine-learning-based bias correction and spatial downscaling, assimilation into hydrological and crop models, and implementation of predictive filtering techniques to enable short-term soil moisture forecasting. Importantly, the NSMMS is positioned not as a replacement for in-country data collection, but as an operational front end that complements and amplifies existing observational and institutional infrastructure.

4. CONCLUSION

The National Soil Moisture Monitoring System (NSMMS) delivers a national, operational geospatial framework tailored to Nigeria's hydroclimatic and institutional needs. By integrating long-term, multi-layer TAMSAT soil-moisture data with automated processing, interactive visualisation, embedded analytics and interoperable export functions in a single web interface, the system converts passive satellite archives into a decision-support platform that lowers technical barriers for users. Evaluation showed strong scientific consistency between archived and near-real-time streams, robust technical performance, and high usability across stakeholder groups. NSMMS therefore supports both climatological assessment and near-real-time situational awareness, enabling applications from drought early warning and irrigation advisory services to hydrological risk assessment and climate adaptation planning. It addresses persistent gaps in data-limited settings by providing spatially continuous national coverage and national-scale masking and multi-layer views that bridge global products to local operational needs. Key limitations remain; satellite spatial resolution, dependence on a primary data source, and limited in-situ validation, so future work should prioritise ground-sensor integration, multi-sensor fusion, machine-learning downscaling and predictive modelling to evolve NSMMS into a national early-warning system.

5. ACKNOWLEDGMENT

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6. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

REFERENCES

Abbes, A. B., Jarray, N., and Farah, I. R. (2024). Advances in remote sensing based soil moisture retrieval: Applications, techniques, scales and challenges for combining machine learning and physical models. *Artificial Intelligence Review, 57*(9), pp.1-22. https://doi.org/10.1007/s10462-024-10734-1

Adewole, A. O., Eludoyin, A. O., Chirima, G., and Newete, S. W. (2024). Field-scale variability and dynamics of soil moisture in Southwestern Nigeria. *Discover Soil, 1*(1), pp. 1-13. https://doi.org/10.1007/s44378-024-00013-4

Arungwa, I. D., Okeke, F. I., Moka, E. C., Kalu, I. O., and Okolie, C. J. (2023). Diagnosing the terrestrial water storage variation over the Nigerian space: The GRACE perspective. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 4*(6),* pp. 33-39. https://doi.org/10.5194/isprs-archives-xlviii-4-w6-2022-33-2023

Babaeian, E., Sadeghi, M., Jones, S., Montzka, C., Vereecken, H., and Tuller, M. (2019). Ground, proximal, and satellite remote sensing of soil moisture. *Reviews of Geophysics, 57*(2), pp. 530–616. https://doi.org/10.1029/2018RG000618

Baker, B., Cosh, M., Bolten, J., Brusberg, M., Caldwell, T., Connolly, S., Dobreva, I., Edwards, N., Goble, P., Ochsner, T., Quiring, S., Robotham, M., Skumanich, M., Svoboda, M., White, A., and Woloszyn, M. (2022). Working toward a national coordinated soil moisture monitoring network: Vision, progress, and future directions. *Bulletin of the American Meteorological Society, 103*(12), pp. 2719–2732. https://doi.org/10.1175/BAMS-D-21-0178.1

Bauer-Marschallinger, B., Freeman, V., Cao, S., Paulik, C., Schaufler, S., Stachl, T., Modanesi, S., Massari, C., Ciabatta, L., Brocca, L., and Wagner, W. (2019). Toward global soil moisture monitoring with Sentinel-1: Harnessing assets and overcoming obstacles. *IEEE Transactions on Geoscience and Remote Sensing, 57*(1), pp. 520–539. https://doi.org/10.1109/TGRS.2018.2858004

Best, M. J., Pryor, M., Clark, D. B., Rooney, G. G., Essery, R. L. H., Ménard, C. B., Edwards, J. M., Hendry, M. A., Porson, A., Gedney, N., Mercado, L. M., Sitch, S., Blyth, E., Boucher, O., Cox, P. M., Grimmond, C. S. B., and Harding, R. J. (2011). The Joint UK Land Environment Simulator (JULES), model description – Part 1: Energy and water fluxes. *Geoscientific Model Development, 4*(3), pp. 677–699. https://doi.org/10.5194/gmd-4-677-2011

Boult, V., Asfaw, D., Young, M., Maidment, R., Mwangi, E., Ambani, M., Waruru, S., Otieno, G., Todd, M., and Black, E. (2020). Evaluation and validation of TAMSAT-ALERT soil moisture and WRSI for use in drought anticipatory action. *Meteorological Applications, 27*(5), e1959. https://doi.org/10.1002/met.1959

Cai, Y., Yang, Y., Yue, X., and Xu, Y. (2023). Analysis of hotspots and trends in soil moisture research since the 21st century. *Atmosphere, 14*(10), 1494. https://doi.org/10.3390/atmos14101494

Chawanda, C. J., Nkwasa, A., Thiery, W., and van Griensven, A. (2024). Combined impacts of climate and land-use change on future water resources in Africa. *Hydrology and Earth System Sciences, 28*(1), pp. 117–134. https://doi.org/10.5194/hess-28-117-2024

Dorigo, W., Wagner, W., Hohensinn, R., Hahn, S., Paulik, C., Xaver, A., … Jackson, T. J. (2011). The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements. *Hydrology and Earth System Sciences, 15*(5), pp. 1675–1697. https://doi.org/10.5194/hess-15-1675-2011

Fan, K., Zhang, Q., Gu, X., Singh, V. P., Xu, C., Shen, Z., and Wang, G. (2022). Global soil moisture drought identification and responses to natural and anthropogenic forcings. *Journal of Hydrology, 610*(1), 127993. https://doi.org/10.1016/j.jhydrol.2022.127993

Foucras, M., Zribi, M., Albergel, C., Baghdadi, N., Calvet, J.-C., and Pellarin, T. (2020). Estimating 500-m resolution soil moisture using Sentinel-1 and optical data synergy. *Water, 12*(3), 866. https://doi.org/10.3390/w12030866

Ganesan, J., Rahima, A. S., Sivasankari, V., Visalichandra, V., and Dhanapriya, M. (2025). Real-time IoT-enabled monitoring and WebGIS-based visualization of soil moisture, temperature, and humidity. *Asian Journal of Current Research, 10*(2), pp. 295-305. https://doi.org/10.56557/ajocr/2025/v10i29412

Greifeneder, F., Notarnicola, C., and Wagner, W. (2021). A machine learning–based approach for surface soil moisture estimations with Google Earth Engine. *Remote Sensing, 13*(11), 2099. https://doi.org/10.3390/rs13112099

Harani, P., Gautam, S., Joshi, S. K., Asirvatham, L. G., and Rakshith, B. L. (2025). Advancements in soil moisture estimation through integration of remote sensing and artificial intelligence techniques. *Science of the Total Environment, 1001*(1), 180503. https://doi.org/10.1016/j.scitotenv.2025.180503

Hervai, A., Pirkhoffer, E., Fábián, S., Halmai, Á., Nagy, G., Dénes, L., and Czigány, S. (2017). Interpolation and 3D visualization of soil moisture. *Acta Geographica Debrecina Landscape and Environment Series, 11*(1), pp. 23-34. https://doi.org/10.21120/LE/11/1/3

Hu, L., Di, L., Yu, E., Yue, P., Tang, J., Lin, L., Zhang, C., Sun, Z., Hu, R., Shrestha, R., and Rahman, M. (2017). Developing geospatial web service and system for SMAP soil moisture monitoring. In *2017 6th International Conference on Agro-Geoinformatic,s* pp. 1–5. https://doi.org/10.1109/Agro-Geoinformatics.2017.8047066

Jimma, T. B., Demissie, T., Diro, G. T., Ture, K., Terefe, T., and Solomon, D. (2023). Spatiotemporal variability of soil moisture over Ethiopia and its teleconnections with remote and local drivers. *Theoretical and Applied Climatology, 151*(1), pp. 1911–1930. https://doi.org/10.1007/s00704-022-04335-7

Khazaei, M., Hamzeh, S., Samani, N., Muhuri, A., Goïta, K., and Weng, Q. (2023). A web-based system for satellite-based high-resolution global soil moisture maps. *Computers and Geosciences, 170*(1), 105250. https://doi.org/10.1016/j.cageo.2022.105250

Lawrence, B. N., Bennett, V. L., Churchill, J., Juckes, M., Kershaw, P., Pascoe, S., Pepler, S., Pritchard, M., and Stephens, A. (2013). Storing and manipulating environmental big data with JASMIN. In *2013 IEEE International Conference on Big Data,* pp. 68–75. https://doi.org/10.1109/BigData.2013.6691556

Leroux, D., Kerr, Y. H., Bitar, A. A., Bindlish, R., Jackson, T. J., Berthelot, B., and Portet, G. (2013). Comparison between SMOS, VUA, ASCAT, and ECMWF soil moisture products over four watersheds in the U.S. *IEEE Transactions on Geoscience and Remote Sensing, 52*(3), pp. 1562–1576. https://doi.org/10.1109/TGRS.2013.2252468

Liu, L., Gudmundsson, L., Hauser, M., Qin, D., Li, S., and Seneviratne, S. I. (2020). Soil moisture dominates dryness stress on ecosystem production globally. *Nature Communications, 11*(1), 4892. https://doi.org/10.1038/s41467-020-18631-1

Liu, Y., Li, Z., Chen, Y., Jin, L., Feng, L., Wang, X., Long, Y., Liu, C., and Kayumba, P. M. (2025). Global greening drives significant soil moisture loss. *Communications Earth and Environment, 6*(1), 600. https://doi.org/10.1038/s43247-025-02470-3

Ma, H., Zeng, J., Chen, N., Zhang, X., Cosh, M. H., and Wang, W. (2019). Satellite surface soil moisture from SMAP, SMOS, AMSR2 and ESA CCI: A comprehensive assessment using global ground-based observations. *Remote Sensing of Environment, 231*(1), 111215. https://doi.org/10.1016/j.rse.2019.111215

Mladenova, I. E., Bolten, J., Crow, W. T., Sazib, N., and Reynolds, C. (2020). Agricultural drought monitoring via the assimilation of SMAP soil moisture retrievals into a global soil water balance model. *Frontiers in Big Data, 3*(1), 10. https://doi.org/10.3389/fdata.2020.00010

Montzka, C., Cosh, M. H., Bayat, B., Bitar, A. A., Berg, A. M., Bindlish, R., … Nickeson, J. (2020). *Soil moisture product validation good practices protocol* (Version 1.0). KU Leuven. https://doi.org/10.5067/doc/ceoswgcv/lpv/sm.001

Moses, M. (2025a). Mapping climatological trends in soil moisture variability across Nigeria. *Journal of Geomatics and Environmental Research, 8*(2), pp. 125–141. https://unilorinjoger.com/wp-content/uploads/2025/12/Moses-2025-Mapping-Climatological-Trends-in-Soil-Moisture-Variability-Across-Nigeria.pdf

Moses, M. (2025b). Machine learning-based calibration of satellite data for accurate soil moisture monitoring using the ISMN stations in Nigeria. *Nigerian Journal of Environmental Sciences and Technology, 9*(1), pp. 125–136. https://nijest.com/wp-content/uploads/2025/04/125-136_20_Vol.-9-No.-1_NIJEST.pdf

Onojeghuo, A. R., Balzter, H., and Monks, P. S. (2017). Tropospheric NO_2 concentrations over West Africa are influenced by climate zone and soil moisture variability. *Atmospheric Chemistry and Physics, 17*(15), pp. 10039–10052. https://doi.org/10.5194/acp-17-10039-2017

Peng, J., Albergel, C., Balenzano, A., Brocca, L., Cartus, O., Cosh, M. H., Crow, W. T., Dąbrowska-Zielińska, K., Dadson, S., Davidson, M. W. J., De Rosnay, P., Dorigo, W., Gruber, A., Hagemann, S., Hirschi, M., Kerr, Y., Lovergine, F., Mahecha, M. D., Marzahn, P., and Mattia, F. (2021). A roadmap for high-resolution satellite soil moisture applications – confronting product characteristics with user requirements. *Remote Sensing of Environment, 257*(1), 112162. https://doi.org/10.1016/j.rse.2020.112162

Peng, Y., Yang, Z., Zhang, Z., and Huang, J. (2024). A machine learning–based high-resolution soil moisture mapping and spatial–temporal analysis: The *mlhrsm* package. *Agronomy, 14*(3), 421. https://doi.org/10.3390/agronomy14030421

Rahmati, M., Amelung, W., Brogi, C., Dari, J., Flammini, A., Bogena, H., … Vereecken, H. (2024). Soil moisture memory: State-of-the-art and the way forward. *Reviews of Geophysics, 62*(2), pp. 1-39. https://doi.org/10.1029/2023RG000828

Reichle, R. H., De Lannoy, G. J. M., Liu, Q., Koster, R. D., Kimball, J. S., Crow, W. T., Ardizzone, J. V., Chakraborty, P., Collins, D. W., Conaty, A. L., Girotto, M., Jones, L. A., Kolassa, J., Lievens, H., Lucchesi, R. A., and Smith, E. B. (2017). Global assessment of the SMAP Level-4 surface and root-zone soil moisture product using assimilation diagnostics. *Journal of Hydrometeorology, 18*(12), pp. 3217–3237. https://doi.org/10.1175/JHM-D-17-0130.1

Rötzer, K., Montzka, C., and Vereecken, H. (2014). Spatio-temporal variability of global soil moisture products. *Journal of Hydrology, 522*(1), pp. 187–202. https://doi.org/10.1016/j.jhydrol.2014.12.038

Sadri, S., Pan, M., Wada, Y., Vergopolan, N., Sheffield, J., Famiglietti, J., Kerr, Y., and Wood, E. (2020). A global near-real-time soil moisture index monitor for food security using integrated SMOS and SMAP. *Remote Sensing of Environment, 246*(1), 111864. https://doi.org/10.1016/j.rse.2020.111864

Sasanya, B. F., Ademola, A. A., and Kolajo, O. O. (2024). Comparative analysis of drought indices for soil moisture estimation in Nigeria's diverse climate zones. In *Floods: Hydraulics and hydrology*. IntechOpen. https://doi.org/10.5772/intechopen.1007115

Sazib, N., Mladenova, I., and Bolten, J. (2018). Leveraging Google Earth Engine for drought assessment using global soil moisture data. *Remote Sensing, 10*(8), 1265. https://doi.org/10.3390/rs10081265

Seneviratne, S. I., Corti, T., Davin, É. L., Hirschi, M., Jaeger, E. B., Lehner, I., … Teuling, A. J. (2010). Investigating soil moisture–climate interactions in a changing climate: A review. *Earth-Science Reviews, 99*(3-4), pp. 125–161. https://doi.org/10.1016/j.earscirev.2010.02.004

Sigopi, M., Shoko, C., and Dube, T. (2024). Advancements in remote sensing technologies for accurate monitoring and management of surface water resources in Africa: An overview, limitations, and future directions. *Geocarto International 39*(1), 2347935. https://doi.org/10.1080/10106049.2024.2347935

Sungmin, O., and Orth, R. (2021). Global soil moisture data derived through machine learning trained with in-situ measurements. *Scientific Data, 8*(1), 170. https://doi.org/10.1038/s41597-021-00964-1

Usman, M., Nichol, J. E., Ibrahim, A., and Buba, L. F. (2018). A spatio-temporal analysis of trends in rainfall from long term satellite rainfall products in the Sudano–Sahelian zone of Nigeria. *Agricultural and Forest Meteorology, 260-261*, pp. 273-286. https://doi.org/10.1016/j.agrformet.2018.06.016

William, I. (2024). Factors influencing soil moisture distribution and its implications for ecosystems and society. *Global Journal of Plant and Soil Sciences*, 8 (1), 001. https://www.internationalscholarsjournals.com/articles/factors-influencing-soil-moisture-distribution-and-its-implications-for-ecosystems-and-society.pdf

Xu, L., Abbaszadeh, P., Moradkhani, H., Chen, N., and Zhang, X. (2020). Continental drought monitoring using satellite soil moisture, data assimilation and an integrated drought index. *Remote Sensing of Environment, 205*(1), 112028. https://doi.org/10.1016/j.rse.2020.112028

Yang, Z., Hu, L., Yu, G., Shrestha, R., Di, L., Boryan, C., and Mueller, R. (2016). Web service-based SMAP soil moisture data visualization, dissemination and analytics based on VegScape framework. In *2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS),* pp. 3624–3627. https://doi.org/10.1109/IGARSS.2016.7729939

Yuan, Z., NourEldeen, N., Mao, K., Qin, Z., and Xu, T. (2022). Spatiotemporal change analysis of soil moisture based on downscaling technology in Africa. *Water, 14*(1), 74. https://doi.org/10.3390/w14010074

Zhang, T., Zhang, Y., Wang, A., Wang, R., Chen, H., and Liu, P. (2022). Intelligent analysis cloud platform for soil moisture–nutrients–salinity content based on quantitative remote sensing. *Atmosphere, 14*(1), 23. https://doi.org/10.3390/atmos14010023.