



Hungarian University of Agriculture and Life Sciences.

The Thesis of the PhD dissertation

**From Legacy Data to a National Knowledge System:
Development of a Namibian Soil Information System, National Soil Map,
and Spatial Predictions of Soil Properties**

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Gödöllő, Hungary
2026**

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1. BACKGROUND AND OBJECTIVES OF THE STUDY

1.1 Background

Soils underpin terrestrial ecosystems, agricultural productivity, and sustainable land use. Interpreted soil information supports land suitability assessment, crop and fertiliser management, yield modelling, and food security. It is equally important for climate assessment, rangeland management, land-degradation and drought monitoring, ecosystem analysis, restoration, infrastructure planning, and resource and risk management (Bispo et al., 2014; Creamer et al., 2021; Omuto et al., 2012). Reliable datasets are essential for evaluating soil functions, ecosystem services, and environmental change, while advances in geospatial technology and modelling have increased demand for accessible, harmonised, spatially referenced information (Adhikari & Hartemink, 2016; Bouma, 2014; Dominati et al., 2010; Greiner et al., 2017; Rabot et al., 2018; Vogel et al., 2018, 2019).

This need is especially pressing in Namibia because of its arid climate, fragile ecosystems, and dependence on agriculture, tourism, and natural resources. Soils are frequently constrained by low fertility, drought, salinity, shallow depth, and limited water-holding capacity. Namibia is highly vulnerable to climate change and land degradation, which threaten food security and environmental sustainability. Reliable soil information is vital for crop production, grazing and bush management, environmental monitoring, biodiversity conservation, land-use planning, policymaking, and international reporting.

1.2 Problem statement

Despite its strategic importance, soil science in Namibia has received limited institutional support. Soil research receives only a small share of agricultural research funding, contributing to shortages of trained scientists, infrastructure, and institutional capacity. Soils are under-researched and poorly represented in national planning.

Several ad hoc surveys have been conducted since the 1950s (AOC Technical Services, 1966, 1967a, 1967b, 1967c; Department of Water Affairs, 1987; Du Plessis & Dohse, 1978; Ellis et al., 1980; Lambrechts, 1977; Lambrechts & Schloms, 1993; Louw, 1957; Loxton et al., 1970, 1974a, 1974b; MAWRD, 1995; Murray et al., 1997; Opperman et al., 1982; Page, 1976, 1978, 1979, 1980; Partridge, 1987a, 1987b; Van Woerkom & Louw, 1971). However, the resulting information is fragmented across institutions, reports, theses, and grey literature. Many records remain in analogue or obsolete formats, while inconsistent sampling, analysis, classification, and data structures hinder integration. Field records, maps, metadata, and undocumented institutional knowledge are also being lost as materials deteriorate and experienced researchers retire.

Namibia therefore lacks a complete national soil map, harmonised public profile database, soil-property maps, and integrated information system. This limits data preservation and use in agriculture, land assessment, environmental management, climate adaptation, and national reporting. With no new state-funded surveys planned, progress depends on rescuing and harmonising legacy data, completing the preliminary national soil map, addressing spatial knowledge gaps, and creating an accessible digital system aligned with national priorities and international environmental obligations.

1.3 Research aim and specific objectives

The study aimed to integrate Namibia's fragmented legacy soil data into an accessible national information system supporting conventional and digital soil mapping for national and global applications. Four interrelated objectives were pursued:

1. To conceptualise, design, and implement an open-access and user-friendly Namibian Soil Information System (NamSIS) that integrates quality-assessed and harmonised soil profile data and supporting resources, compatible with global soil information systems and modelling frameworks.
2. To identify, collect, digitise, and secure Namibian soil documents and legacy datasets, ensuring their long-term preservation and accessibility through a structured and searchable archive.
3. To produce an updated national conventional soil map of Namibia, classified according to the 2015 World Reference Base (WRB) for Soil Resources, providing a coherent pedological framework suitable for national and regional applications.
4. To develop predictive spatial models of selected soil properties using machine learning approaches, generating digital soil maps and associated uncertainty estimates that complement and extend the conventional mapping framework.

2. MATERIALS AND METHODS

2.1 The study area: Republic of Namibia

Namibia lies on the Atlantic coast of southern Africa. Elevation ranges from sea level to 2 573 m (Figure 1). Four broad physiographic regions define the landscape (Figure 2): the Namib Desert, Great Escarpment, Central Plateaus, and Kalahari Basin (Atlas of Namibia Team, 2022).

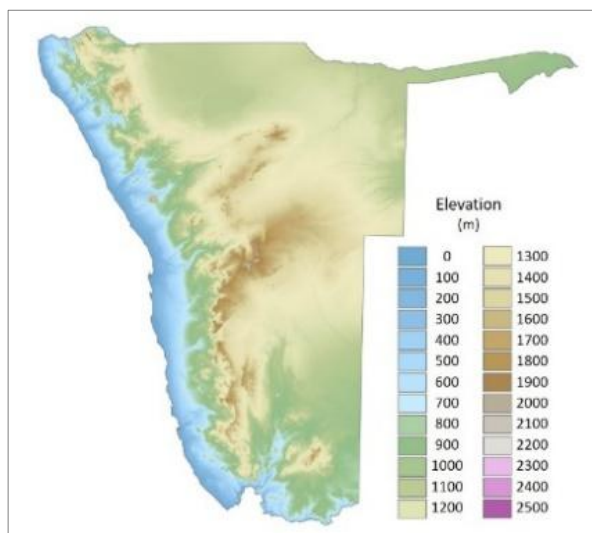


Figure 1. Elevation of Namibia above mean sea level.

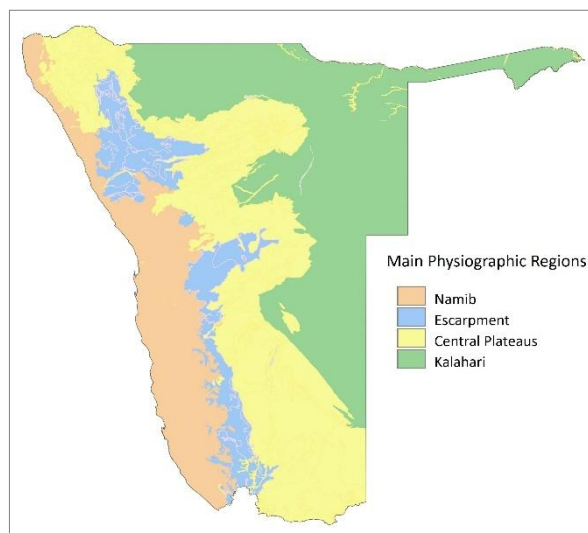


Figure 2. Main physiographic regions of Namibia.

The main landscapes and broad lithological classes are shown in Figures 3 and 4.

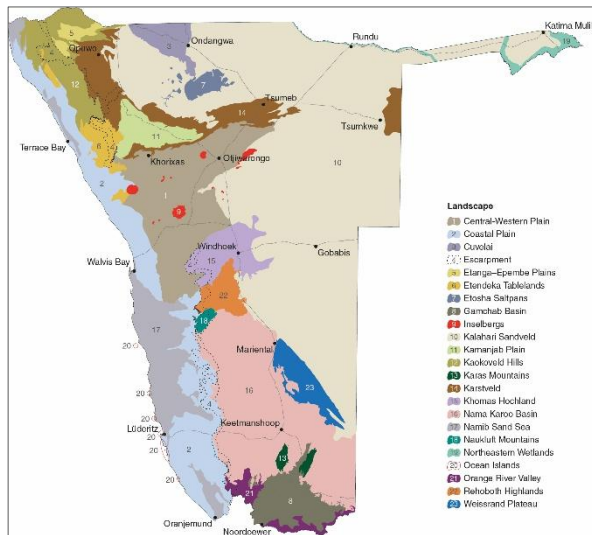


Figure 3. Landscapes of Namibia (Atlas of Namibia Team, 2022)

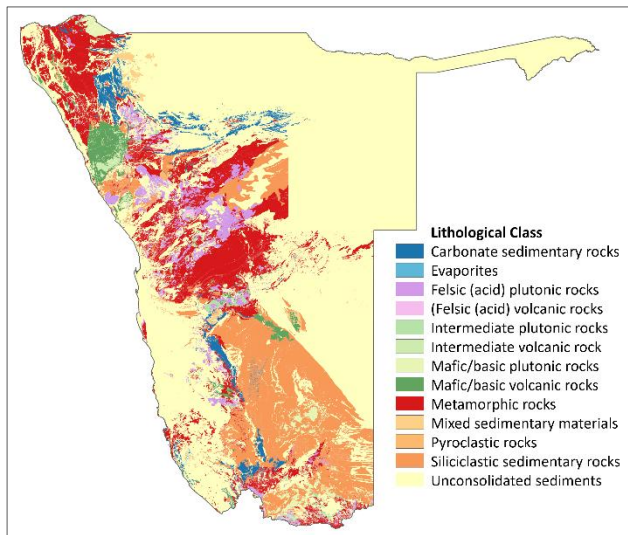


Figure 4. Broad lithological classes of Namibia (derived from Geological Survey of Namibia, n.d.) (mapping incomplete in northeast)

Namibia is the most arid country in sub-Saharan Africa and experiences pronounced spatial, seasonal, and interannual rainfall variability, with median annual rainfall between 50 mm in the Namib Desert and 650 mm in the far northeast (Figure 5). Most of the country is classified as arid, with hyper-arid conditions along the coast and semi-arid conditions in the northeast (Figure 6). Vegetation reflects the country's climatic and topographic gradients. Woodlands and tree savannas dominate the more humid northeast, while shrublands and dwarf-shrub savannas characterise the drier western, central, and southern regions. Agriculture is dominated by extensive grazing, ranching, and sedentary pastoralism. Only about 8% of Namibia is moderately suitable to suitable for rainfed cropping (De Pauw, 1996) and is concentrated in the north and northeast. National land cover is dominated by shrubs (51.2%), bare or sparsely vegetated land (27.6%), and herbaceous vegetation (14.2%), while cultivated land covers only 0.85% (Buchhorn et al., 2020a, 2020b). Land degradation is widespread, especially bush thickening (affecting 56% of Namibia, MEFT, 2024), declining perennial grasses and fodder plants, reduced biomass and soil organic matter, surface crusting, desiccation, and erosion (Republic of Namibia, 2012, 2014c).

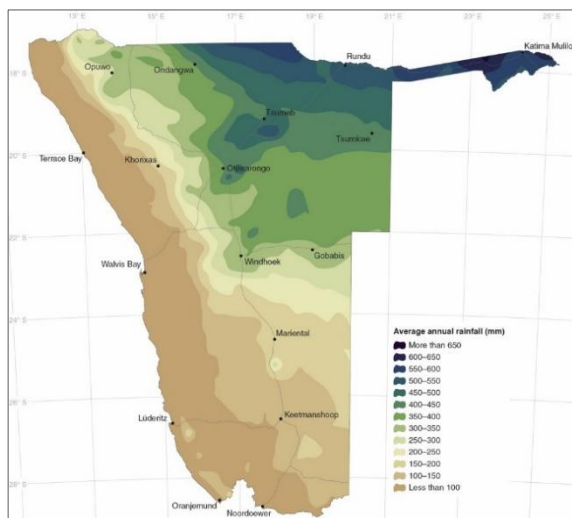


Figure 5. Mean annual rainfall of Namibia (Atlas of Namibia Team, 2022).

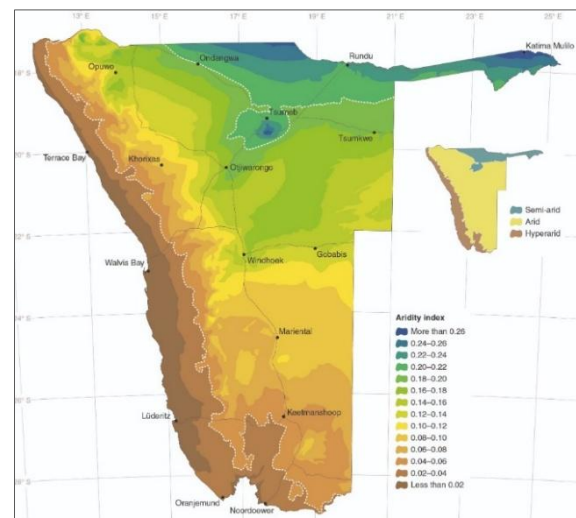


Figure 6. Aridity index of Namibia (Atlas of Namibia Team, 2022).

Namibia's soil diversity is the result of interacting climatic, lithological, geomorphic, hydrological, and biological conditions rather than of aridity alone. *Arenosols* are widespread deep sandy soils occurring mainly in the Namib and Kalahari regions. *Calcisols* occur throughout Namibia, particularly in arid and semi-arid areas where secondary calcium carbonate accumulates. *Cambisols* occur widely in weakly developed colluvial, alluvial, and aeolian deposits. *Durisols* are concentrated in southern Namibia, where silica-cemented horizons develop under stable, alkaline conditions. *Fluvisols* occur in river valleys, floodplains, lake deposits, and coastal sediments. *Gypsisols* are characteristic of the coastal gravel plains, with the best-developed examples in the Central Namib. *Leptosols* dominate actively eroding crests and steep slopes, where soils are shallow or extremely stony. *Regosols* commonly occupy footslopes, concave landforms, and unconsolidated deposits affected by erosion or sedimentation. *Luvissols* are moderately to highly fertile, clay-enriched soils, although their distribution in Namibia is limited. *Solonchaks* occur in coastal salt pans, desert playas, Etosha Pan, the Cuvelai–Etosha system, and other saline, poorly drained depressions. *Solonetzs* occur in clay-rich coastal pans and the Cuvelai–Etosha drainage system, often alongside *Solonchaks*. *Vertisols* are clay-rich, shrink–swell soils found in low-lying landscape positions where fine materials and water accumulate. *Kastanozems* occur locally near Otjiwarongo, between upslope *Calcisols* and downslope *Vertisols*. *Phaeozems* have been recorded locally in the Otavi Mountains.

Temperature fluctuations, wetting and drying, wind abrasion, and salt crystallisation physically disintegrate rock, while episodic moisture enables localised hydrolysis, dissolution, oxidation, hydration, and carbonation (Goudie, 2013; Schaetzl & Thompson, 2015). Limited downward percolation restricts leaching, although episodic infiltration redistributes carbonates, gypsum, salts, clay, iron, and organic compounds over short distances within soil profiles. Repeated dissolution and precipitation of calcium carbonate form calcic horizons and may decalcify surface layers; prolonged accumulation and cementation produce petrocalcic horizons or calcrete (Ellis, 1988, 1990; IUSS Working Group WRB, 2015). Under highly arid conditions, evaporation and limited leaching promote gypsum accumulation, forming gypsic or cemented petrogypsic horizons, particularly in the Namib Desert (Heine & Walter, 1996; Miller, 2008). Silica accumulation and cementation under alkaline conditions and prolonged landscape stability produce duric or petroduric horizons, especially in southern Namibia (Ellis, 1988, 1990, 2002; Francis, 2008). Evaporation and saline or sodic groundwater concentrate soluble salts and exchangeable sodium, particularly in coastal and interior pans, closed depressions, and the Cuvelai–Etosha system. Erosion restricts soil development on steep or exposed terrain, whereas fluvial, colluvial, aeolian, and lacustrine deposition rejuvenates soils and creates spatial variation in texture, depth, fertility, and water-holding capacity. Desert pavements, vesicular crusts, and biological soil crusts develop on exposed dryland surfaces and influence infiltration, erosion, and nutrient cycling. Sparse vegetation limits organic inputs, while warm conditions accelerate decomposition, resulting in generally low soil organic carbon except in productive, flooded, depositional, or groundwater-supported environments. Downward removal and accumulation of clay, iron, and organic matter are generally weak but become locally important in wetter regions, fine-textured soils, and sites receiving concentrated water flow. Periodic or prolonged saturation in wetlands, pans, floodplains, drainage channels, and shallow-groundwater areas creates reducing conditions and redoximorphic features. Quartz-rich materials generally form coarse, weakly buffered, nutrient-poor soils, whereas mafic and fine-grained rocks produce finer, more base-rich and clayey soils; these effects are modified by transported materials, relief, drainage, aridity, and landscape stability (Gray et al., 2016; Zádorová et al., 2025).

2.2 Conceptualisation and design NamSIS

The workflow of the study, shown in Figure 7, covers (1) conceptualising the Namibian Soil Information System (NamSIS); (2) rescuing, harmonising, and integrating legacy soil information into the Namibian Soil Profile Database (NSPD); (3) producing the conventional National Soil Map of Namibia (NSMN); and (4) generating national predictive soil property maps.

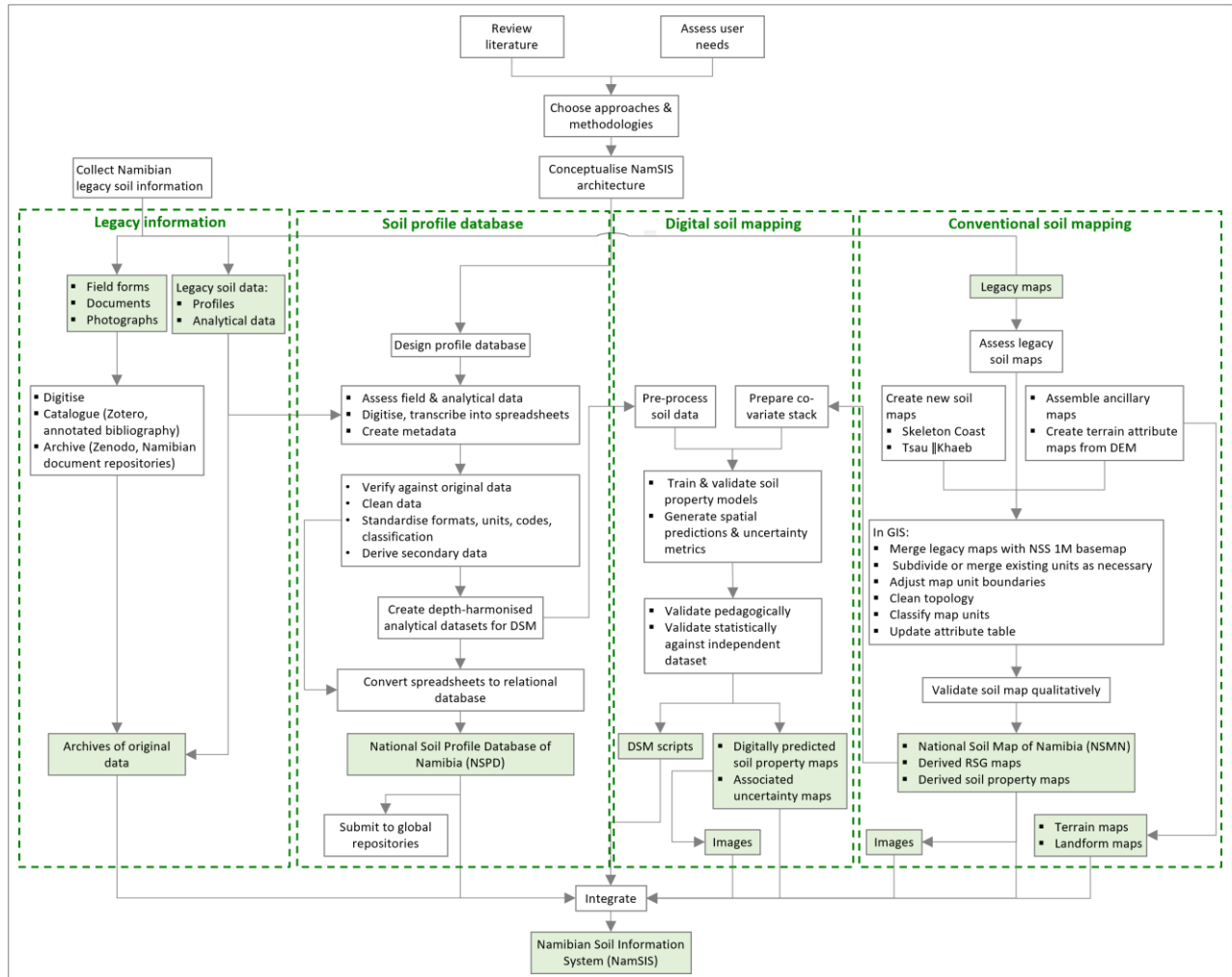


Figure 7. Workflow of the study — Development of a Namibian soil information system, national soil map, and spatial predictions of soil properties

NamSIS was conceived as a modular national platform for soil-data stewardship, conventional mapping, digital soil prediction, and dissemination. Its design responded to the fragmented condition of Namibia’s soil information, the limited likelihood of a national resurvey, and the need for compatibility with international standards and FAIR (findable, accessible, interoperable, and reusable) principles. Development involved assessing user requirements, reviewing established soil information systems, and defining an expandable system architecture. The study focused on the scientific and data-management components rather than developing web or mobile interfaces.

2.2.1 User needs and international standards

User needs were identified through research workshops and long-term engagement with farmers, researchers, extension officers, planners, environmental scientists, engineers, educators, investors, and policymakers. Requirements ranged from detailed profile and laboratory observations to

generalised maps and soil function indicators for fertility management, crop suitability, land-degradation monitoring, carbon modelling, conservation, infrastructure planning, and land-potential assessment.

The design of NamSIS was informed by WoSIS, AfSIS, GlobalSoilMap, SOTER, SoilGrids, the Harmonized World Soil Database, WRB, and the FAO Guidelines for Soil Profile Description (Arrouays et al., 2014, 2017b; Batjes et al., 2017, 2020, 2024; FAO, 1990, 2006; FAO & IIASA, 2023; IUSS Working Group WRB, 2015, 2022; ISRIC, 2019). These systems provided guidance on database structure, terminology, metadata, depth harmonisation, uncertainty reporting, and international data exchange.

2.2.2 System architecture and FAIR principles

NamSIS was designed around the relational NSPD, which stores linked site, profile, horizon, analytical, and metadata records. Both original and depth-harmonised observations are retained to preserve source information and allow future reprocessing. The modular architecture permits the later addition of new observations, proximal-sensing measurements, biological data, models, and visualisation tools without restructuring the core database.

Standardised formats, descriptive field names, coding systems, metadata, coordinate-reference documentation, version control, and uncertainty information support findability, accessibility, interoperability, and reuse. NamSIS is therefore intended as a durable national knowledge system rather than a project-specific database (Bui, 2004).

2.3 Legacy data rescue and development of the NSPD

Legacy-data revitalisation comprised three stages: data archaeology, data rescue, and data renewal.

2.3.1 Data discovery and rescue

A systematic search was conducted across ministries, parastatals, universities, research institutes, engineering firms, libraries, and private collections. Materials included technical reports, journal articles, theses, maps, handwritten profile forms, laboratory records, photographs, and project databases. Reconnaissance and irrigation surveys dating from the 1950s were also obtained from South African institutions. Each source was assessed for provenance, spatial coverage, scale, analytical content, and relevance.

Paper documents, field forms, and laboratory records were scanned to PDF, while existing digital documents were consolidated. The document collection was archived in two national repositories, catalogued in Zotero, and documented through an annotated bibliography published on Zenodo. Analogue maps were scanned, georeferenced in QGIS using graticules and identifiable landmarks, and stored as GeoTIFFs or vector datasets. Profile and analytical observations were transcribed into spreadsheets, and photographs were preserved in standard image formats.

Metadata recorded data origin, ownership, collection date, spatial coverage, coordinate-reference system, analytical methods, related publications, photographs, and institutional contacts. Original scanned records were retained to enable later verification and reinterpretation.

2.3.2 Source datasets

The *NARIS Soil Dataset* formed the principal source and structural foundation of the NSPD. It

originated from the 1998–2000 National Soil Survey and subsequent Ministry of Agriculture surveys conducted between 2000 and 2009 (ICC & MAWRD, 2000; MAWRD-AEZ, 2009). Original forms and laboratory reports were re-examined to recover information omitted from the digital records. Data from 30 additional datasets were collected, processed and added, after extensive quality control and standardisation to account for differences in survey purpose, sampling design, observation depth, analytical method, and data quality.

2.3.3 Data entry, harmonisation and quality control

Data were initially managed in a master Excel workbook containing Profile Registration, Site Description, Horizon Field Data, and Horizon Laboratory Data worksheets. Digital datasets were aligned with the master structure, and paper records were transcribed manually. Existing records were checked against original forms, laboratory reports, and grey literature. Transcription errors, duplicate profiles, coordinates outside Namibia, omitted negative latitudes, and transposed coordinates were corrected. Where coordinates were absent, locations were inferred from route descriptions and landscape features when sufficiently reliable. Unverified but internally consistent records were retained and flagged.

Units were standardised, coordinates converted to decimal degrees, and attribute definitions reconciled. Site and horizon terminology was harmonised with FAO and SOTER conventions (FAO, 2006; ISRIC, 2019). Soil classifications based on South African, FAO/UNESCO, Soil Taxonomy, and earlier WRB systems were translated to WRB 2015 where adequate diagnostic information was available (IUSS Working Group WRB, 2015). Quality control followed Leenaars et al. (2014) and included valid-range checks, particle-size totals of $100 \pm 1\%$, agreement between sand fractions and total sand, consistency between horizon thickness and depth limits, and compatibility between soil properties and classifications. Automated spreadsheet checks were supplemented by expert assessment of anomalous values in relation to location, soil chemistry, and pedological context. Records that could not be corrected or corroborated were excluded. Analytical methods for phosphorus and organic carbon could not be converted reliably because too few samples had been analysed using multiple methods; results were therefore retained in method-specific fields.

2.3.4 Depth harmonisation and database implementation

Profiles with at least three sampled depths were harmonised using an equal-area quadratic spline fitted to 200 cm with the *ea_spline* function in the R *ithir* package. A smoothing parameter of $\lambda = 0.1$ balanced fidelity to measured values against excessive horizon discontinuities. Outputs were aggregated to the six GlobalSoilMap intervals (0–5, 5–15, 15–30, 30–60, 60–100, and 100–200 cm) and to three agriculturally relevant intervals (0–30, 30–60, and 60–100 cm) (Arrouays et al., 2017b). Cleaned data were migrated into a relational structure comprising linked site, profile, horizon, analytical, and metadata tables. Limited redundancy, including parallel units, coded and descriptive fields, and alternative date formats, was retained to improve usability and compatibility with external systems. The original horizon-based dataset and both depth-harmonised versions were preserved. The NSPD will be maintained as an authoritative master database for curation and analysis and a controlled public version for dissemination. This separation protects data integrity while supporting accessibility and the appropriate management of incomplete or sensitive records.

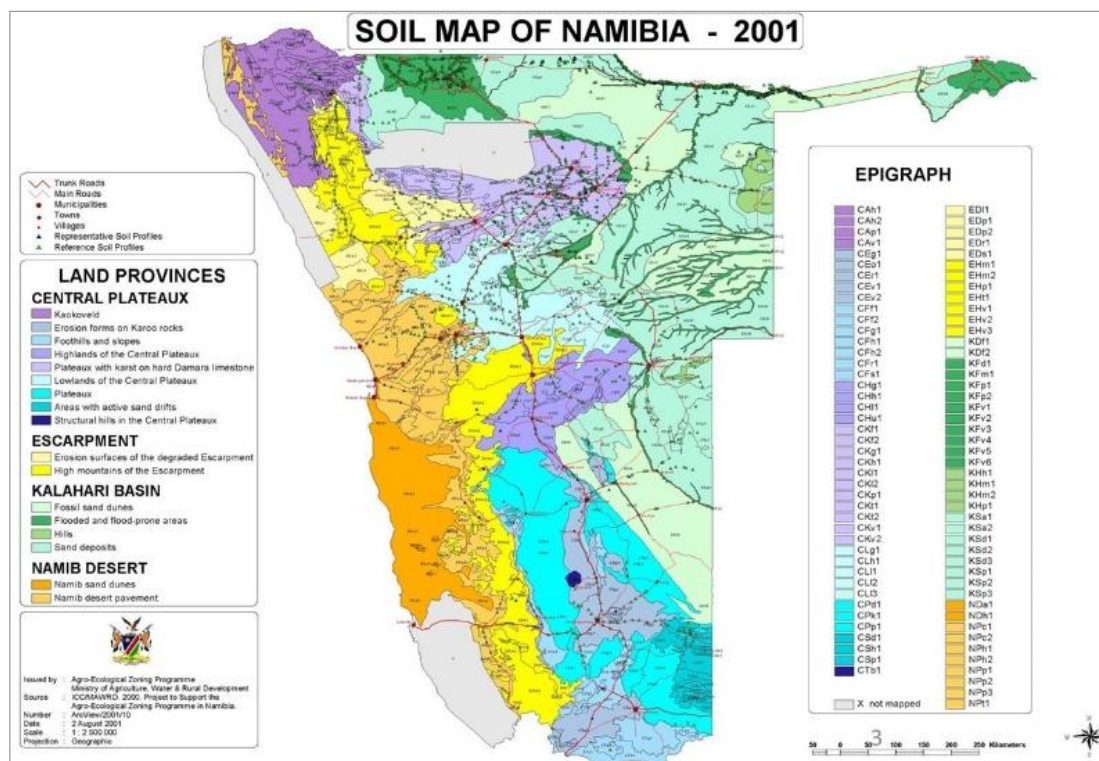
2.4 Production of a National Soil Map of Namibia

The NSMN was produced through expert-driven integration of existing soil maps, profile observations, terrain information, geology, satellite imagery, and other environmental evidence. Digital tools supported interpretation and editing but did not automatically generate polygons or assign soil classes.

2.4.1 Basemap and legacy sources

The spatial foundation was the incomplete 1:1 million preliminary soil map of Namibia derived from the 1998–2000 National Soil Survey (Figure) (Coetzee, 2001; ICC & MAWRD, 2000). The survey also produced more detailed maps of the wetter northeast at 1:250 000 and the Okavango Terrace and Cuvelai Basin at 1:100 000 (**Error! Reference source not found.**). Global and continental products were examined but not incorporated because they contained less national detail than the available legacy sources.

Additional Ministry surveys from 2000–2009 improved national coverage. Earlier irrigation and development surveys contributed local soil maps and profile information, although their use was complicated by missing coordinates, analogue formats, and older South African classification systems. Ecological projects (including BIOTA, SASSCAL, The Future Okavango, GIZ–Bush–SOC, LDN, and LandPKS) supplied further observations. Research from Etosha National Park was particularly important because the area had been omitted from the original national survey (Beugler-Bell & Buch, 1997; Buch, 1990, 1993, 1997; Trippner, 1997, 1998). Additional regional information was obtained for Kunene, Kavango, Caprivi, and north-central Namibia. The Atlas of Namibia, agro-ecological land systems, geological mapping, and related landscape studies provided further interpretive support.



2.4.2 Environmental interpretation layers

Terrain derivatives were produced from the 30 m SRTM digital elevation model and, where necessary, resampled to 90 m. Elevation, slope, aspect, terrain ruggedness, topographic position, drainage, and landforms were examined as evidence of soil depth, erosion, drainage, sediment redistribution, and landscape position. Slope was mapped continuously and using Global Agro-Ecological Zones classes; the proportion of each map unit exceeding an 8% slope threshold was calculated as an indicator of erosion risk and limitations to mechanised cultivation. Following exploratory comparison of several terrain-complexity measures, the Riley Terrain Ruggedness Index (Riley et al., 1999) was selected to help distinguish valley floors, canyon walls, rock outcrops, plains, and inselbergs. Topographic Position Index and Topographic Wetness Index were used selectively at local scale. Drainage networks and hydrological derivatives supported the delineation of alluvial soils, floodplains, sediment-accumulation areas, and ephemeral rivers. A Namibian Land Systems map provided the geomorphic framework (Van der Waal et al., 2021a, 2021c).

The 1:250 000 Geological Map of Namibia represented parent material and guided delineation where lithological boundaries corresponded with soil transitions. Natural colour satellite imagery from Bing and Google was used to refine boundaries and identify features such as dunes, gravel plains, pans, inter-dune depressions, calcrete plateaus, and dolines. Satellite imagery was interpreted visually; no spectral classification was performed. NSPD profiles served as ground-control observations for classifying soils and identifying recurring soil–landscape relationships.

2.4.3 Map compilation and classification

The Skeleton Coast and Tsau I!Khaeb National Parks were mapped using satellite imagery, terrain, geology, limited profiles, and observations from botanists and geologists. Confidence is lower in Tsau I!Khaeb because access for survey purposes was limited. Their inclusion nevertheless provided complete national coverage at a scale more detailed than 1:4 million for the first time.

The preliminary 1:1 million NSS map provided national structural continuity and was refined to a nominal 1:250 000 scale using the detailed NSS maps, other legacy surveys, 1:250 000 geology, terrain attributes, satellite imagery, and profile observations. Information from maps more detailed than 1:100 000 was generalised to maintain consistency with the national scale.

Selected analogue maps were digitised, georeferenced, and imported into QGIS. NSS maps of the northeast, Okavango, and Cuvelai were merged with the basemap through manual editing and edge matching, followed by the Etosha map and newly mapped national parks. Remaining sources were incorporated by subdividing, merging, or adjusting polygons in relation to terrain, geology, drainage, vegetation, land systems, agro-ecological zones, and profile evidence.

Editing was generally undertaken at display scales of 1:20 000–1:50 000, although the evidential support and intended use remain smaller-scale. The final map is considered reliable at 1:250 000 or smaller and moderately reliable between 1:100 000 and 1:250 000. It should not be interpreted as a detailed farm- or site-scale survey. Polygon topology was checked for gaps, overlaps, and slivers, and the resulting dataset was structured for future revision.

Source classifications were manually correlated with WRB 2015 using profile morphology, laboratory thresholds, diagnostic horizons, known pedogenic processes, and published correlations (Fey, 2010; IUSS Working Group WRB, 2015). Where direct correlation was impossible, classifications were reconstructed from the underlying evidence.

2.4.4 Quality control and validation

Validation included iterative consistency checks, field observations, comparison with legacy maps, and consultation with scientists familiar with Namibian soils. Reviews considered boundary placement, soil transitions, internal map unit consistency, WRB classification, source overlap, scale generalisation, and terrain complexity. Discrepancies were investigated using profiles, analytical data, photographs, terrain attributes, and geological context. Where several interpretations remained plausible, decisions favoured regional pedogenic consistency over isolated anomalies. The final map is therefore a transparent synthesis of available evidence, with spatially variable confidence reflecting observation density, accessibility, and landscape complexity.

2.5 Predictive spatial modelling

2.5.1 Modelling framework and soil observations

Digital soil mapping generated continuous predictions of 16 soil properties (Table 1) at three depths across Namibia.

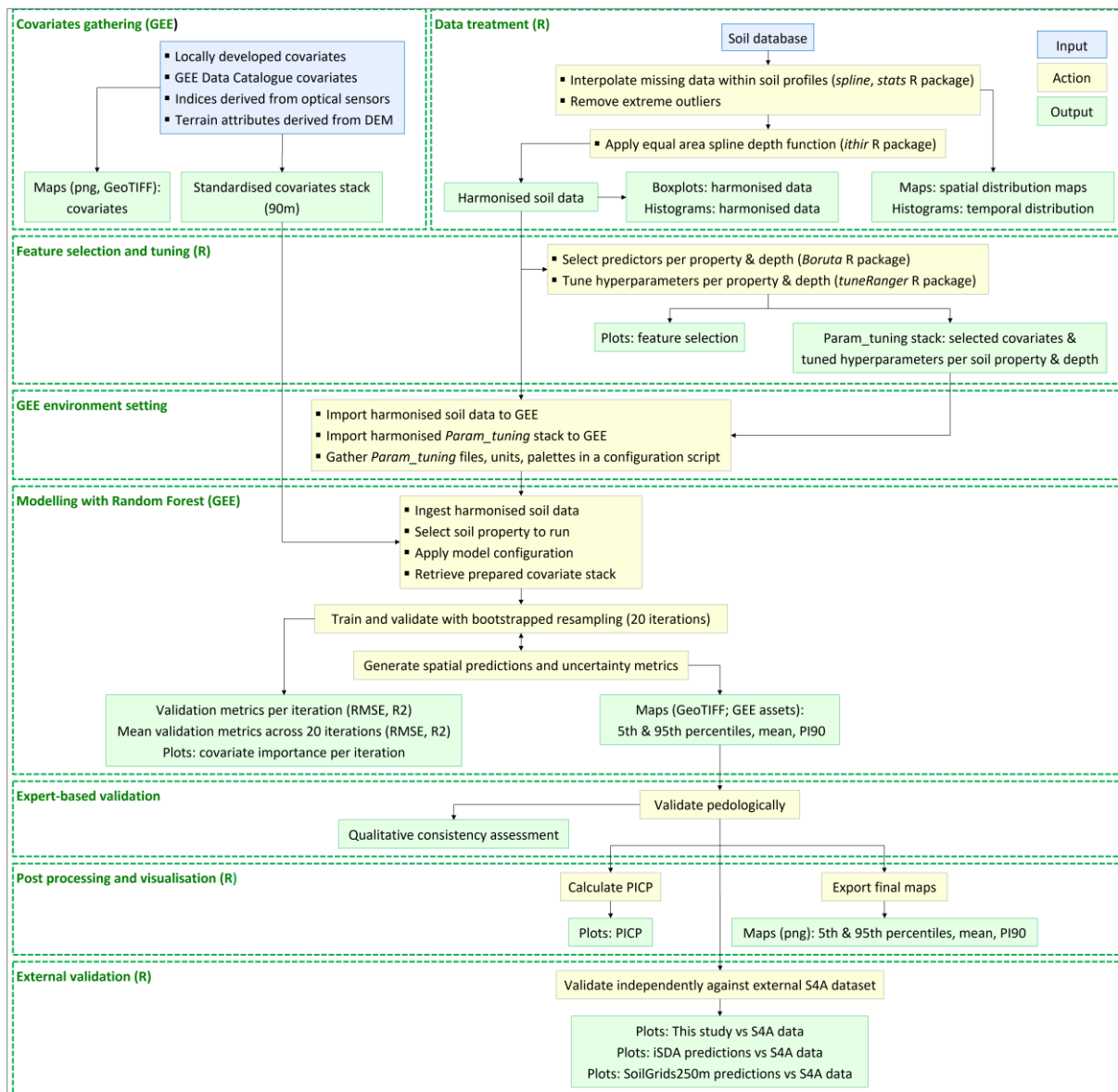


Figure 9. Digital soil mapping workflow.

The workflow comprised soil data preparation, covariate assembly, feature selection, model tuning, bootstrap modelling, uncertainty estimation, pedological evaluation, and external validation (Figure 9).

Table 1. Soil properties selected for modelling

Soil property	Abbreviation	Unit
bulk density	BD	kg dm ⁻³
base saturation	BS	%
pH (1:2.5 soil:water)	pH (H ₂ O)	
cation exchange capacity	CEC	cmol(+) kg ⁻¹
extractable calcium, magnesium, potassium, and sodium	Ca, Mg, K, Na	mg kg ⁻¹
electrical conductivity (1:2.5 soil:water supernatant)	EC (1:2.5)	μS cm ⁻¹
electrical conductivity (saturated paste extract)	EC (sat)	μS cm ⁻¹
organic carbon	OC	%
plant-available phosphorus	P	mg kg ⁻¹
total nitrogen	N	mg kg ⁻¹
sand (>53 μm), silt (2–53 μm), clay (<2 μm)		%

Google Earth Engine (GEE) provided cloud processing and access to environmental datasets, while R was used for depth harmonisation, feature selection, hyperparameter tuning, visualisation, and validation. Random Forest (RF) was selected as the primary algorithm because preliminary trials with alternatives produced similar accuracy and RF offered stability, interpretability, and an operational basis for future updates.

Modelling used 4 958 georeferenced profiles and augerings and 13 362 samples from the NSPD. Coordinates were checked, Schwarzeck coordinates transformed to WGS84, and only records with spatial precision better than 0.0001° retained. Extreme values and laboratory inconsistencies were screened and missing within-profile values were interpolated where appropriate. Equal-area quadratic splines with $\lambda = 0.1$ normalised profiles to 0–30, 30–60, and 60–100 cm before modelling

2.5.2 Environmental covariates

Sixty-five covariates represented the SCORPAN soil-forming factors:

- *Soil*: WRB Reference Soil Groups from the NSMN.
- *Climate*: WorldClim precipitation and temperature, the Global Aridity Index, potential evapotranspiration, and CHILI (Fick & Hijmans, 2017; Trabucco & Zomer, 2022).
- *Organisms*: seasonal Landsat 5 and 8 reflectance composites; NDVI, EVI, SAVI, MSAVI, and kNDVI; global land cover; and Namibian vegetation, productivity, carrying-capacity, and agro-ecological layers.
- *Relief*: elevation, slope, aspect, northness, eastness, convexity, topographic position and diversity, landforms, and curvature derived principally from NASADEM and ALOS.
- *Parent material*: detailed and generalised geological units and Landsat- and ASTER-derived mineral indices for carbonates, ferrous and mafic minerals, kaolinite, quartz, and calcite.
- *Neighbourhood*: distance to drainage and hydrological variables from MERIT Hydro and HydroSHEDS.
- *Age*: omitted as a direct variable because suitable data were unavailable, although maturity was represented indirectly by soil type and mineralogical indices.

Landsat composites used winter and summer observations with less than 1% cloud cover from 1985–2011 and 2013–2024 to reduce short-term vegetation variability. Covariates were reprojected to WGS84, converted to compatible data types, resampled to 90 m, and processed with a 2 km buffer to limit edge effects.

2.5.3 Feature selection and model training

A hybrid feature-selection procedure combined expert screening with automated assessment. Recursive Feature Elimination was tested, but the *Boruta* algorithm generally produced better validation accuracy and was therefore adopted as the primary method (Guyon et al., 2002; Kursa & Rudnicki, 2010). Expert overrides were permitted where pedologically justified.

Predictor values were extracted at soil-observation locations and paired with measured property values. The *tuneRanger* package optimised the number of trees (*ntree*), predictors considered per split (*mtry*), minimum terminal-node size (*nodesize*), bootstrap sample size (*sampsize*), and maximum terminal nodes (*max_Nodes*) for each property–depth combination (Probst et al., 2019b).

Each model was evaluated through 20 bootstrap iterations using random 80% training and 20% validation partitions and a fixed seed. This produced 960 models: 20 iterations $\times$ 16 properties $\times$ three depths. Performance was assessed using root mean square error (RMSE), coefficient of determination (R^2), and Lin’s concordance correlation coefficient (CCC), with CCC calculated from the mean predictions to assess agreement, precision, and bias (Lin, 1989).

2.5.4 Spatial predictions and uncertainty

Each bootstrap model generated a national prediction at 90 m resolution. The pixel-wise mean of the 20 predictions formed the final estimate for each property and depth. The 5th and 95th percentiles provided the lower and upper limits of a 90% prediction interval (PI90), while their difference represented interval width.

Prediction Interval Coverage Probability (PICP) measured the proportion of observations falling within PI90. Values near 90% indicate appropriately calibrated uncertainty; lower or higher values suggest under- or overestimation (Malone et al., 2011; Poggio et al., 2021).

Statistical assessment was supplemented by pedological evaluation. Predicted distributions and depth trends were compared with known climatic gradients, terrain–soil relationships, geological units, existing maps, field knowledge, and dryland processes such as carbonate accumulation, limited leaching, aeolian deposition, textural differentiation, and organic-matter dynamics. Abrupt discontinuities and implausible patterns were examined for possible covariate artefacts.

2.5.5 External validation

The Soils4Africa dataset was excluded from calibration and used for independent validation. It comprised 63 wet-chemistry analyses from 33 locations and 131 samples estimated from mid-infrared spectra (Gelsleichter & Coetzee, 2026). Predictions from this study, SoilGrids250m V2 (Poggio et al., 2021), and iSDA (Miller et al., 2021) were extracted at the validation locations and converted to common units. Differences in depth intervals were reconciled using mass-preserving equal-area splines to the Soils4Africa intervals of 0–20 and 20–50 cm.

2.5.6 Processing pipeline

The complete reproducible pipeline comprised: (1) data cleaning and depth harmonisation; (2) feature selection and RF tuning in R; (3) covariate assembly, bootstrap modelling, and uncertainty prediction in GEE; (4) post-processing and application of physically meaningful limits; (5) calculation of PI90 and PICP; and (6) external validation (Gelsleichter, 2026b; Gelsleichter &

Coetzee, 2026).

2.6 Integration within NamSIS

The NSPD, NSMN, and predictive soil maps were integrated conceptually through common spatial references, standardised formats, metadata, and relational linkages. NSPD observations support map-unit interpretation and model calibration; the NSMN represents soil–landscape relationships and serves as a modelling covariate; and the digital maps provide continuous quantitative information, identify knowledge gaps, and support future refinement of the conventional map.

NamSIS therefore treats data storage, expert interpretation, and predictive modelling as interdependent components of a unified and incrementally updateable national soil-information architecture. Although the study did not develop APIs, dashboards, or other web services, its structures and standards provide the foundation for future dissemination through national and international spatial-data infrastructures.

3. RESULTS AND DISCUSSION

The Namibian Soil Information System (NamSIS) represents the first systematic consolidation of Namibia’s soil knowledge. It integrates preserved legacy materials, the Namibian Soil Profile Database (NSPD), the National Soil Map of Namibia (NSMN), digital soil-property predictions, associated uncertainty estimates, and supporting geospatial and modelling resources.

3.1 Legacy data preservation and documentation

A major study outcome was the recovery and preservation of previously fragmented and vulnerable soil information. The *original data archive* contains the four databases (NSD1000, NSD250, NSDkava, and NSDowa) generated by the 1998–2000 National Soil Survey and the consolidated NARIS Soil Dataset as it existed in 2009. Additional project datasets were retained in their original spreadsheet, laboratory, field-note, or documentary formats, with links to external repositories where available. Most National Soil Survey and MAWF–AEZ field forms were scanned, although forms associated with several surveys could not be located and are presumed lost.

Analytical procedures were compiled separately to assist interpretation of measurements generated by different laboratories. Approximately 78% of samples were analysed by the Ministry of Agriculture’s AgricLab and 16.5% by the University of Hamburg, with the remainder analysed by other regional institutions. The archive includes AgricLab standard operating procedures, AgriLASA methods, the GLOSOLAN Walkley–Black procedure, and Soils4Africa analytical guidelines (AgriLASA, 2004; FAO/GLOSOLAN, 2019; Paterson, 2021).

The *documents archive* comprises published research, dissertations, survey reports, and grey literature catalogued in Zotero (https://www.zotero.org/groups/6649154/soil_literature_-_namibia/library). Publicly shareable documents were also deposited in the Environmental Information Service eLibrary (<http://the-eis.com/elibrary/>) and the Namibia University of Science and Technology Special Collections (<http://specialcollections.nust.na:8080/greenstone3/library/collection/soils/page/about>). More than 900 georeferenced *site and profile photographs* were

linked to NSPD records, while scanned and digitised *legacy maps* were preserved as raster or vector datasets. Together, these archives safeguard the provenance and contextual information required to verify, reinterpret, and update Namibia's soil knowledge.

3.2 The Namibian Soil Profile Database

The NSPD forms the observational core of NamSIS. It is maintained as a relational MS Access database, an Excel workbook, and CSV files. Linked tables contain profile registration, site descriptions, field and laboratory horizon observations, environmental information, metadata, and depth-harmonised analytical data. Each observation has a unique profile identifier (PRID), while horizon number (HONU) connects individual horizons or depth layers with their field and analytical records (Figure 10).

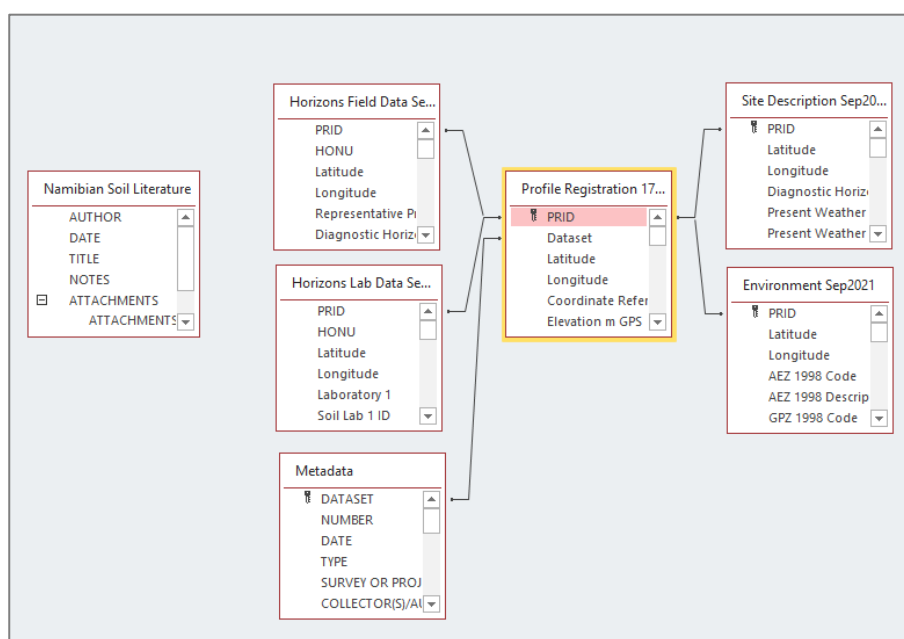


Figure 10. Relational structure of the Namibian Soil Profile Database (NSPD).

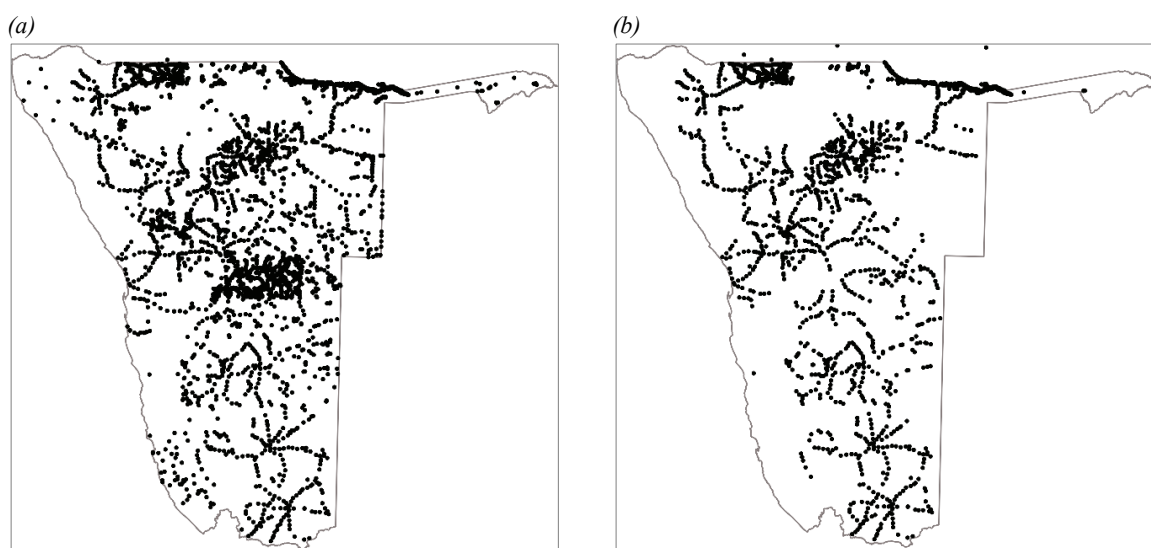


Figure 11. Distribution of soil point data in (a) the Namibian Soil Profile Database (NSPD) and (b) the 1998-2000 National Soil Survey of Namibia.

The database contains 5 099 georeferenced profiles, augerings, and sampling locations associated with 13 425 horizons or depth layers. This more than doubles the 2 155 points and 6 204 horizons

contained in the 2009 NARIS dataset and improves national spatial coverage substantially (Figure 11). The increase resulted from recovering information from original field forms and integrating 30 additional project datasets. Record completeness varies because the source projects differed in objectives, sampling designs, budgets, depths, and analytical methods. Some records contain only site and field observations, whereas others include complete morphological descriptions and extensive laboratory results. This heterogeneity is retained and documented rather than concealed. The database preserves observations recorded by genetic horizons or predefined layers, together with two standardised depth products. The first represents agriculturally relevant intervals of 0–30, 30–60, and 60–100 cm; the second follows the six GlobalSoilMap intervals of 0–5, 5–15, 15–30, 30–60, 60–100, and 100–200 cm. These tables can be regenerated when new observations are added. Retaining both original and harmonised data protects provenance while enabling conventional interpretation, digital modelling, and exchange with international systems.

3.3 The National Soil Map of Namibia (NSMN)

3.3.1 Map coverage and structure

The principal outputs of the expert-driven spatial component of NamSIS are the 1:250 000 scale National Soil Map of Namibia (NSMN), maps of individual WRB Reference Soil Groups (RSGs), thematic maps of diagnostic soil attributes, and supporting terrain and land-system products. All are available in updateable GIS formats.

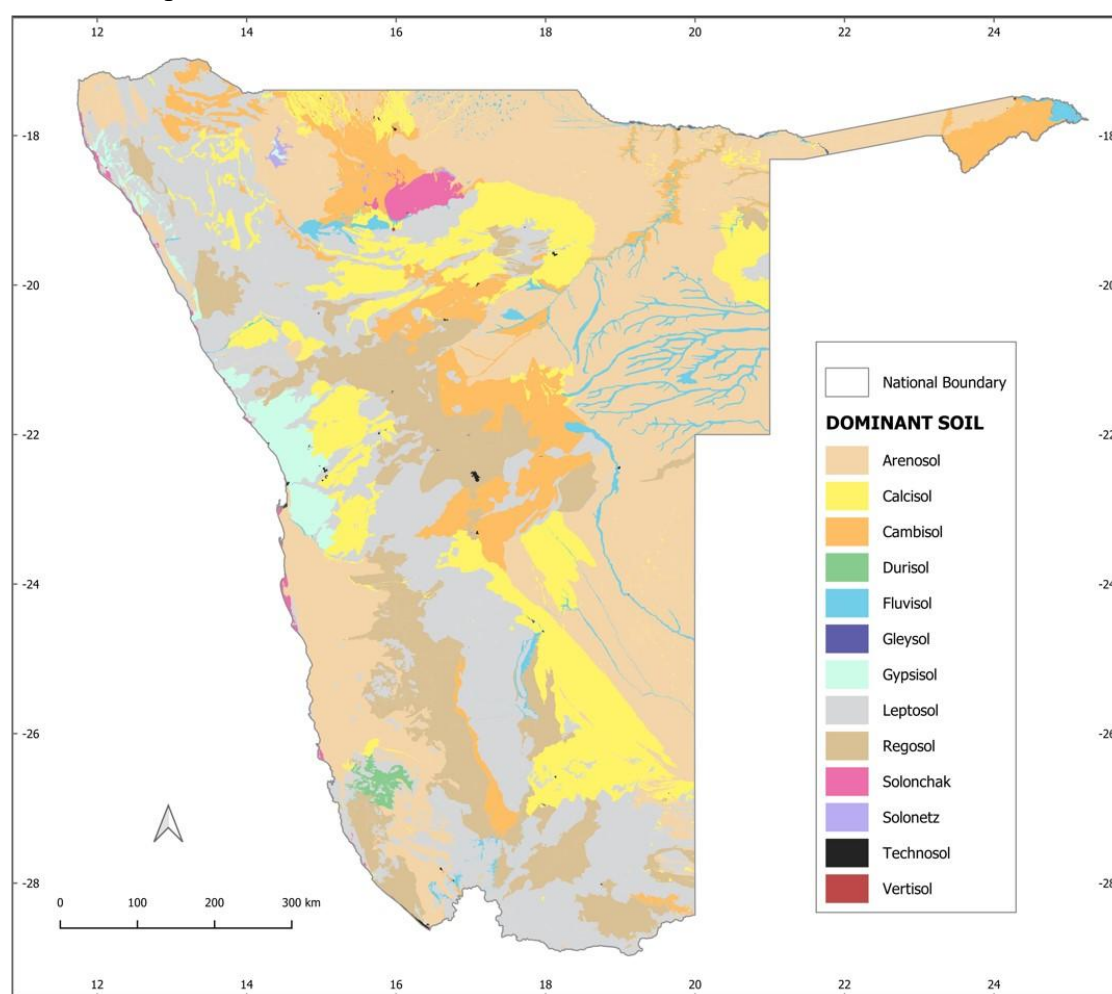


Figure 12. The new National Soil Map of Namibia — dominant World Reference Base (WRB) Reference Soil Groups (RSGs).

The map identifies 13 dominant RSGs: Arenosols, Leptosols, Regosols, Calcisols, Cambisols, Gypsisols, Solonchaks, Solonetz, Fluvisols, Durisols, Gleysols, Vertisols, and Technosols (Figure 12). Local occurrences of Luvisols, Stagnosols, Planosols, Histosols, and palaeo-Kastanozems are also represented.

The NSMN contains 4 787 polygons, 490 soil map units (SMUs), and 212 soil typological units (STUs) (Figure 13). Each SMU comprises a dominant STU, estimated to cover more than 50% of the polygon, and may include an associated soil occupying approximately 25–50% and up to two included soils occupying approximately 5–25%. This structure represents recurring soil associations and acknowledges within-unit heterogeneity. Previously unmapped areas in Etosha, Skeleton Coast, and Tsau ǁKhaeb national parks are now included, giving Namibia complete national soil-map coverage for the first time.



Figure 137. The new National Soil Map of Namibia (NSMN) — outlines of all soil map units.

3.3.2 Soil distribution and land-use implications

The map clarifies relationships among climate, geology, topography, hydrology, soil development, and land-use potential. *Leptosols* dominate extensive rocky and mountainous landscapes. Their shallow rooting depth, low water-storage capacity, and stoniness restrict cultivation, but they support grazing, wildlife conservation, and tourism. *Regosols* are also weakly developed and often erodible, limiting agricultural potential while retaining value for extensive grazing. *Arenosols* dominate the Kalahari and Namibia's principal crop producing regions. Their low nutrient and water retention capacities require careful organic matter management, staged fertilisation,

vegetation protection, and efficient irrigation where water is available. Exposed sands are vulnerable to compaction, wind erosion, and dune remobilisation. *Cambisols* generally offer better agricultural potential because weathering and early horizon development improve structure, nutrient retention, and water storage. *Calcisols* and calcrete formations occur throughout Namibia. Crop production is possible where rainfall or irrigation is sufficient, but surface crusting, nutrient imbalances, salinity, and shallow petrocalcic horizons can restrict infiltration and rooting. *Durisols* occur mainly along the eastern margins of the central and southern Namib and are associated with stable, alkaline landscapes. Their cemented horizons, low rainfall, and occasional salinity or boron toxicity limit cultivation, and they mainly support wildlife and small-stock production. *Gypsisols* occur principally on stable coastal gravel plains influenced by hyper-aridity, fog, and marine sulfate inputs. They are best developed in the central Namib and have little agricultural potential, but they contribute to gravel-plain stability and support specialised ecosystems. *Solonchaks* and *Solonetz* are concentrated in endorheic basins, coastal salt pans, and terminal playas, particularly the Cuvelai–Etosha system. Their salinity, sodicity, poor structure, and restricted plant-water availability impose severe agricultural limitations. *Fluvisols* and *Gleysols* occur in river systems, floodplains, and seasonally or permanently saturated depressions. They can be relatively productive but are affected by flooding, variable sedimentation, drainage constraints, and local salinity. *Vertisols* are spatially limited but potentially fertile; their strong shrink–swell behaviour makes cultivation and infrastructure development difficult. *Technosols* are restricted mainly to urban, mining, industrial, and waste-disposal areas.

3.3.3 Derived thematic and terrain products

Maps of individual RSGs distinguish where each soil is dominant, associated, included, or absent (Full resolution maps at <https://soilsofnamibia.com/maps.html>). Maps derived from WRB qualifiers depict functional characteristics including shallow depth, stoniness, calcrete, dolomitic parent materials, undeveloped sands, desert pavements, colluvial and fluvial deposition, and hydromorphic conditions (Full resolution maps at <https://soilsofnamibia.com/properties.html>).

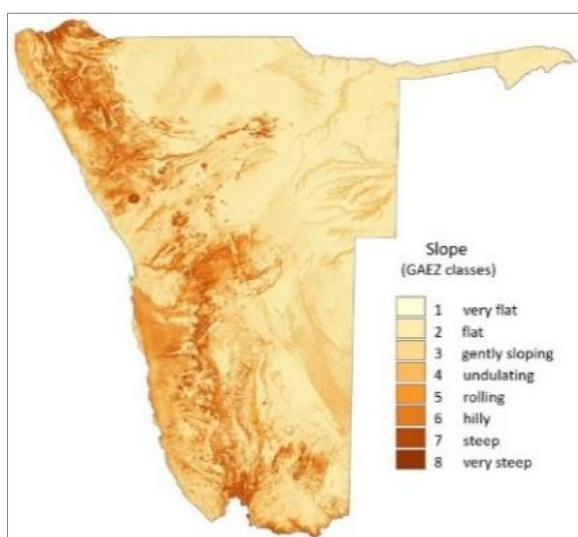


Figure 14. Slope Map of Namibia (GAEZ classes).

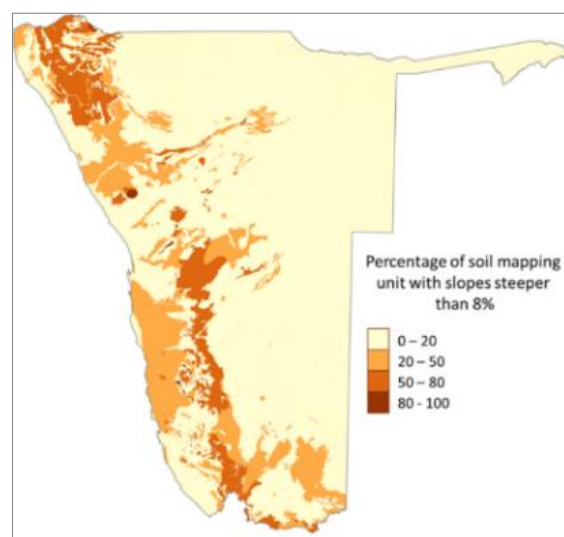


Figure 8. Percentage of each SMU with slopes steeper than 8% in Namibia.

Shallow soils cover approximately 46% of Namibia, particularly the Central Plateaus, Escarpment, Kaokoveld, Damaraland, Karstveld, southern Namibia, and rocky desert features. *Stony* soils are similarly widespread and constrain tillage, rooting, and water storage. *Hypercalcic* and *petrocalcic*

soils indicate extensive carbonate accumulation, while *Protic* and *Yermic* qualifiers respectively delineate active sands and desert-pavement environments. *Stagnic* and *Gleyic* conditions are uncommon and occur mainly north of Etosha and within the Cuvelai, Okavango, and Zambezi floodplains.

Terrain products provide additional context for interpreting soils and land use. Steep and rugged terrain is concentrated along the Escarpment, Central Highlands, northern Kunene, and parts of southern Namibia, where erosion risk and access limitations are high (Figure 14). Flat and gently sloping land dominates the climatically more suitable crop-producing regions in the north and northeast (Figure 15). Aspect, terrain ruggedness, topographic position, and wetness indices improve recognition of dunes, ridges, valleys, depositional areas, and subtle drainage systems.

3.3.4 Advances and limitations of the national soil map

The NSMN is a substantial improvement over the preliminary national map. Polygon numbers increased from 321 to 4 787, STUs from 36 to 212, and SMUs from 89 to 490. Modern GIS, high-resolution imagery, a 30 m elevation model, terrain derivatives, improved profile coverage, and WRB 2015 classification enabled greater spatial and typological detail. Multiple soils and diagnostic qualifiers within each SMU also represent landscape complexity and management constraints more effectively.

The map nevertheless inherits limitations from uneven observation density, inaccessible regions, and source maps produced at different scales and for different purposes. Boundary and classification confidence is highest in well-surveyed northern regions and lower in remote parks, communal areas, and heterogeneous terrain. The map is suitable with high confidence at 1:250 000 or smaller scales and with moderate confidence between 1:100 000 and 1:250 000. It is not a substitute for detailed local surveys in high-stakes land-use decisions.

3.4 Digital soil property maps

Digital soil mapping generated continuous predictions for 16 properties at 0–30, 30–60, and 60–100 cm at a 90 m spatial resolution.

3.4.1 Data characteristics and feature selection

The underlying observations were collected over several decades and are spatially uneven, temporally clustered, and concentrated in accessible and agriculturally important regions. Sampling is sparse in the Namib, national parks, rugged terrain, and remote communal areas, and observation numbers decline with depth.

Depth-harmonised data show that organic carbon, nitrogen, phosphorus, calcium, magnesium, potassium, and silt generally decline with depth, while pH and clay commonly increase through carbonate accumulation and translocation of fine material. Sand contents and base saturation are frequently high, reflecting extensive aeolian deposits and limited leaching. The Kalahari is dominated by deep, slightly acidic quartz sands, whereas the Central Highlands and Escarpment contain finer and more base-rich soils derived from varied lithologies.

Boruta feature selection, supplemented by expert adjustment, retained between four and 60 predictors per model. Elevation, rainfall, temperature, potential evapotranspiration, downstream flow length, rock outcrops, and vegetation indices were frequently selected (Table 2). Fine-scale terrain variables contributed less consistently at national resolution. Locally developed soil,

geology, vegetation, agro-ecological-zone, and carrying-capacity maps were retained in more than half the models, demonstrating the value of contextual expert information alongside global covariates.

Table 2. Frequency (%) with which environmental covariates were included in all Random Forests models.

Covariate	Freq	Covariate	Freq	Covariate	Freq	Covariate	Freq
DEM	94	SAVI _w	65	NIR _w	52	ALOS landform	15
Precipitation	90	KNDVI _w	63	SWIR2 _s	52	Eastness	8
Temperature	88	NIR _s	63	SWIR1 _s	50	Flow accumulation	8
ASPP	79	AEZ (2021)	60	TPI	50	Distance to drainage	8
Flow length down	79	Carbonate norm	60	SWIR1 _w	48	Maximum curvature	6
EVI _w	73	Green _s	60	Iron norm	46	Flow direction	4
MSAVI _s	73	NDVI _w	60	Clay norm	44	Horizontal curvature	4
Vegetation types	73	ALOS topo divers	60	Land cover	42	Northness	4
MSAVI _s	71	Blue _s	58	Iwahasi landform	42	Aspect	2
SAVI _s	71	KNDVI _s	58	Red _w	40	Carbonate index	2
AEZ (1996)	69	NDVI _s	58	Ferrous min norm	38	Kaolinite index	2
Blue _w	69	Namibia soil map	56	Slope	35	GAI	0
EVI _s	69	Geology (2022)	54	Height above drainage	25	Calcite index	0
PET	69	Green _w	54	Vertical curvature	23	Convexity	0
Rock outcrops norm	69	Red _s	54	Flow length upstream	15	Mafic index	0
Carrying capacity	67	SWIR2 _w	54	Lithology (Geology 1977)	15	Quartz index	0
CHILI	65						

Note: The _w and _s suffixes associated with spectral bands and vegetation indices refer to two seasonal windows: winter and summer. More covariate information and clarification on the abbreviations/acronyms are provided in Appendix **Error! Reference source not found.**

3.4.2 Model performance and environmental controls

Random Forest hyperparameters were optimised for each property–depth combination. The number of trees was fixed at 150 after performance stabilised, while node size, predictors per split, and sample size were tuned individually.

Model performance varied considerably by property and depth (Table 3).

Table 3. Mean model performance metrics (RMSE and R^2) across 20 bootstrap iterations for each soil property and depth interval.

	R^2			RMSE		
	0–30 cm	30–60 cm	60–100 cm	0–30 cm	30–60 cm	60–100 cm
Bulk density (kg dm^{-3})	0.37	0.21	0.29	0.13	0.12	0.13
Base saturation (%)	0.45	0.44	0.46	18.3	21.3	21.7
pH (H_2O)	0.52	0.46	0.49	0.87	1.07	1.13
Cation exchange capacity ($\text{cmol}(+) \text{ kg}^{-1}$)	0.46	0.49	0.19	5.5	5.1	6.0
Calcium (mg kg^{-1})	0.46	0.45	0.32	1081	830	836
Magnesium (mg kg^{-1})	0.31	0.27	0.30	82.2	101.8	90.3
Potassium (mg kg^{-1})	0.40	0.42	0.32	87.0	91.9	96.0
Sodium (mg kg^{-1})	0.11	0.15	0.22	95.7	114.2	76.9
Electrical conductivity (1:2.5) ($\mu\text{S cm}^{-1}$)	0.35	0.19	0.10	614	792	754
Electrical conductivity (sat) ($\mu\text{S cm}^{-1}$)	0.13	0.37	0.39	1266	1602	1512
Organic carbon (%)	0.31	0.18	0.15	0.24	0.21	0.22
Phosphorus (mg kg^{-1})	0.31	0.27	0.19	3.59	3.50	3.74
Nitrogen (mg kg^{-1})	0.57	0.75	0.25	211.3	131.7	101.5
Sand (%)	0.45	0.36	0.33	11.6	13.3	13.9
Silt (%)	0.44	0.39	0.34	7.0	7.2	7.5

Clay (%)

0.32

0.22

0.28

7.0

9.2

9.1

Base saturation, pH, extractable calcium and potassium, sand, and silt were predicted comparatively well because their distributions correspond strongly with climate, parent material, carbonate occurrence, aeolian deposits, and regional hydrology. Cation-exchange capacity and nitrogen also showed useful predictability through their relationships with texture, mineralogy, vegetation, and organic matter.

Organic carbon and phosphorus are strongly affected by local biological processes and management histories that are poorly represented by national covariates. Inconsistencies among legacy analytical methods added uncertainty. Sodium and electrical conductivity performed poorly because salt-affected soils are localised, highly skewed in the dataset, and underrepresented by agricultural surveys. Accuracy generally decreased with depth because subsoil observations were sparser and less directly related to remotely sensed surface conditions.

Variable importance patterns (Figure 16) indicate that climate controls weathering, leaching, carbonate and salt accumulation, vegetation productivity, and organic-matter turnover. Terrain affects erosion, deposition, drainage, and redistribution of sediments. Vegetation indicators represent both biological inputs and responses to soil moisture and substrate conditions. Geology and conventional soil classes capture parent-material controls on texture, mineralogy, base status, and salinity. The frequent importance of national categorical datasets shows that embedded expert knowledge adds information not fully represented by global continuous covariates.

3.4.3 Spatial predictions and pedological plausibility

Mean predictions from 20 bootstrap realisations produced national 90 m maps for each property and depth (Appendix A). Many maps display a strong diagonal transition between the geologically diverse Escarpment and Central Highlands and the quartz-rich Kalahari Basin. This pattern is reinforced by increasing rainfall towards the northeast. Kalahari soils generally have lower pH, base saturation, cation-exchange capacity, and exchangeable bases because of their sandy texture and greater leaching. Central, western, and southern Namibia display higher base concentrations associated with calcareous parent materials, limited leaching, and high evapotranspiration. Organic carbon and nitrogen are highest in the more humid northeast and along ephemeral rivers, where riparian vegetation increases organic inputs. Phosphorus enrichment corresponds with limestone, dolomite, schist, and basalt landscapes. Texture predictions show extensive sands in the Kalahari and finer soils in the Central Highlands and the Cuvelai, Okavango, Kwando–Linyanti–Chobe, and Zambezi floodplains. Slight increases in clay and silt with depth are consistent with translocation in semi-arid soils. Predicted patterns were generally pedologically plausible and aligned with known climatic, geological, vegetation, and terrain gradients. Sodium was the principal exception: its models produced low accuracy and unrealistic patterns and should not be released for public use.

3.4.4 Uncertainty and external validation

Prediction uncertainty was represented by the 5th and 95th percentiles and their 90% prediction interval (PI90) (Example of pH shown in Appendix B). Uncertainty generally increased with depth and was highest in sparsely sampled or environmentally heterogeneous regions. The relatively uniform Kalahari showed narrower intervals for most properties.

Prediction Interval Coverage Probability values (Table 4) for pH, base saturation, calcium, cation-exchange capacity, and sand were close to the nominal 90% target. Most other models produced conservative intervals, particularly organic carbon, phosphorus, electrical conductivity, and

sodium.

Table 4. Prediction Interval Coverage Probability (PICP) for each soil property and depth interval, to assess the robustness of the 90% prediction intervals.

	PICP 90		
	0–30 cm	30–60 cm	60–100 cm
Bulk density (kg dm ⁻³)	92.1	89.4	90.1
Base saturation (%)	90.6	90.6	90.7
pH (H ₂ O)	90.5	91.1	91.0
Cation exchange capacity (cmol(+) kg ⁻¹)	90.3	91.9	94.4
Calcium (mg kg ⁻¹)	91.3	91.0	92.3
Magnesium (mg kg ⁻¹)	94.4	93.8	92.0
Potassium (mg kg ⁻¹)	94.5	92.1	96.0
Sodium (mg kg ⁻¹)	96.7	96.9	96.3
Electrical conductivity (1:2.5) (μS cm ⁻¹)	96.7	95.3	95.6
Electrical conductivity (sat) (μS cm ⁻¹)	94.5	92.3	91.1
Organic carbon (%)	94.7	95.2	96.0
Phosphorus (mg kg ⁻¹)	93.3	95.2	96.6
Nitrogen (mg kg ⁻¹)	94.9	90.0	89.8
Sand (%)	91.3	91.7	91.2
Silt (%)	92.8	92.7	93.0
Clay (%)	93.8	93.3	93.6

Independent validation against Soils4Africa measurements showed that the models produced here generally had comparable or lower RMSE values than SoilGrids250m V2 and iSDA, with the greatest improvements for particle-size fractions (Table 5). R² values were also generally higher, except for subsoil cation-exchange capacity and topsoil clay. Low R² values for some properties partly reflect the narrow ranges and small, unevenly distributed independent dataset; RMSE is therefore the more informative measure in these cases.

Table 5. External validation metrics (RMSE and R²) comparing predictions from this study with iSDA and SoilGrids250m V2 products, against independent Soils4Africa observations.

Variable	Depth (cm)	Namibia	iSDA	SoilGrids	Namibia	iSDA	SoilGrids
		R ²			RMSE		
pH (H ₂ O)	0–20	0.44	0.15	0.37	1.07	1.02	1.22
	20–50	0.35	0.15	0.32	1.03	1.13	1.37
CEC (cmol(+) kg ⁻¹)	0–20	0.16	-	0.07	5.9	-	10.1
	20–50	0.13	-	0.16	4.5	-	8.7
Organic carbon (%)	0–20	0.20	0.17	0.01	0.21	0.20	0.34
	20–50	0.21	0.19	0.08	0.17	0.16	0.18
Nitrogen (mg kg ⁻¹)	0–20	0.61	0.43	0.39	192.4	213.3	333.1
	20–50	0.48	0.37	0.29	210.0	188.9	227.1
Sand (%)	0–20	0.33	0.35	0.14	8.1	16.2	13.3
	20–50	0.34	0.33	0.21	8.5	15.3	12.5
Silt (%)	0–20	0.51	0.39	0.35	3.2	6.4	4.8
	20–50	0.12	0.08	0.07	6.9	7.9	7.6
Clay (%)	0–20	0.06	0.21	0.02	6.6	9.5	10.2
	20–50	0.25	0.31	0.08	6.1	9.2	9.9

Several limitations of the digital soil mapping should be acknowledged: The legacy observations differ in sampling design, period, depth, and laboratory method. Depth harmonisation can obscure sharp horizon boundaries, while temporal differences between soil measurements and remote-sensing products add uncertainty for dynamic properties. Covariates differ in resolution and date, and categorical geology, vegetation, and soil maps do not represent all sub-pixel variability. Random Forest provides a robust operational approach but is less flexible than ensemble or hybrid methods. Processing quotas in Google Earth Engine also required compromises among resolution, model complexity, and bootstrap iterations.

Uncertainty maps are therefore essential outputs rather than supplementary illustrations. They identify where predictions should be interpreted cautiously and where new sampling would most improve future models.

3.4.5 Complementarity of conventional and digital mapping

Conventional and digital mapping provide different but complementary forms of information. The NSMN synthesises expert knowledge into interpretable soil–landscape units, whereas digital models estimate continuous property variation within and across those units. The national map provides contextual information and a useful modelling covariate; digital predictions reveal within-unit variation and gaps requiring additional investigation. Their agreement across most mapped patterns supports the conventional–digital convergence hypothesis, while the poor sodium result demonstrates the importance of expert plausibility assessment.

3.5 The integrated Namibian Soil Information System

NamSIS integrates original legacy materials, quality-controlled profile data, depth-harmonised observations, the NSMN, environmental covariates, digital predictions, uncertainty layers, analytical protocols, metadata, and reproducible modelling scripts (Figure 17). Its GIS contains NSPD locations, soil polygons, derived thematic maps, terrain and environmental layers, satellite and web-service connections, and digital soil-property rasters in standard vector and GeoTIFF formats.

The modelling component contains R and Google Earth Engine scripts for preprocessing, depth harmonisation, feature selection, tuning, model fitting, uncertainty estimation, and external validation. The modular workflow enables predictions to be updated or extended to new properties, depths, or resolutions. Static map images are also provided for users without GIS or modelling software.

The system’s principal strengths are its modularity, preservation of provenance, compatibility with FAIR principles, use of standardised metadata, and integration of observational, expert, and predictive information. Providing relational, spreadsheet, CSV, GIS, image, and document formats improve access for both specialist and non-specialist users. These outcomes support the data-integration hypothesis by substantially improving the accessibility, interoperability, preservation, and utility of Namibia’s soil information.

Limitations include uneven spatial and depth coverage, unrecovered source materials, variation among analytical methods, and uncertainty inherited by conventional and digital products. MS Access was practical for development but is proprietary and should eventually be replaced by an open-source spatial database such as PostgreSQL/PostGIS. Maintaining synchronised public and authoritative master versions will also require sustained technical oversight.

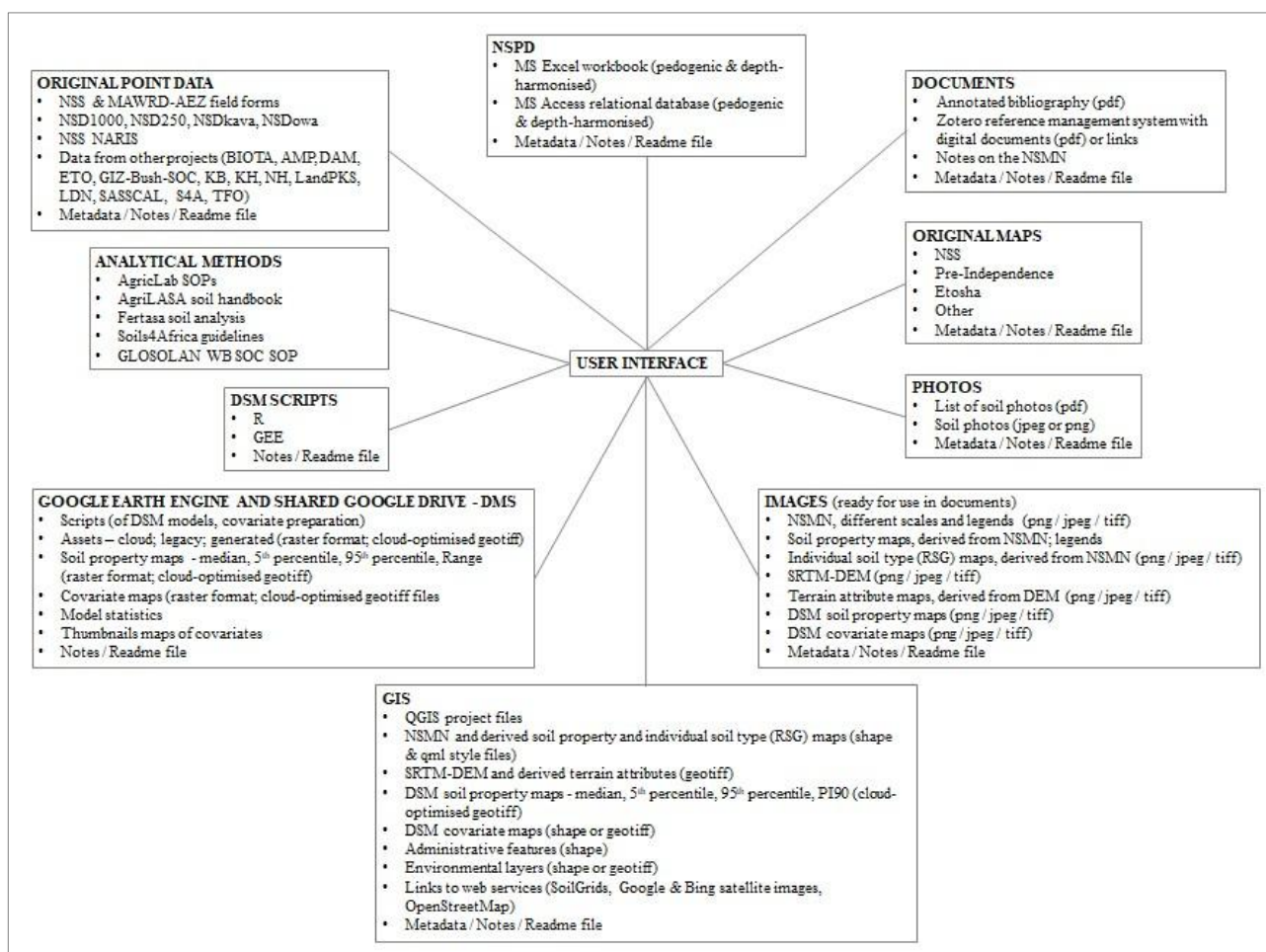


Figure 179. Components of the Namibian Soil Information System (NamSIS).

Long-term success depends on stable institutional stewardship. Government remains the logical custodian of national spatial information, although present capacity and accessibility constraints may make a university-based arrangement more viable in the medium term. Until a permanent institutional home is established, the Soils of Namibia website provides access to datasets, archives, and DOI-based records. Interactive web and mobile applications remain a future development phase.

4. CONCLUSIONS

The overarching aim of transforming Namibia's fragmented legacy soil information into an integrated national soil knowledge system was achieved through four complementary objectives.

The first objective was achieved through the development of the Namibian Soil Information System (NamSIS). This modular framework integrates soil observations, archives, conventional and digital maps, metadata, analytical protocols, and modelling resources. It accommodates future data, methods, and products and therefore establishes a cumulative national resource rather than a collection of isolated project outputs.

The second objective was achieved by recovering, digitising, cataloguing, and preserving previously dispersed or endangered soil documents, maps, datasets, field records, photographs, and laboratory information. These resources were consolidated within structured archives and the

Namibian Soil Profile Database. Original observations were retained alongside quality-controlled, standardised, and depth-harmonised versions, preserving provenance while enabling verification, reanalysis, and integration with contemporary soil-information systems.

The third objective was achieved through the production of the National Soil Map of Namibia at a nominal scale of 1:250 000. The map provides complete national coverage and substantially improved spatial and typological detail. It integrates legacy surveys, soil observations, environmental information, and expert interpretation within a consistent WRB 2015 classification framework. Derived thematic maps further communicate soil constraints and opportunities relevant to land assessment and management. Nevertheless, detailed site-level decisions still require local field investigation.

The fourth objective was achieved through the production of Namibia's first national machine-learning predictions of key soil properties at multiple depths. Model performance was moderate to good for most properties, although accuracy generally declined with depth. Predictions for sodium and electrical conductivity were weak and require cautious interpretation. Spatial uncertainty estimates indicate where predictions are less reliable, while independent validation showed that the national models generally performed comparably to or better than existing global and continental products.

The study demonstrates that Namibia's soil variability is strongly structured by climate, terrain, vegetation, parent material, and associated dryland pedogenic processes. Conventional mapping provides an interpretable representation of soil–landscape relationships, while digital mapping describes continuous variation within and between map units. Their integration strengthens both the coherence and practical value of national soil information.

Collectively, NamSIS, the soil-profile database, the national soil map, and the digital soil-property maps constitute Namibia's first comprehensive national soil-information infrastructure. They provide an important baseline for agricultural and rangeland management, land-degradation assessment, biodiversity conservation, climate adaptation, environmental monitoring, and evidence-based natural-resource governance. The study also provides a transferable framework for revitalising legacy soil information in other data-limited countries.

5. RECOMMENDATIONS

NamSIS should be maintained as an evolving national system. Future surveys should prioritise under-sampled areas, deeper soil layers, locations of high prediction uncertainty, and regions of particular agricultural or environmental importance. New observations should follow standardised field, laboratory, metadata, and quality-control protocols so they can be incorporated directly into the system.

The national soil map and digital predictions should be refined through targeted field verification, independent validation, improved environmental covariates, and evaluation of alternative modelling methods. A national soil-monitoring network should also be established to assess changes resulting from climate, land use, degradation, salinisation, and rehabilitation.

Greater emphasis should be placed on translating soil information into practical products, including crop-suitability, land-capability, erosion-risk, nutrient-management, and ecosystem-monitoring tools. Online viewers, query and download services, user guidance, and training would improve access for planners, extension officers, land managers, and other non-specialists.

Long-term sustainability requires formal institutional stewardship, stable funding, professional data curation, laboratory quality assurance, and collaboration among government, universities, and research institutions.

NamSIS should ultimately migrate to an open, server-based spatial database. Historical soil samples should be catalogued and secured under a formal national archiving policy, while continued participation in regional and global soil-information initiatives should be encouraged.

6. NEW SCIENTIFIC RESULTS

1. This research **developed the first integrated national soil knowledge infrastructure for Namibia** which brings quality-controlled soil observations, legacy data archives, conventional soil maps, digital soil maps with uncertainty assessments, metadata, photographs, analytical protocols, and reproducible modelling scripts into a single FAIR-aligned, extensible framework.
2. The study **rescued and preserved Namibia's at-risk soil science legacy** by recovering, verifying, digitising, cataloguing, and publicly archiving historical soil datasets, maps, field records, photographs, laboratory methods, reports, and grey literature that had previously been dispersed and largely inaccessible.
3. The research produced the **first complete and internally coherent National Soil Map of Namibia at a scale of 1:250 000**, providing full territorial coverage — including previously unmapped areas — and substantially increasing spatial and typological detail to 4 787 polygons, 212 Soil Typological Units, and 490 Soil Map Units classified according to the 2015 World Reference Base for Soil Resources.
4. The study produced the **first comprehensive, quality-controlled, standardised, publicly accessible Namibian Soil Profile Database**, consolidating 5 099 georeferenced observation sites and 13 425 soil horizons or layers, in addition to depth-harmonised versions suitable for modelling.
5. The research generated **Namibia's first spatially continuous national predictions of physical and chemical soil properties at 90 m resolution** for the 0–30, 30–60, and 60–100 cm depth intervals, together with prediction means, 5th and 95th percentile uncertainty boundaries, and 90% prediction intervals. Independent validation produced comparable or better metrics than global and pan-African datasets. It was shown that locally developed environmental datasets contain substantial process-relevant information and should be used to supplement generic global covariates in national digital soil mapping.
6. The study **validated a hybrid conventional–digital soil-mapping strategy** in which expert-derived conventional maps provide environmental knowledge, spatial stratification, and pedological plausibility checks for machine-learning models, while digital predictions quantify continuous within-unit variation and identify priorities for conventional map refinement.
7. The study **established a foundation for soil research and practical applications in Namibia** that did not exist before — a baseline for agricultural and rangeland management, ecosystem protection, land-degradation assessment, climate-change adaptation, environmental monitoring, and evidence-based natural resource governance.

8. The research developed a **methodology for constructing national soil information systems** that is **reproducible and transferable to other countries**. The methodology integrates legacy data revitalisation, database harmonisation, conventional mapping, machine-learning spatial prediction, uncertainty quantification, and external validation within a comprehensive, interconnected framework.

LIST OF PUBLICATIONS

1. Bünemann, M., **Coetzee, M.E.**, Kutuahupira, J., Maynard, J.J., Herrick, J.E. (2023). Errors in soil maps: The need for better on-site estimates and soil map predictions. *PLoS ONE* 18(1): e0270176. DOI: <https://doi.org/10.1371/journal.pone.0270176>
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5. **Coetzee, M.E.** (2023). A tale of freshwater scarcity: Water resources in Namibia. *Journal of Central European Green Innovation* 11(2), 3–16. DOI: <https://doi.org/10.33038/jcegi.4847>
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3. **Coetzee, M.**, & Gelsleichter, Y. (2026). NamSoil v1.0: Predicted Bulk Density (kg dm⁻³) for Namibia at 90 m resolution (0–30, 30–60 and 60–100 cm) (1.0.0) [Data set]. *Zenodo*. <https://doi.org/10.5281/zenodo.18832925>
4. **Coetzee, M.**, & Gelsleichter, Y. (2026). NamSoil v1.0: Predicted Cation Exchange Capacity (cmolc kg⁻¹) for Namibia at 90 m resolution (0–30, 30–60 and 60–100 cm) (1.0.0) [Dataset]. *Zenodo*. <https://doi.org/10.5281/zenodo.18833128>
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APPENDIX A

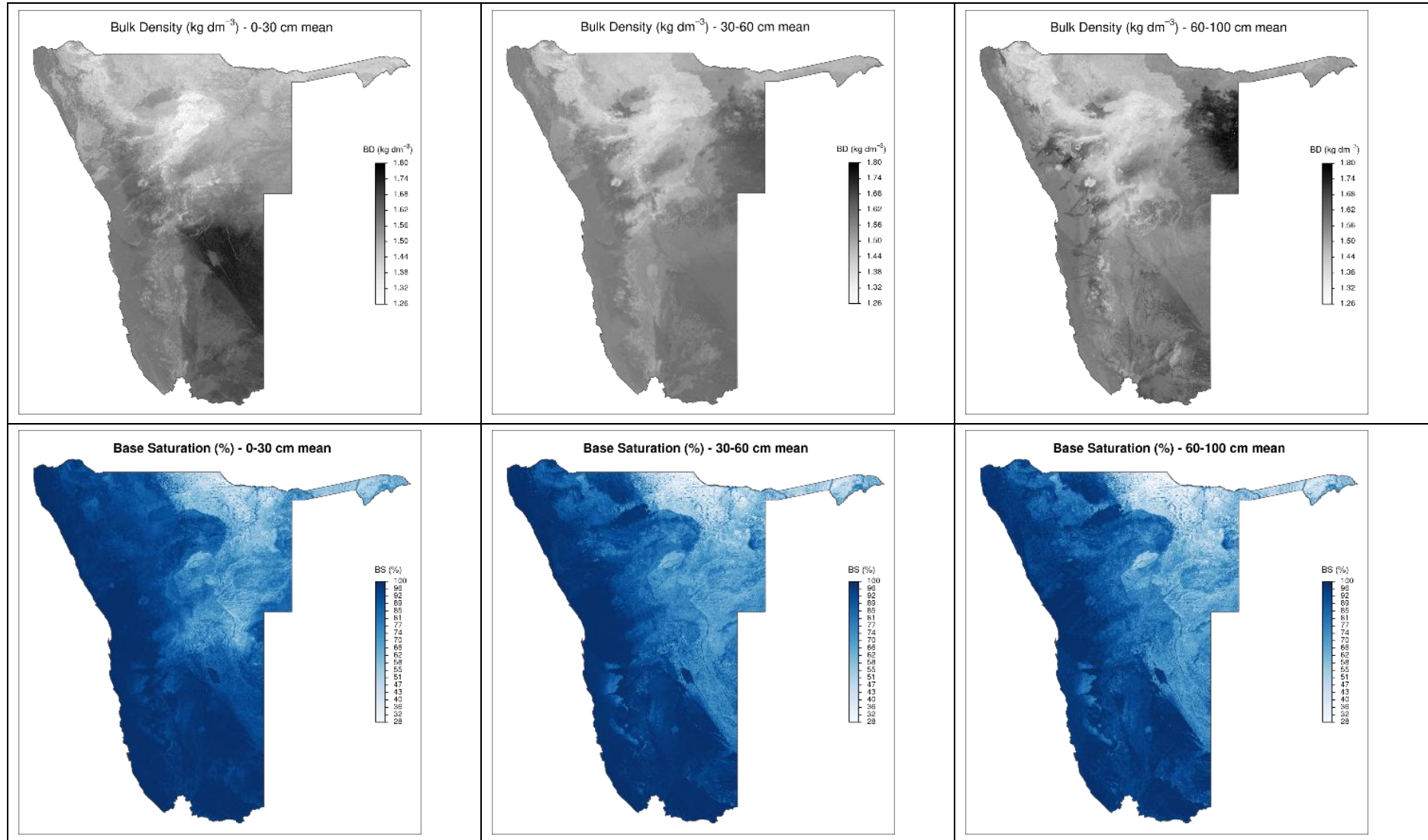


Figure 18. National-scale spatial predictions of bulk density (BD) (top) and base saturation (BS) (bottom) at 90 m resolution, shown as the mean of 20 bootstrap realisations for three depth intervals (0–30, 30–60, and 60–100 cm) (left to right) in Namibia. (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>).

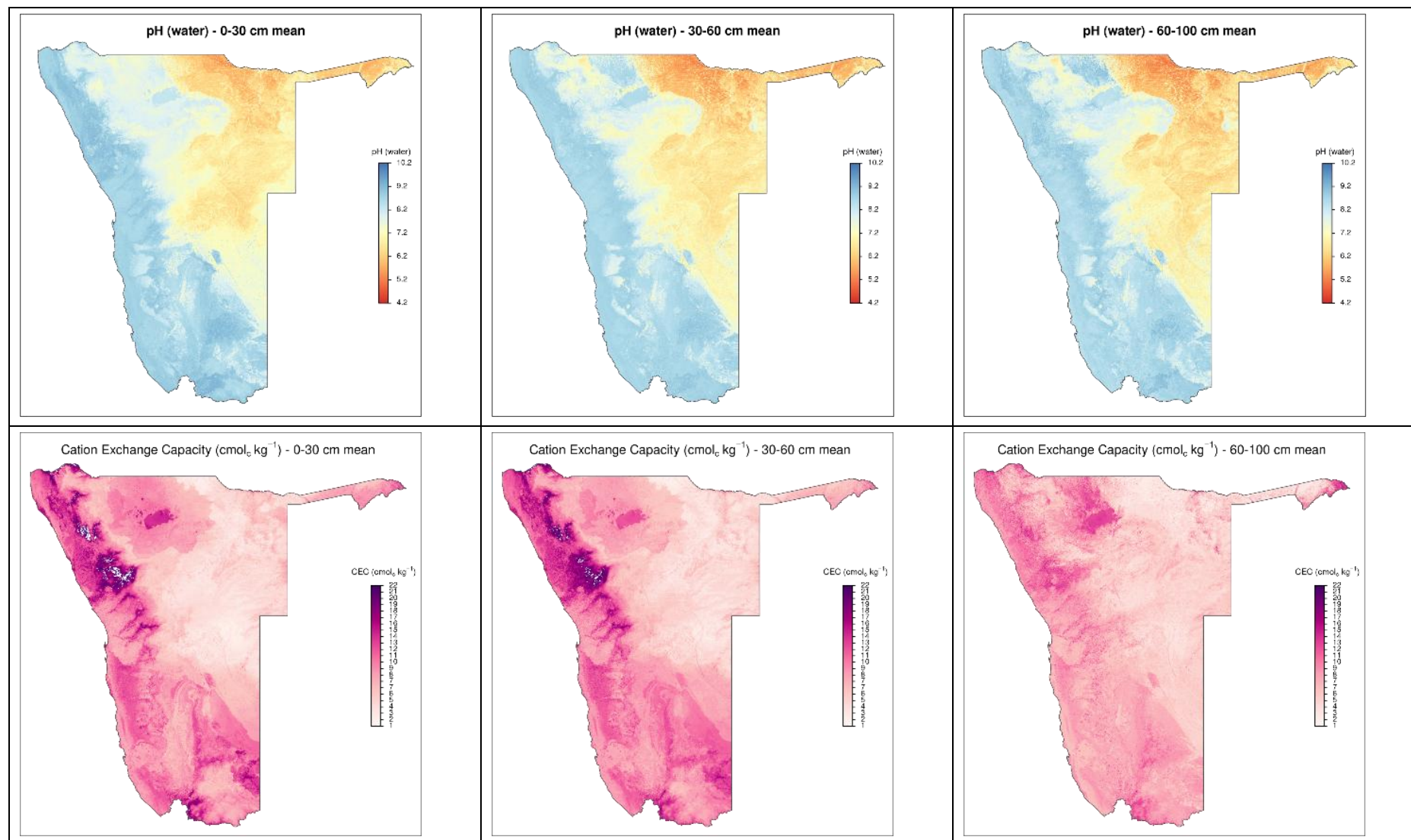


Figure 19. National-scale spatial predictions of pH (H₂O) (top) and cation exchange capacity (CEC) (bottom) at 90 m resolution, shown as the mean of 20 bootstrap realisations for three depth intervals (0–30, 30–60, and 60–100 cm) (left to right) in Namibia. (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>).

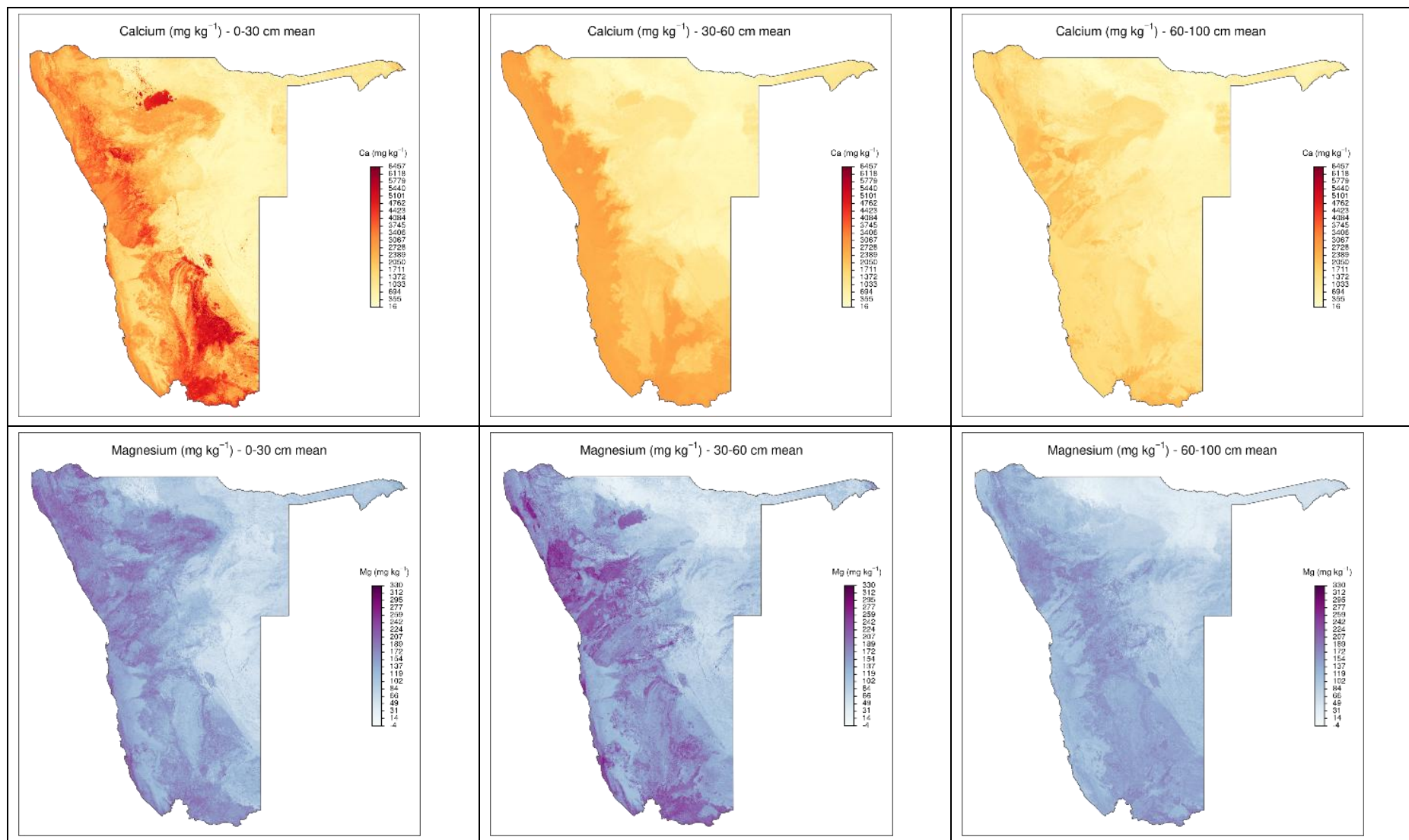


Figure 20. National-scale spatial predictions of extractable calcium (Ca) (top) and magnesium (Mg) (bottom) at 90 m resolution, shown as the mean of 20 bootstrap realisations for three depth intervals (0–30, 30–60, and 60–100 cm) (left to right) in Namibia. (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>).

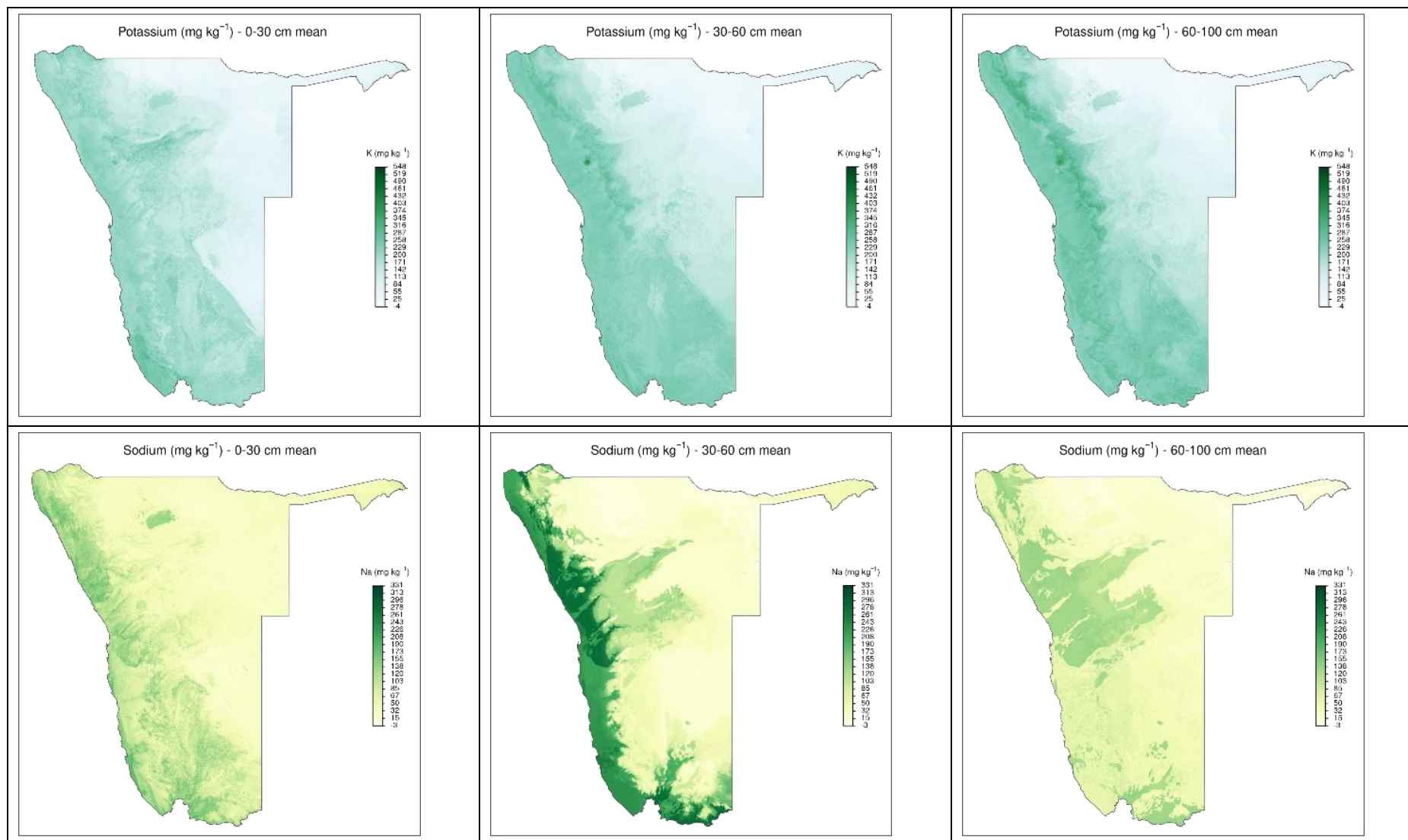


Figure 21. National-scale spatial predictions of extractable potassium (K) (top) and sodium (Na) (bottom) at 90 m resolution, shown as the mean of 20 bootstrap realisations for three depth intervals (0–30, 30–60, and 60–100 cm) (left to right) in Namibia. (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>).

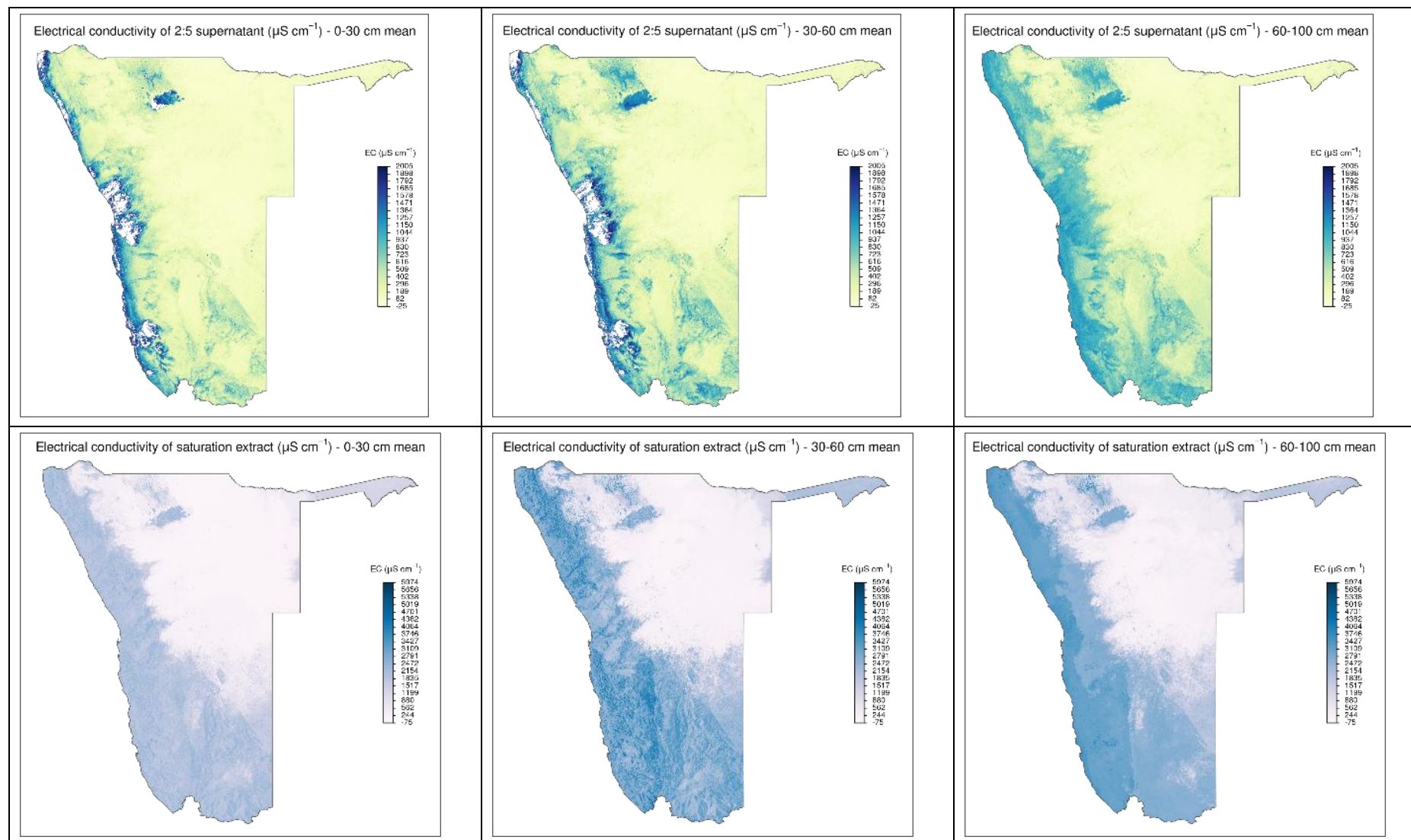


Figure 22. National-scale spatial predictions of electrical conductivity (EC) measured in a 1:2.5 soil:water extract (top) and in a saturated paste extract (bottom) at 90 m resolution, shown as the mean of 20 bootstrap realisations for three depth intervals (0–30, 30–60, and 60–100 cm) (left to right) in Namibia. (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>).

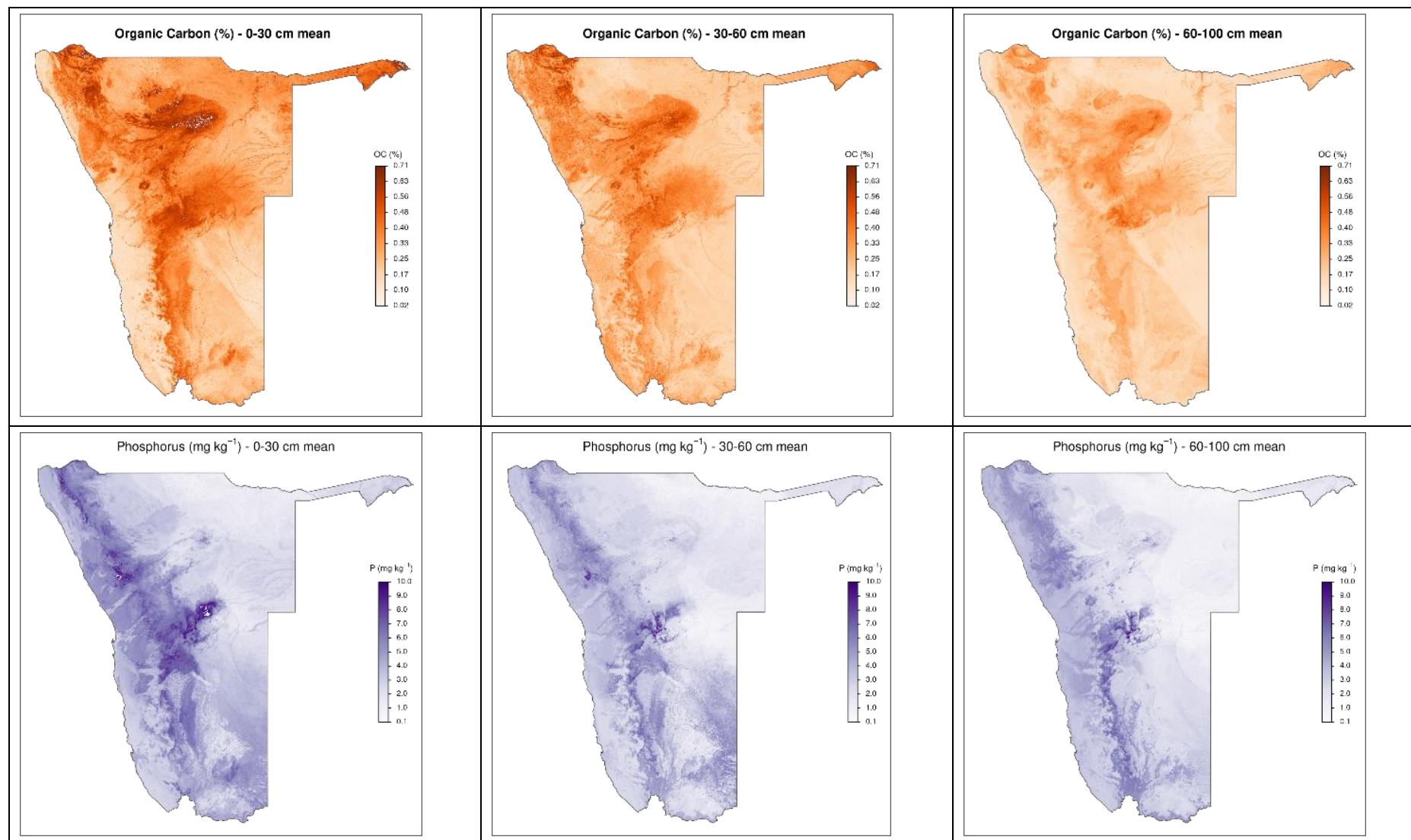


Figure 23 National-scale spatial predictions organic carbon (OC) (top) and plant-available phosphorus (P) (bottom) at 90 m resolution, shown as the mean of 20 bootstrap realisations for three depth intervals (0–30, 30–60, and 60–100 cm) (left to right) in Namibia. (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>).

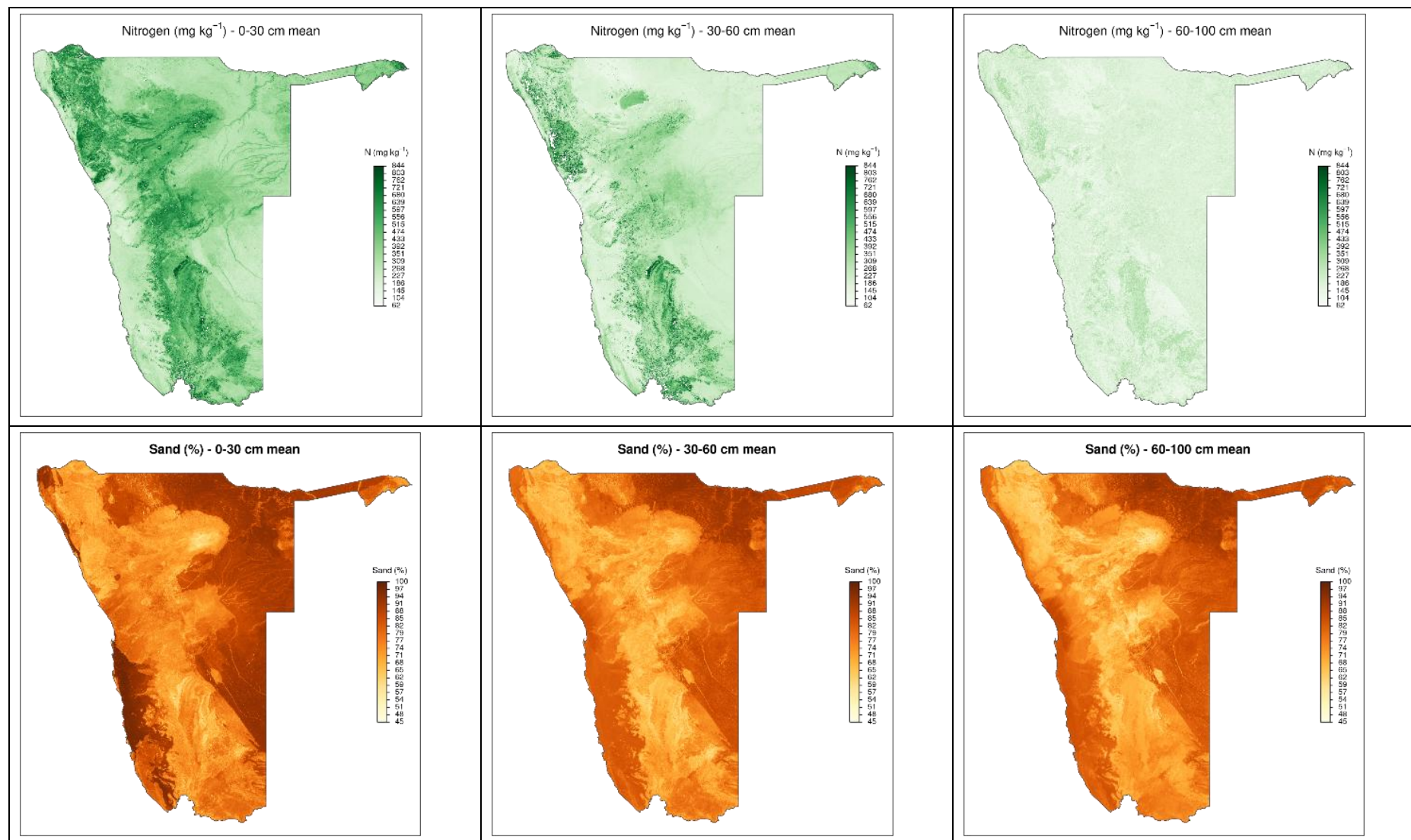


Figure 24. National-scale spatial predictions of total nitrogen (N) (top) and sand content (bottom) at 90 m resolution, shown as the mean of 20 bootstrap realisations for three depth intervals (0–30, 30–60, and 60–100 cm) (left to right) in Namibia. (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>).

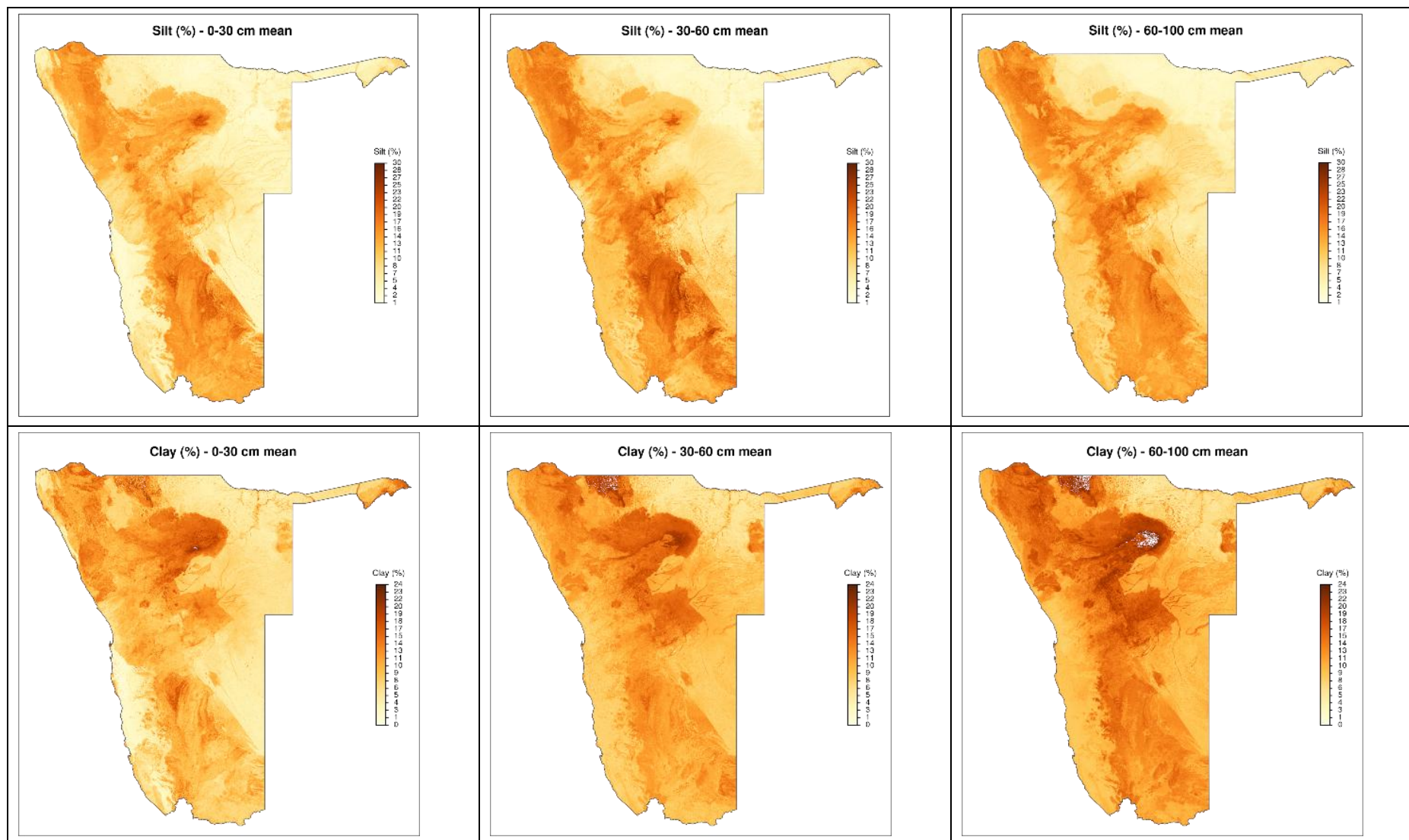


Figure 25. National-scale spatial predictions of silt (top) and clay content (bottom) at 90 m resolution, shown as the mean of 20 bootstrap realisations for three depth intervals (0–30, 30–60, and 60–100 cm) (left to right) in Namibia. (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>).

APPENDIX B

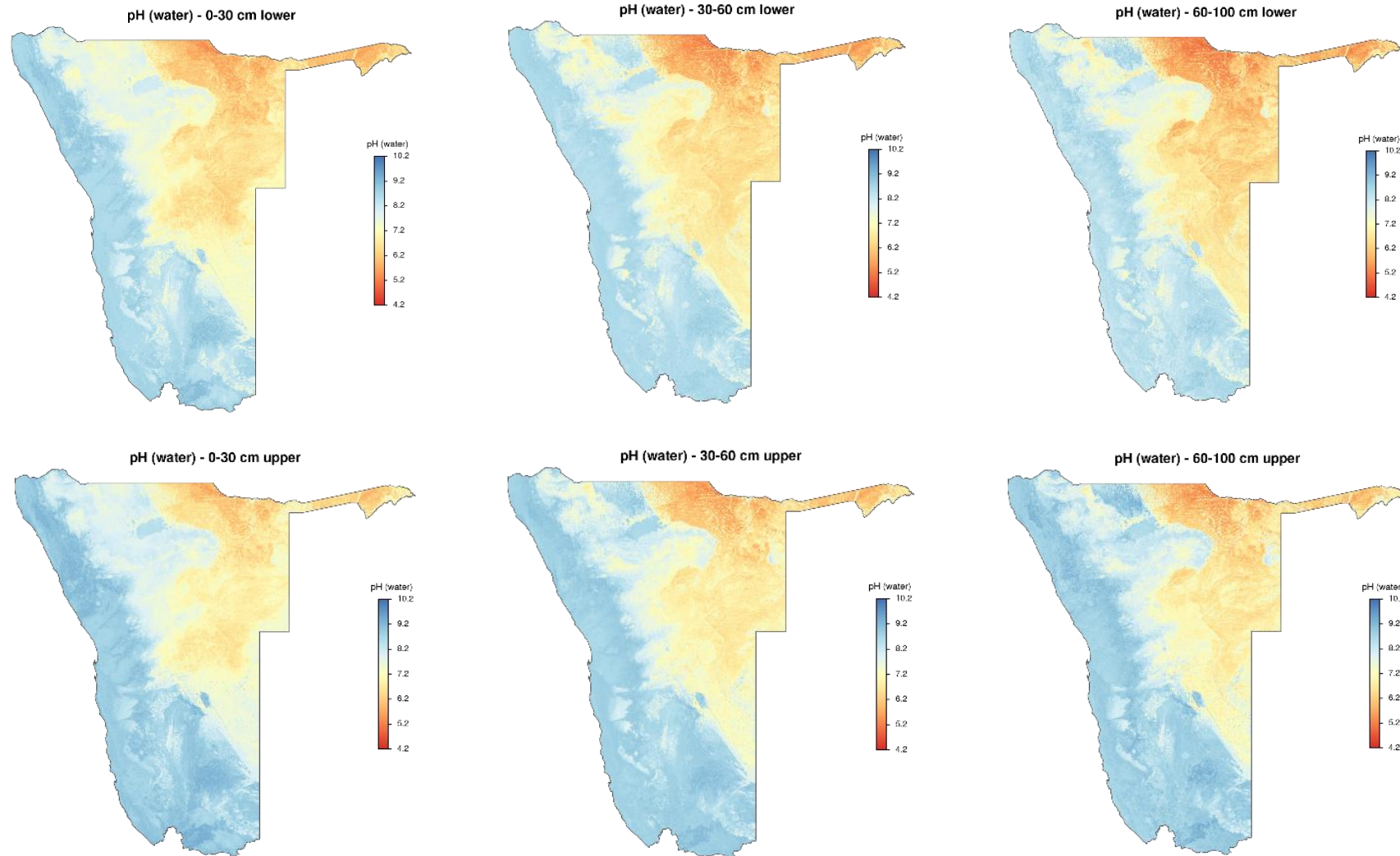


Figure 26. Spatial distribution of prediction uncertainty for pH (H₂O) in Namibia. For each depth interval (0–30, 30–60, and 60–100 cm) (left to right), maps show the 5th (top row) and 95th percentile (bottom row) predictions. (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>).

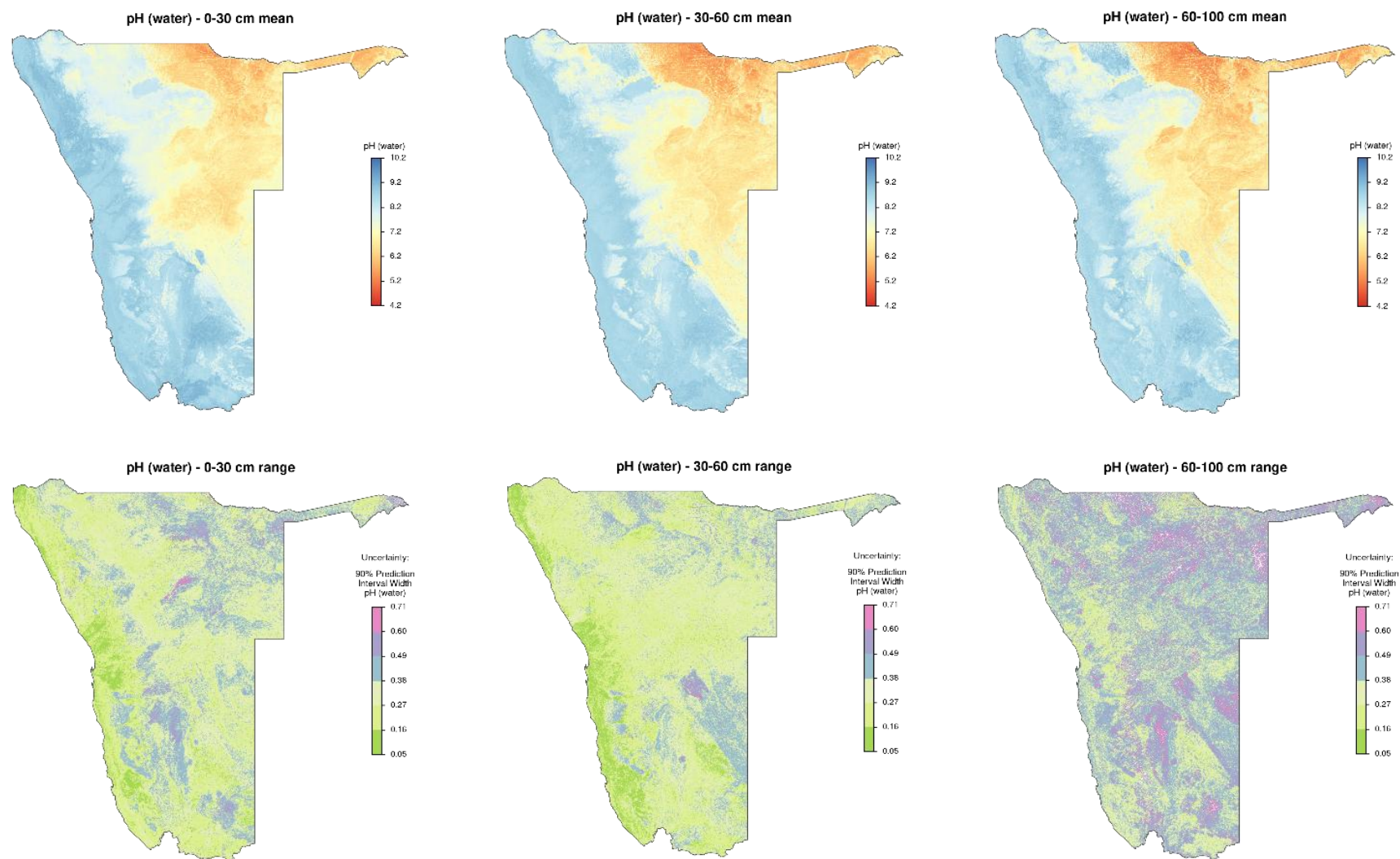


Figure 27. Spatial distribution of prediction uncertainty for pH (H_2O) in Namibia. For each depth interval (0–30, 30–60, and 60–100 cm) (left to right), maps show the mean prediction (top row) and 90% prediction interval (PI90) (bottom row). (Full resolution maps can be viewed and downloaded at <https://soilsofnamibia.com/properties.html>)