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Update and expansion of the soil and landscape grid of Australia

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ABSTRACT

The Soil and Landscape Grid of Australia (SLGA) has been significantly updated and expanded. The initial version, released in 2015, provided the first continental-scale characterization of soil resources adhering to GlobalSoilMap specifications. It featured digital maps for 11 key soil attributes (including bulk density, organic carbon, soil texture, pH, available water capacity, total nitrogen, total phosphorus, effective cation exchange capacity, and soil thickness) at a 90 m × 90 m spatial resolution and served as a widely accessed national resource with substantial global influence.

The updated version, developed between 2018 and 2023, includes enhancements to the original 11 soil attributes and introduces 13 additional products. These additions improve the representation of key soil characteristics, such as soil carbon composition, soil microbial distribution, and soil moisture fluxes, contributing to a more comprehensive understanding of Australia's soil and landscape resources.

The updated data and methodologies offer a robust foundation for developing a national soil monitoring program and other applications. The advancements in the SLGA and its associated data systems are detailed, and all products are freely available for public use.

1. Introduction

The Soil and Landscape Grid of Australia (SLGA) was launched in 2015, providing a nationally consistent, high-resolution digital mapping of continuous soil and landscape attributes across the Australian continent (Grundy et al., 2015). This initiative applied digital soil mapping techniques to create the first continental implementation of the GlobalSoilMap concept (Arrouays et al., 2014).

The development of SLGA Version 1 (Grundy et al., 2020) aimed to ensure the relevance of its products—national mapping of 11 key soil attributes—to a wide range of users. It also emphasized the importance of systematic updates and improvements as new data sources and modelling approaches became available. Building on this foundation, a substantial program of work commenced in 2018, supported by the Terrestrial Ecosystem Research Network (TERN; https://www.tern.org.au/) and a network of soil information organisations across Australia. This effort leveraged advancements in digital soil mapping and related technologies to enhance and expand upon the original SLGA products.

This paper outlines the activities undertaken to enhance the SLGA and highlights the new products, findings, and methodological advancements introduced in SLGA Version 2, with references provided for detailed insights into each aspect.

2. At a glance: soil and landscape grid of Australia Version 2

Table 1 outlines the products included in SLGA Version 2, detailing key information for each product, including their spatial and depth coverage, along with a concise summary of the modelling processes used in their development. Additionally, URLs are provided for downloading the corresponding data.

The SLGA adheres to GlobalSoilMap specifications (Arrouays et al., 2014), providing soil attribute estimates at the centre of 3 arcsecond grid

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Table 1
Products in Version 2 of the Soil and Landscape Grid of Australia. This table summarizes the products included in SLGA Version 2, providing their names, corresponding units, and status (indicating whether the product is an update from Version 1). Each product is briefly described, with details on its spatial and vertical (depth) resolution and a summary of the methodologies used for its generation. For some Version 2 products, a model extrapolation risk assessment was performed, identifying and quantifying areas where digital soil mapping models may have limitations due to being outside the calibration data domain. Citable references and download links are provided for each product.

Soil Physical Properties								
Attribute	Units	Status	Description	Depth and Spatial Support	Modelling framework	Defined model extrapolation risk	Reference	Downloadable data link/ further information
Clay	% mass	Updated	< 2 µm mass fraction of the < 2 mm soil material determined using the pipette method	– Point support with 90 m grid cell resolution. – Interval depth support for layers: 0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, 100–200 cm.	– Integrative random forest ML modelling pairing lab and field-based data. – Predictand data transformed to isometric log-ratio. – Uncertainties derived through bootstrap resampling method.	N	Malone and Searle (2021a)	https://doi.org/10.25919/hc4s-3130
Silt	% mass	Updated	2–20 µm mass fraction of the < 2 mm soil material determined using the pipette method			N	Malone and Searle (2021a)	https://doi.org/10.25919/2ew1-0w57
Sand	% mass	Updated	20 µm – 2 mm mass fraction of the < 2 mm soil material determined using the pipette method			N	Malone and Searle (2021a)	https://doi.org/10.25919/rjmy-pa10
Volumetric soil moisture at –33 kPa moisture potential	% vol	NEW	Volumetric soil moisture at –33 kPa moisture potential		– Random forest ML modelling – Soil moisture at-33 kPa and –1.5 MPa moisture potentials derived via pedotransfer functions using soil texture, bulk density and soil carbon as inputs at point locations – Uncertainties derived through bootstrap resampling method	N	Searle and Somarathna (2022b)	https://doi.org/10.25919/jnvd-3a26
Volumetric soil moisture at –1.5 MPa moisture potential	% vol	NEW	Volumetric soil moisture at –1.5 MPa moisture potential			N	Searle and Somarathna (2022a)	https://doi.org/10.25919/awp8-nv68
Available Water Capacity	%	Updated	Readily available water for plant extraction: Volumetric soil moisture at –33 kPa – Volumetric soil moisture at –1.5 MPa moisture potential			N	Searle et al. (2022b)	https://doi.org/10.25919/4jwj-na34
Bulk Density (whole soil)	g/cm^3	Updated	Bulk Density of the whole soil (including coarse fragments) in mass per unit volume		– Integrative random forest ML modelling pairing measured and derived bulk density data from spatial predictive function based on soil texture, CEC, soil carbon and environmental covariate data. – Uncertainties quantified through local error and fuzzy clustering method.	Y	Malone (2023)	https://doi.org/10.25919/gxyn-pd07
Coarse Fragments	% vol	NEW	Proportion of coarse fragments size class	– Point support with 90 m grid cell resolution. – Interval depth support for layers: 0–5 cm, 5–15 cm, 15–30 cm.	– Volumetric abundance of coarse fragments sourced from field assessments of coarse fractions. – Gravimetric measures of coarse fractions converted to volumetric ones	N	Román Dobarco et al. (2023b)	https://doi.org/10.25919/c583-fd02

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Table 1 (*continued*)

Soil Physical Properties								
Attribute	Units	Status	Description	Depth and Spatial Support	Modelling framework	Defined model extrapolation risk	Reference	Downloadable data link/ further information
					where available. – Probability random forest modelling for both predictions and uncertainties.			
Soil Moisture Information Processing System (SMIPS)	Total volumetric soil moisture content (mm) Proportion of 'rootzone' full (%)	NEW	Estimates of national daily volumetric soil water contents	Point support with 1 km grid cell resolution. Daily time step – Interval depth support for layers: 0–10 cm, 10–90 cm	SMIPS system ingests daily climate data and runs a simple soil water bucket model. SLGA mapping of texture, AWC and thickness help drive model. The model calculates daily soil moisture fluxes which are also adjusted according to the SMOS satellite observations. Prediction uncertainties not explicitly defined.	N	Stenson et al. (2021)	https://data.tern.org.au/landscapes/smips/
Carbon Materials								
Soil Organic Carbon	% mass	Updated	Mass fraction of carbon by weight in the < 2 mm soil material as determined by dry combustion at 900 Celsius.	– Point support with either 30 m or 90 m grid cell resolution. – Interval depth support for layers at both resolutions: 0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, 100–200 cm.	– Quantile regression forest for both prediction and uncertainty quantification.	N	Wadoux et al. (2023)	30 m grid resolution https://doi.org/10.25919/5qjv-7 s27 90 m grid resolution https://doi.org/10.25919/ejhm-c070
Soil Organic Carbon Fractions	0–1	NEW	Proportions of mineral-associated organic carbon (MAOC), particulate organic carbon (POC) and pyrogenic organic carbon (PyOC). Available only for 0–5 cm, 5–15 cm, 15–30 cm.	– Point support with 90 m grid cell resolution. – Interval depth support for layers: 0–5 cm, 5–15 cm, 15–30 cm.	– Quantile regression forest modelling for both prediction and uncertainty quantification. – SOC fraction data predicted with mid-infrared and near-infrared spectral models and transformed to isometric log-ratios.	N	Román Dobarco et al. (2023b)	https://doi.org/10.25919/fa46-ey49
Soil Organic Fraction densities and stock	Mg C ha^{-1}	NEW	Soil organic carbon fractions (MOAC, POC. PyOC) per volume or area of soil.	– Point support with 90 m grid cell resolution. – SOC fraction density estimates for: 0–5 cm, 5–15 cm, 15–30 cm. SOC fraction stock estimated for: 0–30 cm.	– Stocks estimated using estimates of total soil carbon, bulk density, volumetric gravel, and layer/soil thickness – Uncertainties quantified via conditional simulation taking into consideration uncertainties of input data.	N	Román Dobarco et al. (2023b)	https://doi.org/10.25919/fa46-ey49

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Table 1 (*continued*)

Attribute	Units	Status	Description	Depth and Spatial Support	Modelling framework	Defined model extrapolation risk	Reference	Downloadable data link/ further information
Soil Physical Properties								
Soil Microbial Biodiversity	Unitless	NEW	Soil bacteria and fungi beta diversity	– Point support with 90 m grid cell resolution. – Surface soil estimate only	– Non-metric multidimensional scaling (NMDS) used to investigate dissimilarities in microbial community compositions. – NMDS axes modelled and mapped using quantile regression forest.	N	Román Dobarco et al. (2022)	https://doi.org/10.25919/4x7n-y874
Soil Chemical attributes								
Soil pH (1:5 water)	pH units	NEW	pH of a 1:5 soil water solution	– Point support with 90 m grid cell resolution. – Interval depth support for layers: 0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, 100–200 cm.	– Integrative random forest ML modelling pairing lab and field-based data. – Uncertainties quantified through local error and fuzzy clustering method.	Y	Malone (2022b)	https://doi.org/10.25919/37z2-0q10
Soil pH (1:5 $CaCl_2$)	pH units	Updated	pH of 1:5 soil/ 0.01 M calcium chloride extract			Y	Malone and Searle (2021a)	https://doi.org/10.25919/7320-hw30
Total Nitrogen	% mass	Updated	Mass fraction of total nitrogen in the soil by weight		– Random forest ML modelling – Uncertainties quantified through local error and fuzzy clustering method.	Y	Malone and Searle (2023)	https://doi.org/10.25919/pm2n-ww12
Total Phosphorus	% mass	Updated	Mass fraction of total phosphorus in the soil by weight			Y	Malone and Searle (2024)	https://doi.org/10.25919/7j78-md43
Available Phosphorus	mg/kg	NEW	The inherent (not treated) plant available P as measured by Colwell P method		– Random forest ML modelling – Uncertainties quantified k-fold cross-validation	N	Zund (2022)	https://doi.org/10.25919/6qzh-b979
Cation Exchange capacity	$cmol_{(+)}$/kg	NEW	The total amount of exchangeable bases which are mostly sodium, potassium, calcium and magnesium (collectively termed as bases) in non-acidic soils and bases plus aluminium and hydrogen in acidic soils.		– Integrative random forest ML modelling pairing measured and derived CEC data from spatial predictive function based on soil texture and soil carbon and environmental covariate data. – Uncertainties quantified through local error and fuzzy clustering method.	N	Malone (2022a)	https://doi.org/10.25919/pkva-gf85
Other attributes								
Australian soil classes	Categorical data	NEW	Mapped classes (14) to the Order level of the Australian Soil Classification	Point support with 90 m grid cell resolution.	– Random forest ML modelling – Uncertainties expressed in terms of confusion index	N	Searle (2021)	https://doi.org/10.25919/vkjn-3013
Soil Colour	RGB colour space	NEW	Surface and subsoil estimated of dry soil colour according to Munsell soil colour classes	– Point support with 90 m grid cell resolution. – Surface and dominant subsoil horizon.	– Random forest ML modelling – Predictands derived from field observations of soil Munsell colour, then convert to CIELAB colour space for modelling – Prediction uncertainties not	N	Malone (2022c)	https://doi.org/10.25919/h5g4-qm95

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Table 1 (*continued*)

Soil Physical Properties								
Attribute	Units	Status	Description	Depth and Spatial Support	Modelling framework	Defined model extrapolation risk	Reference	Downloadable data link/ further information
					quantified			
Soil mapping library optimised for Habitat Condition Assessment System	As defined for each thematic layer	NEW	Remodelled estimates of selected SLGA attributes with efforts to eliminate anthropogenic influences of output maps	Point support with 90 m and 250 m grid cell resolution products. – Interval depth support for layers: 0–30 cm, 30 cm-maxiumum soil thickness.	– Random forest ML modelling – Uncertainties quantified via bootstrap method.	N	Searle (2023)	https://esoil.io/TERNLandscapes/Public/Products/TERN/NonAnthropogenic/
Pedogenons	Categorical data	NEW	Conceptual taxa that define groups of homogeneous environmental variables	Point support with 90 m grid cell resolution.	– Unsupervised classification (k-means clustering) to a set of state variables, proxies of the soil-forming factors for a given reference time.	N	Román Dobarco et al. (2021)	https://doi.org/10.25919/r8rv-8617
Library of DSM-ready environmental covariates	As defined for each thematic layer	NEW	Library of environmental data at both 30 m and 90 m resolution, aligned for data modelling purposes. Several Australian agency contributions	Point support with products either at 30 m or 90 m grid cell resolution.	The covariate rasters (over 150) in this dataset were obtained from a broad range of original data sources. All these datasets are publicly available. They original data sets were processed to all have the same spatial support for the 90 m and 30 m stacks respectively.	N	Searle et al. (2022a)	https://esoil.io/TERNLandscapes/Public/Pages/SLGA/GetData-COGSDataStore.html
Soil thickness	m	Updated	Estimate of thickness of soils to lithic contact (Mostly A and B horizon thickness)	m	– Integrated modelling and model combination powered by random forest ML modelling – Uncertainties quantified in terms of exceedance probabilities of soil thickness occurring beyond specified depths.	N	Malone and Searle (2020)	https://doi.org/10.25919/djdn-5x77
Regolith depth	m	No update performed	Depth to hard rock. Depth is inclusive of all regolith	m	– Cubist ML modelling – Uncertainties quantified via bootstrap method.	N	Wilford et al. (2016)	https://doi.org/10.4225/08/55C9472F05295

cells (~90 m × 90 m) across Australia, along with a broad range of landscape and regolith attributes. All SLGA products use the World Geodetic System 1984 (WGS84) datum. Version 1 of the SLGA produced digital soil maps for 11 soil attributes, including bulk density, organic carbon, soil texture (clay, silt, sand fractions), pH ($CaCl_2$), available water capacity, total nitrogen, total phosphorus, effective cation exchange capacity, and soil thickness. These maps were informed by the National Soil Site Data Collation (Searle, 2014), consisting of 281,202 soil profile observations from CSIRO and state and territory soil survey agencies. To enhance coverage and sample numbers, these data were integrated with vis-NIR soil spectral libraries. Final products were generated through a combination of site-data modelling (Viscarra Rossel et al., 2015) and soil map disaggregation and attribution (Odgers et al., 2014, 2015). Harmonized soil profile data conformed to depth intervals: 0–0.05 m, 0.05–0.15 m, 0.15–0.3 m, 0.3–0.6 m, 0.6–1.0 m, and 1.0–2.0 m.

SLGA Version 2 maintains consistency with Version 1 in terms of datum, spatial resolution, and depth support, except for specific products, such as daily soil moisture mapping and soil colour, which use alternative depth supports. While most products remain at a 3 arcsecond resolution, some (e.g., soil organic carbon concentration) are also available at 1 arcsecond (~30 m), and others (e.g., daily soil moisture mapping) at ~ 30 arcsecond (1 km) resolution.

SLGA Version 2 comprises 24 soil attribute products, including updates to the original 11 and three new product suites:

(1) Soil Moisture Information Processing System (SMIPS) (Stenson et al., 2021).
(2) Soil mapping products for the National Habitat Condition Assessment System (HCAS; Harwood et al. 2021), incorporating customized mapping and depth specifications (Searle, 2023).
(3) A dataset of over 150 landscape covariates based on SCORPAN factors (McBratney et al., 2003), including national climate data, digital elevation models, geology mapping, geophysical surveys, surficial geochemistry, and optical remote sensing products (Searle et al., 2022a). These covariates have been post-processed to ensure consistency in resolution, geometry, and extent, supporting digital soil mapping tasks.

New products in SLGA Version 2 enhance modelling and understanding of soil water dynamics. These include maps of soil moisture where soil water potential is equivalent to −33 kPa and −1.5 MPa (Searle & Somarathna, 2022a; 2022b). These data supported the redevelopment of the SMIPS unsaturated soil water flow model and have broad applicability for studying soil moisture dynamics at a continental scale.

Additional products focus on carbon dynamics, including soil organic carbon (SOC) fraction stocks, coarse fragments (Román Dobarco et al., 2023b), and soil microbial diversity (Román Dobarco et al., 2022). These products, along with enhanced mapping of soil carbon concentrations and bulk density, provide a robust foundation for process-based modelling and assessment of soil carbon changes due to land management and climate variability.

Version 2 also introduces mapping of soil types (Soil Order level) following the 2nd Edition of the Australian Soil Classification (Searle, 2021), and mapping of dominant surface and subsurface soil colours (Malone, 2022c). Furthermore, Pedogenon mapping offers a conceptual framework for national soil assessment and monitoring (Román Dobarco et al., 2021). Pedogenons represent homogeneous environmental variable groups, which, combined with land use intensity data, facilitate realistic evaluations of soil conditions and functions (Román Dobarco et al., 2023a).

3. Accessing SLGA Version 2 products

All collections within SLGA Version 2 are freely available under a Creative Commons Attribution Licence (CC BY), permitting sharing, adaptation, and use for any purpose. The datasets can be accessed through two primary portals:

- **CSIRO Data Access Portal**: Search for "Soil and Landscape Grid".
- **TERN Data Portal**: Soil datasets on TERN.

Products adhere to standardized naming conventions, and continuous attributes comply with the precision requirements of GlobalSoilMap specifications (Arrouays et al., 2014). All raster data are provided as Cloud Optimised GeoTIFFs (COGs), enhancing efficiency in cloud storage, retrieval, and processing via features like internal tiling, pyramidal storage, and HTTP Range Requests.

3.1. Data access and visualisation options

SLGA datasets can be accessed through several mechanisms tailored for diverse user needs:

(1) GIS Download via Web Coverage Services (WCS)
Open GIS Consortium (OGC) WCS protocols enable direct integration with most GIS platforms, allowing raster data to be downloaded and saved locally. Access: GIS Downloads.
(2) Web Clipping Tool
Subset and download rasters via a web browser without additional software requirements, apart from a GIS tool for viewing and analysis. Access: SLGA Viewer Tool.
(3) SLGACloud R Package
Programmatically retrieve datasets using the SLGACloud R package, designed for efficient data access. Further details are available on GitHub. See Appendix 1 for example scripts for using SLGACloud to retrieve SLGA data
(4) API for Per-Pixel Data Access
The SLGA web service API (Application Programming Interface) allows users to query specific locations by latitude and longitude, returning soil attribute data without downloading full datasets. This service supports formats tailored for open data and specialized applications. Access: SLGA API.

The API is instrumental in applications such as:

- Research into climate change impacts on soil carbon (Luo et al., 2019).
- Supporting drought policy through forecast-informed assessments (ABARES, 2022).
- Providing real-time agricultural decision support tools, such as the SoilWaterApp (Freebairn et al., 2018).

3.2. Transparency and community engagement

SLGA Version 2 emphasizes transparency, reproducibility, and updatability through documented workflows and version-controlled repositories, ensuring robust digital soil mapping (DSM) practices. The associated production workflows are hosted on GitHub.

Additionally, a dedicated website serves as an information hub for technical and general audiences, supporting the Australian digital soil mapping community and aligning with the broader international digital soil mapping community.

4. Notable advancements of SLGA Version 2

4.1. Soil data

4.1.1. SoilDataFederator

Australia benefits from having extensive publicly available soil profile data observations and measurements, which support a growing range of applications. The development of SLGA Version 1 (Grundy et al., 2015) demonstrated the value of these datasets, which are collected and managed by a diverse group of custodians across the country. These custodians maintain data for their specific purposes, often using disparate management systems. Historically, users seeking to unify these datasets had to independently approach custodians, acquire the data on a case-by-case basis, and transform it into a format suitable for their application.

Data unification can conceptually range from centralised databases to ad hoc collation efforts, such as the national Soil Site Data Collation that supported SLGA Version 1. For SLGA Version 2 and future developments, a federation-based approach offers a more dynamic and efficient solution for integrating and retrieving soil data from disparate sources. This approach led to the creation of the SoilDataFederator (SDF), a system where data remains with the original custodians but is federated on demand into a consistent and usable format (Searle, 2020) (Fig. 1).

The SDF is implemented as a web-based API developed in the R programming language. It utilises the Plumber R package (Schloerke & Allen, 2025) to expose a set of queryable RESTful API endpoints. Being implemented as an API, users can use their programming language of choice to access soil data via the API. Details about using the API are available and code examples in the R language can be downloaded.

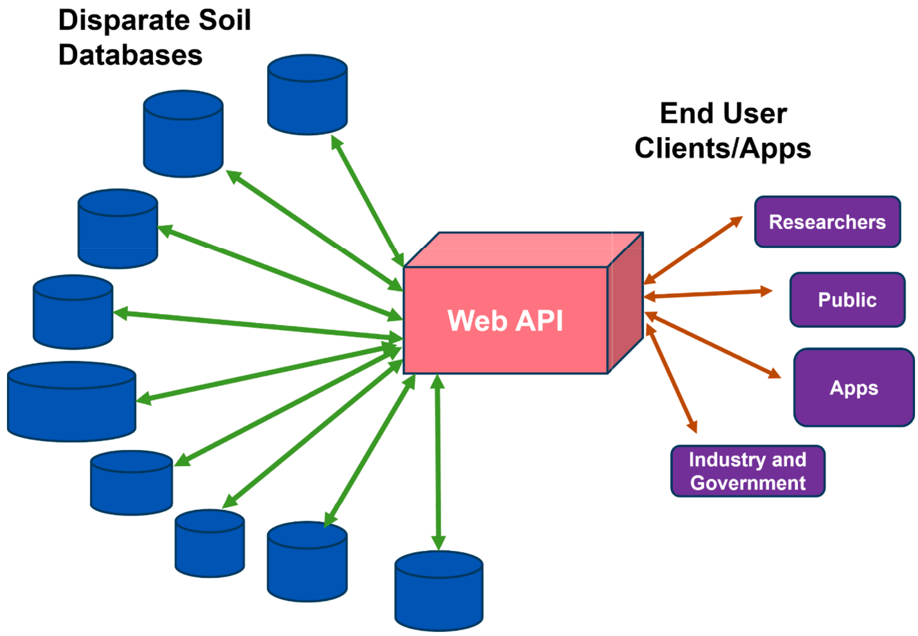

Fig. 1. Conceptual diagram of the SoilDataFederator web API.

There is a SwaggerUI available to explore the syntax of the API. The API accesses datasets that are already publicly available. The API is used to query data over the internet via a standardised set of URLs with standardised parameters. Data can be returned in a range of formats but always in a standard form optimised for delivering data on a per attribute basis. The SDF consists of a catalogue of available datasets and a series of associated "backend" modules which query the individual data systems and transform the data on the fly to the standard form.

The general workflow for a SDF request is that the user sends a request via a URL to the API with a standard set of parameters defining the soil attribute data to be retrieved. The API then transforms this request into the specific format required to query each of the provider datasets. The data provider data sources are made available in a range of forms, including web APIs, database systems or static data files. There are no standard format requirements for these data sources, with the one exception being that the data source needs to be accessible to the SDF. These requests are then sent to each of the data providers and data is returned from the data sources in the native data structure of each individual provider. These variable format data responses are then transformed into the standard data output structure of the SDF, merged into a single response and returned to the requestor in JSON, XML or CSV format.

There is work currently underway in Australia to develop a successor soil data access platform called the Australian Soil Data Information System (ANSIS). ANSIS will have similar but improved capabilities to those of the SDF.

This federation approach streamlines access to Australia's diverse soil data, enhancing usability while respecting the autonomy of data custodians.

4.1.2. *Soil spectral libraries*

The CSIRO National Soil Site Database (CSIRO, 2020) and the associated National Soil Archive (https://www.csiro.au/en/research/natural-environment/land/soil-archive) house extensive soil data and specimens collected across Australia. The archive includes over 32,000 specimens scanned with visible near-infrared (vis-NIR) spectrometers and more than 4,000 scanned using mid-infrared (MIR) spectrometers, capturing high-resolution diffuse reflectance data in the 350–2500 nm and 1334–16,666 nm spectral ranges, respectively.

When paired with soil attribute data from CSIRO National Soil Site Database, these spectral datasets enable the development of soil spectral inference models, which often demonstrate high predictive accuracy depending on the target analyte (Soriano-Disla et al., 2014). As in SLGA Version 1 (Viscarra Rossel et al., 2015), data inferred from soil spectra have been pivotal in filling gaps in sparsely sampled regions, contributing to updates in SLGA Version 2.

The development of new SOC fraction maps also leveraged measurement data and MIR spectra from the Australian Soil Carbon Research Program (SCARP; Baldock et al., 2013). These resources were critical in producing new national products for SLGA Version 2.

Another significant asset is the vis-NIR soil spectral library associated with soil specimens collected under the AusPlots program (Sparrow et al., 2020). This initiative, part of the TERN Ecosystem Surveillance platform, supports plot-based monitoring across Australia's rangeland environments. As of 2018, the library encompassed over 19,000 specimens with vis-NIR spectra, including reference measurements for soil attributes from 367 specimens (Malone et al., 2020). The inclusion of this spectral library has been vital for SLGA Version 2, particularly in addressing data gaps in remote and rangeland areas of the country.

These combined resources enhance SLGA Version 2′s capacity to deliver improved national soil attribute mapping, leveraging cutting-edge spectral methods to address data limitations effectively.

4.2. *Landscape attributes*

SLGA Version 2 includes a collection of terrain and landscape variable datasets designed for use in digital soil mapping as well as broader landscape modelling applications. These datasets encompass climate, relief, geology, landcover, and their derivatives. While the original data can be retrieved at native resolutions, this compilation provides standardized layers that ensure consistency in datum, spatial extent, and resolution, simplifying workflows for tasks such as mapping soil layers in SLGA Version 2. The data are available as rasters in 1-arcsecond (∼30 m) and 3-arcsecond (∼90 m) grid cell resolutions.

4.2.1. *Terrain and elevation data*

Terrain and elevation data are derived from the Shuttle Radar Topography Mission (SRTM). For SLGA Version 2, these data were processed by Gallant et al. (2011) for 1-arcsecond DEMs and Gallant et al. (2009) for 3-arcsecond DEMs. Derivative terrain covariates follow the methods described by Gallant and Austin (2015) for the 1-arcsecond products.

4.2.2. Climatology data

The climatology layers used in SLGA Version 2 are long-term (1976–2005) summaries adjusted for elevation and radiation effects, derived at 3-arcsecond resolution (Harwood et al., 2018). These replace the 9-arcsecond climatology summaries used in SLGA Version 1, offering improved spatial resolution and accuracy.

4.2.3. Gamma radiometric data

The SLGA Version 2 incorporates updated gamma radiometric data from Geoscience Australia (Wilford and Kroll, 2018). These updates feature new flight survey data and enhanced algorithms for addressing voids in earlier maps, providing more complete and accurate radiometric information.

4.2.4. Optical remote sensing data

New remote sensing datasets have been integrated into SLGA Version 2. Derived from over 30 years of Landsat program data, these layers were processed using a novel high-dimensional statistical method to produce noise-reduced, cloud-free estimates of the spectral response during the least vegetated (barest) states across Australia (Roberts et al., 2019; Wilford and Roberts, 2020). The resulting data include bare-earth reflectance values across key optical bands (e.g., red, green, NIR) and several derived variables, such as normalized band ratios and PCA-derived variables, optimized for identifying soil components like clays and iron oxides.

4.2.5. Lithology data

A new dataset on simplified surface lithology classes (Gray et al., 2016, unpublished) enhances geological information for digital soil mapping. Lithology is categorized into 11 classes, including eight siliceous material types (e.g., ultramafic to extremely siliceous) and three non-alumino-silicate materials (calcareous, sesquioxide, and organic). This streamlined classification improves the performance of geological covariates in soil modelling tasks, as compared to less defined or overly complex geological units. See Table 1 and follow relevant links there for further information on this data resource.

4.2.6. Access and use

These libraries of covariate data can be accessed from the TERN Landscapes platform, providing an essential resource for both soil and landscape modelling projects. By standardizing and enhancing these datasets, SLGA Version 2 supports a wide array of applications, from soil attribute mapping to broader environmental and landscape analyses.

4.3. Modelling advancements

4.3.1. Quantitative improvements made with SLGA Version 2 products

SLGA Version 2 marks a significant advancement in data systems, workflow transparency, and readiness for future updates to national soil mapping products.

Table 2 provides a quantitative comparison between SLGA Versions 1 and 2, focusing on the data used in modelling and their associated accuracies. Metrics include Lin's concordance correlation coefficient (CCC) and root mean square error (RMSE) for continuous variables, and overall accuracy and, occasionally, the kappa coefficient for categorical variables. These metrics summarize model performance and product comparisons. Readers are encouraged to refer to the cited sources for detailed descriptions of methods and additional evaluation approaches specific to each SLGA Version 2 product.

Notably, SLGA Version 1 did not report Lin's CCC values. To enable quantitative comparison, Lin's CCC values for Version 1 were calculated using the external validation sets employed in Version 2. However, some of the data used in the Version 1 CCC calculations may have contributed to model development, potentially inflating these values for Version 1.

A suite of new approaches was applied in Version 2 to enhance the previously created products, leading to improvements based on external model evaluations. Real-time access to data through the SDF contributed to significant increases in the data available for modelling. For instance, the number of observations used for SOC mapping grew from over 43,000 in Version 1 to over 90,000 in Version 2, despite limiting the data to between 1970 and 2020. This resulted in improved spatial pattern capture at local levels given the product was modelled and created at 1-arcsecond resolution (~30 m) (Wadoux et al. 2023).

For total phosphorus and nitrogen mapping, the number of available data cases remained similar between the versions, but model accuracy improved significantly. Concordance, measured by Lin's CCC, increased from 0.09 to 0.79 for total phosphorus and from 0.20 to 0.89 for total nitrogen across all depth intervals. Additionally, Version 2 showed that 90 % of test data cases were encapsulated within the model's prediction envelopes at a 90 % confidence level, demonstrating a marked improvement over Version 1, where discrepancies were larger.

Version 2 also addressed issues in soil texture modelling by employing compositional data analysis, resolving summing inconsistencies between clay, silt, and sand fractions. This improvement contributed to a more accurate product compared to Version 1 and SoilGrids Version 2 (Malone and Searle 2021b). Furthermore, the modelling of soil thickness was refined, with Version 2 successfully incorporating previously overlooked areas such as rock outcrops and deep soils (Malone and Searle 2020).

In summary, SLGA Version 2 reflects clear advancements in terms of data coverage, model accuracy, and systematic incorporation of uncertainty quantification evaluations. These improvements underscore the ongoing commitment by TERN and the Australian soil information community to enhance soil spatial data, ensuring that users have access to the most reliable information available at any given time.

4.3.2. Integration of soil morphological and field data into models

Integration, both in terms of models and data, has been a key feature of SLGA Version 2. For example, the modelling of soil thickness (Malone and Searle 2020) was achieved by integrating three models: one for predicting rock outcrops, one for predicting deep soils, and one for predicting thickness between these extremes. This integrated approach was more effective in addressing the right-censored nature of soil thickness data than standalone methods.

Another significant integration occurred through the incorporation of field-observed data into digital soil mapping. Methods were developed to integrate field observations of soil texture with lab-based measurements (Malone and Searle 2021b). An algorithm was created to estimate complete soil profile characterizations from field hand texture measurements (Malone and Searle 2021c). The uncertainty associated with this process was incorporated into spatial modelling workflows alongside lab measurements, which were treated as error-free. This integration resulted in substantial improvements, with field observation data contributing over 180,000 sites to the approximately 17,000 sites from laboratory data alone.

For soil pH mapping (both 1:5 H_2O and 1:5 $CaCl_2$), large quantities of field-measured data from Raupach's indicator test method (Raupach and Tucker 1959) were integrated into the spatial models. Over 55,000 field measurements were assessed, allowing the development of a transfer model to relate field measurement data to pseudo-lab measurements, with associated uncertainty. While laboratory measurements of soil pH are more common in soil databases, the inclusion of field measurement data significantly expanded spatial coverage and increased depth information. For example, 45 % of sites with field data had measurements deeper than 1 m, compared to only 29 % of sites with lab data. Although field measurements are generally considered less precise, when properly integrated, they help fill significant gaps in spatial and vertical coverage. A direct comparison of SLGA Version 1 and Version 2 for soil pH (1:5 $CaCl_2$) found modest improvements based

Table 2
Quantitative model evaluations based on external data of SLGA Version 2 and 1 digital soil mapping products. Where possible, numbers of data cases used in modelling are provided (excluding test data) for each depth interval. Model evaluations focus on either Lin's concordance correlation coefficient (CCC) and root mean square error (RMSE), or for categorical variables, overall accuracy and sometimes the kappa coefficient (as indicated by * in row entries).

			SLGA Version 2			SLGA Version 1			
Attribute	Units	Depth (cm)	Number of observations used in spatial modelling	Lin's CCC or *Overall Accuracy*	RMSE or *Kappa Statistic*	Number of observations used in spatial modelling	Lin's CCC or *Overall Accuracy*	RMSE or *Kappa Statistic*	Further information
Soil Physical Properties									
Clay	% mass	0–5	112 602	0.71	10.6	14 227	0.51	12.8	– Malone and Searle (2021b, 2021c) – Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/soil-texture – See Table 1 for details on accessing dataset.
		5–15	111 804	0.72	10.8	14 095	0.51	13.1	
		15–30	107 055	0.69	12.8	12 970	0.46	15.2	
		30–60	101 032	0.66	14.0	12,290	0.41	16.4	
		60–100	82 033	0.63	13.5	10 560	0.40	15.4	
		100–200	50 016	0.63	13.5	6239	0.40	15.4	
Silt	% mass	0–5	112 602	0.44	5.8	14 227	0.36	7.9	
		5–15	111 804	0.50	5.2	14 095	0.39	7.7	
		15–30	107 055	0.49	5.1	12 970	0.37	7.1	
		30–60	101 032	0.43	5.0	12,290	0.33	6.6	
		60–100	82 033	0.37	5.2	10 560	0.27	6.9	
		100–200	50 016	0.34	5.0	6239	0.27	6.7	
Sand	% mass	0–5	112 602	0.72	13.1	14 227	0.54	16.4	
		5–15	111 804	0.73	13.1	14 095	0.53	16.8	
		15–30	107 055	0.70	15.0	12 970	0.49	18.7	
		30–60	101 032	0.68	15.9	12,290	0.47	19.1	
		60–100	82 033	0.64	16.0	10 560	0.45	18.8	
		100–200	50 016	0.64	15.6	6239	0.42	18.6	
Volumetric soil moisture at –33 kPa moisture potential	% vol	0–5	Models of soil moisture specified soil moisture potentials and AWC were based off 20,545 soil profiles with these data. Those data were estimated for these profiles using a pedotransfer function that included soil texture, soil organic carbon and bulk density. The pedotransfer function was constructed from data collected at 1190 sites from across Australia (Searle et al. 2022c)	0.87	4.19	–	–	–	– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/soil-hydraulic-properties – See Table 1 for details on accessing dataset.
		5–15		0.87	4.22		–	–	
		15–30		0.85	4.63		–	–	
		30–60		0.82	4.85		–	–	
		60–100		0.84	4.58		–	–	
		100–200		0.82	4.59		–	–	
Volumetric soil moisture at −1.5 MPa moisture potential	% vol	0–5		0.92	3.02	–	–	–	
		5–15		0.91	3.21		–	–	
		15–30		0.88	3.69		–	–	
		30–60		0.85	3.99		–	–	
		60–100		0.87	3.74		–	–	
		100–200		0.85	3.76		–	–	
Available Water Capacity	%	0–5		0.64	1.96	From Viscarra Rossel et al. (2015) models were constructed from a pool of 11,440 cases.	–	–	
		5–15		0.63	1.86		–	–	
		15–30		0.59	1.85		–	–	
		30–60		0.61	1.73		–	–	
		60–100		0.65	1.76		–	–	
		100–200		0.50	1.69		–	–	
Bulk Density (whole soil)	g/cm^3	0–5	21 277	0.79	0.10	From Viscarra Rossel et al. (2015) models were constructed from a pool of 17,498 data cases.	0.49	0.16	– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/whole-soil-bulk-density – See Table 1 for details on accessing dataset.
		5–15	21 277	0.80	0.09		0.47	0.14	
		15–30	14 973	0.70	0.11		0.52	0.13	
		30–60	9 456	0.79	0.08		0.43	0.13	
		60–100	7 880	0.79	0.07		0.38	0.13	
		100–200	3 940	0.79	0.06		0.49	0.10	
Coarse Fragments	% vol	0–5	95 380	67	0.39	–	–	–	– Román Dobarco et al. (2023b) – Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/soc-fractions – See Table 1 for details on accessing dataset.
		5–15	100 625	66	0.38		–	–	
		15–30	101 529	63	0.37		–	–	
Carbon Materials									
Soil Organic Carbon (30 m)	% mass	0–5	24 372		1.25	From Viscarra Rossel et al. (2015) models were constructed from a pool of 43,404 data cases.	–	–	– Wadoux et al. (2023) – Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/total-soil-organic-carbon-content – See Table 1 for
		5–15	24 055		1.07		–	–	
		15–30	17 301		0.90		–	–	
		30–60	10 378		0.74		–	–	
		60–100	8 028		0.50		–	–	
		100–200	4 592		0.38		–	–	

(*continued on next page*)

Table 2 (*continued*)

Attribute	Units	Depth (cm)	SLGA Version 2: Number of observations used in spatial modelling	SLGA Version 2: Lin's CCC or *Overall Accuracy*	SLGA Version 2: RMSE or *Kappa Statistic*	SLGA Version 1: Number of observations used in spatial modelling	SLGA Version 1: Lin's CCC or *Overall Accuracy*	SLGA Version 1: RMSE or *Kappa Statistic*	Further information
									details on accessing dataset.
Soil Organic Carbon Fractions: MAOC	0–1	0–5	14 399	0.85	0.08	–	–	–	– Román Dobarco et al. (2023b) – Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/soc-fractions – See Table 1 for details on accessing dataset.
		5–15	14 389	0.85	0.09		–	–	
		15–30	13 078	0.82	0.10		–	–	
POC		0–5	14 399	0.80	0.07		–	–	
		5–15	14 389	0.79	0.06		–	–	
		15–30	13 078	0.74	0.07		–	–	
PyOC		0–5	14 399	0.89	0.08		–	–	
		5–15	14 389	0.89	0.08		–	–	
		15–30	13 078	0.87	0.09		–	–	
Soil Chemical attributes									
Soil pH (1:5 water)	pH units	0–5	140 834	0.69	0.67	From Viscarra Rossel et al. (2015) models were constructed from a pool of 132,226 data cases.	Digital soil mapping product for this attribute was not published.		– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/soil-ph-15-water – See Table 1 for details on accessing dataset.
		5–15	139 828	0.74	0.62				
		15–30	133 280	0.73	0.69				
		30–60	125 805	0.73	0.75				
		60–100	102 809	0.73	0.83				
		100–200	61 759	0.73	0.86				
Soil pH (1:5 $CaCl_2$)	pH units	0–5	134 358	0.68	0.70	From Viscarra Rossel et al. (2015) models were constructed from a pool of 81,123 data cases.	0.53	0.83	– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/soil-ph-15-cacl2 – See Table 1 for details on accessing dataset.
		5–15	133 442	0.73	0.65		0.59	0.78	
		15–30	128 245	0.70	0.74		0.62	0.82	
		30–60	120 193	0.71	0.80		0.64	0.88	
		60–100	97 271	0.72	0.86		0.63	0.97	
		100–200	57 871	0.71	0.89		0.59	1.05	
Total Nitrogen	% mass	0–5	7197	0.83	0.09	From Viscarra Rossel et al. (2015) models were constructed from a pool of 43,721 data cases.	0.41	0.15	– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/total-soil-nitrogen – See Table 1 for details on accessing dataset.
		5–15	6963	0.89	0.07		0.31	0.14	
		15–30	6421	0.89	0.06		0.22	0.13	
		30–60	4380	0.89	0.06		0.09	0.17	
		60–100	3302	0.94	0.05		0.07	0.15	
		100–200	1861	0.61	0.06		0.11	0.08	
Total Phosphorus	% mass	0–5	8911	0.79	0.06	From Viscarra Rossel et al. (2015) models were constructed from a pool of 55,915 data cases	0.09		– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/total-soil-phosphorus – See Table 1 for details on accessing dataset.
		5–15	8896	0.76	0.05		0.16	0.08	
		15–30	9179	0.81	0.04		0.15	0.07	
		30–60	8829	0.80	0.04		0.15	0.07	
		60–100	7770	0.77	0.04		0.10	0.07	
		100–200	5982	0.77	0.05		0.14	0.07	
Available Phosphorus	mg/kg	0–5	13 948	0.52	24	–	–	–	– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/available-phosphorus – See Table 1 for details on accessing dataset.
		5–15	13 948	0.51	19		–	–	
		15–30	12 311	0.24	14		–	–	
		30–60	10 568	0.25	10		–	–	
		60–100	9969	0.35	6		–	–	
		100–200	8930	0.16	11		–	–	
Cation Exchange capacity	$cmol_{(+)}/kg$	0–5	17 366	0.78	7.56	–	–	–	– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/cation-exchange-capacity – See Table 1 for details on accessing dataset.
		5–15	17 128	0.74	8.72		–	–	
		15–30	11 981	0.78	7.63		–	–	
		30–60	8453	0.77	7.96		–	–	
		60–100	6583	0.75	7.96		–	–	
		100–200	3954	0.83	7.55		–	–	
Other attributes									
Australian soil classes	Categorical data		195 383	61	–		–	–	– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/australian-soil-classification-map – See Table 1 for

(*continued on next page*)

Table 2 (*continued*)

Attribute	Units	Depth (cm)	SLGA Version 2: Number of observations used in spatial modelling	SLGA Version 2: Lin's CCC or *Overall Accuracy*	SLGA Version 2: RMSE or *Kappa Statistic*	SLGA Version 1: Number of observations used in spatial modelling	SLGA Version 1: Lin's CCC or *Overall Accuracy*	SLGA Version 1: RMSE or *Kappa Statistic*	Further information
									details on accessing dataset.
Soil Colour	CIELAB colour space	Topsoil L	129 153	61	0.31		–	–	– Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/soil-colour – See Table 1 for details on accessing dataset.
		Topsoil A	129 153	0.81	2.69		–	–	
		Topsoil B	129 153	0.55	5.05		–	–	
		Subsoil L	113 381	46	0.29		–	–	
		Subsoil A	113 381	0.72	4.84		–	–	
		Subsoil B	113 381	0.48	8.84		–	–	
Soil thickness	m	Rock Outcrops	184 197	99	0.88		–	–	– Malone and Searle (2020) – Webpage: https://aussoilsdsm.esoil.io/slga-version-2-products/soil-thickness – See Table 1 for details on accessing dataset.
		Deep Soil (>2m)	277 943	85	0.64		–	–	
		0–2 m	184 197	0.77	0.26		–	–	

on concordance evaluations (Table 2). Despite the increase in data and improvements in machine learning capabilities, challenges remain in modelling soil pH, particularly due to land management practices influencing pH in ways that are difficult to account for with available covariate data. The accuracy of subsoil pH modelling also remains challenging, as models typically decrease in accuracy with depth, compounded by difficulties in assembling appropriate covariate data (e.g., geological or lithological data) to improve estimates.

Additional soil morphological data integrated into SLGA Version 2 included soil colour (Malone 2022c) and coarse fragment data (Román Dobarco et al. 2023b). These attributes are critical for soil classification and estimating SOC stocks. They are commonly observed in the field and are well-represented in soil databases. When appropriately mapped, these data provide valuable contributions to models and processes that rely on such attributes.

4.3.3. Spatial prediction functions to expand data coverage of difficult to measure soil attributes

Several important soil attributes are difficult and time-consuming to measure, resulting in limited collections of attributes like soil hydraulic properties and bulk density in soil databases, despite their relevance in soil moisture studies and SOC fraction estimations. SLGA Version 2 addressed this data sparsity through the use of pedotransfer functions and spatial prediction models. Pedotransfer functions infer difficult-to-measure soil attributes using more commonly measured, easier-to-collect data. Searle and Somarathna (2022a, 2022b) effectively applied these functions to model and map soil water drained upper and lower limits by leveraging the more widely available data on soil texture, organic carbon, and bulk density.

For mapping whole soil bulk density (Malone 2023) and cation exchange capacity (CEC) (Malone 2022a), a spatial prediction approach was used. This method first exploited the relationships between these attributes and more easily measured variables, such as soil texture and organic carbon, and then modified the models using environmental covariate data. While pedotransfer functions are typically limited to the data and region from which they are developed (Van Looy et al. 2017), incorporating spatial environmental covariates and machine learning techniques allows for greater applicability across different regions and facilitates the use of larger soil databases.

The integration of actual and inferred data, coupled with an expanded suite of environmental covariate predictors, led to considerable improvements in the estimation of whole soil bulk density compared to Version 1, as indicated by model evaluations with test data (Table 2). For both CEC and bulk density mapping, the machine learning process accounted for the inherent imprecision of the inferred data, ultimately quantifying uncertainties in the final estimates. Despite some increased uncertainty due to the integration of less precise data, prediction interval ranges were narrower for bulk density in Version 2 compared to Version 1. Evaluation of the uncertainties, based on prediction interval coverage probability plots, indicated that the quantified uncertainties were appropriately defined.

4.3.4. Uncertainty quantification

Uncertainty quantification is a crucial aspect of digital soil mapping. In SLGA Version 2, several approaches were employed to quantify uncertainty for continuous soil attributes, including non-parametric bootstrapping (Wilford et al. 2016), prediction intervals via quantile regression forests (Vaysse and Lagacherie 2017), and a local errors and fuzzy clustering method (Solomatine and Shrestha 2009). The choice of quantification method did not demonstrate a clear advantage over the others, except that both the non-parametric and local errors and fuzzy clustering approaches can be applied universally to any machine learning algorithm.

One drawback of using non-parametric bootstrapping is its high computational demand, as it requires multiple model iterations and extension to covariate data for mapping. Additionally, internal testing revealed that the variance attributed to sampling data with replacement during model iterations was minimal, with the bulk of variance (at least 95 %) being attributed to systematic (bias) and random errors, as estimated from external data. This resulted in relatively uniform prediction interval widths at each mapping grid cell.

The local errors and fuzzy clustering approach, by contrast, is computationally less demanding. Importantly, this method allows prediction intervals to be defined based on the landscape setting. In this way, model errors can vary between locations depending on the attributes of the landscape at each site. This is particularly useful at a national scale, where considerable variability exists in soil-forming factors. The local errors and clustering approach, therefore, offers desirable properties compared to non-parametric bootstrapping for uncertainty quantification in such diverse landscapes.

For categorical variables, such as soil classes, uncertainties were expressed as probabilities using the random-forest algorithm's built-in method. For soil thickness, a continuous attribute, uncertainties were expressed in terms of exceedance probabilities, indicating the likelihood that soil thickness exceeds a given depth threshold. This approach was deemed appropriate, given that a significant proportion of the data were right-censored due to the nature of soil sampling (Malone and Searle 2020).

4.3.5. Quantifying model extrapolation risk

The assessment of digital soil mapping models in terms of their ability to operate outside the spatial domain of sample points used for training is central to quantifying extrapolation risk. This topic has been extensively researched and explored through various approaches. Lagacherie et al. (1995) developed a quantitative and probabilistic assessment method for automating the extension of soil pattern rules from a reference area to unmapped regions. Grinand et al. (2008) used a classification and regression tree algorithm to test the extent to which predictions could remain valid beyond the training domain. More recent approaches have involved distance-based methods (Malone et al. 2019; Meyer and Pebesma 2021) and hull-based methods (van den Hoogen et al. 2019). Distance-based methods calculate the differences between the multidimensional space of model training data and the entire predictor space. Hull-based methods, on the other hand, project the broader multidimensional predictor space into convex hull geometries defined by the model training data.

For SLGA Version 2, a combination of these methods was used to assess extrapolation risk. The hull-based method (multidimensional convex hull assessment, van den Hoogen 2019) served as a binary "in/out" estimator to determine if a mapping pixel lies outside the domain of the multidimensional covariate used for model training. This was paired with the distance-based count-of-observations method (Malone et al. 2019), which counts the number of training data observations with a near-pattern match at each mapping grid cell. The hull-based method is computationally efficient, providing a quick assessment where data points outside the convex hulls do not match any training data, given a distance threshold. The count-of-observations method, though more computationally intensive, offers a significant advantage: it is not binary, allowing for the quantification of gradients of risk.

Fig. 2 illustrates the outputs from the combined hull assessment and count-of-observations methods. The distribution of data points across Australia is shown, with measurements from 6,116 sites with directly measured bulk densities, as well as 15,735 sites where bulk density was inferred using a spatial prediction function. The extrapolation risk maps reveal a clear disparity in the available training data for capturing environmental variation at depth. The model data space appears relatively consistent with the data space for the 0–5 cm depth interval, indicating a high concentration of measurements near the surface. However, for the 100–200 cm depth interval, there are notably fewer measurements, suggesting a higher level of extrapolation risk for deeper soil layers.

While these methods effectively illustrate disparities in observation data across different soil depths and provide a useful assessment of training data relative to the broader multivariate data space, they must be linked to uncertainty quantification approaches and the type of model used. Factors such as the coefficient of variation and the differences between surface and subsoil observations need to be considered, as some attributes vary depending on whether the measurements are taken near the surface or at greater depths in the soil profile. Additionally, the contribution of covariates in the model may vary across depth intervals, meaning the current assumption of equal covariate contributions in the paired approach may not be realistic. Nonetheless, the work undertaken for SLGA Version 2 model extrapolation risk assessments has laid the foundation for integrating these workflows into the national digital mapping system. This helps address broader scientific concerns regarding the use of sparse and potentially non-representative reference data in map generation, particularly in the context of increasing reliance on machine learning for predictive tasks (Meyer and Pebesma 2022).

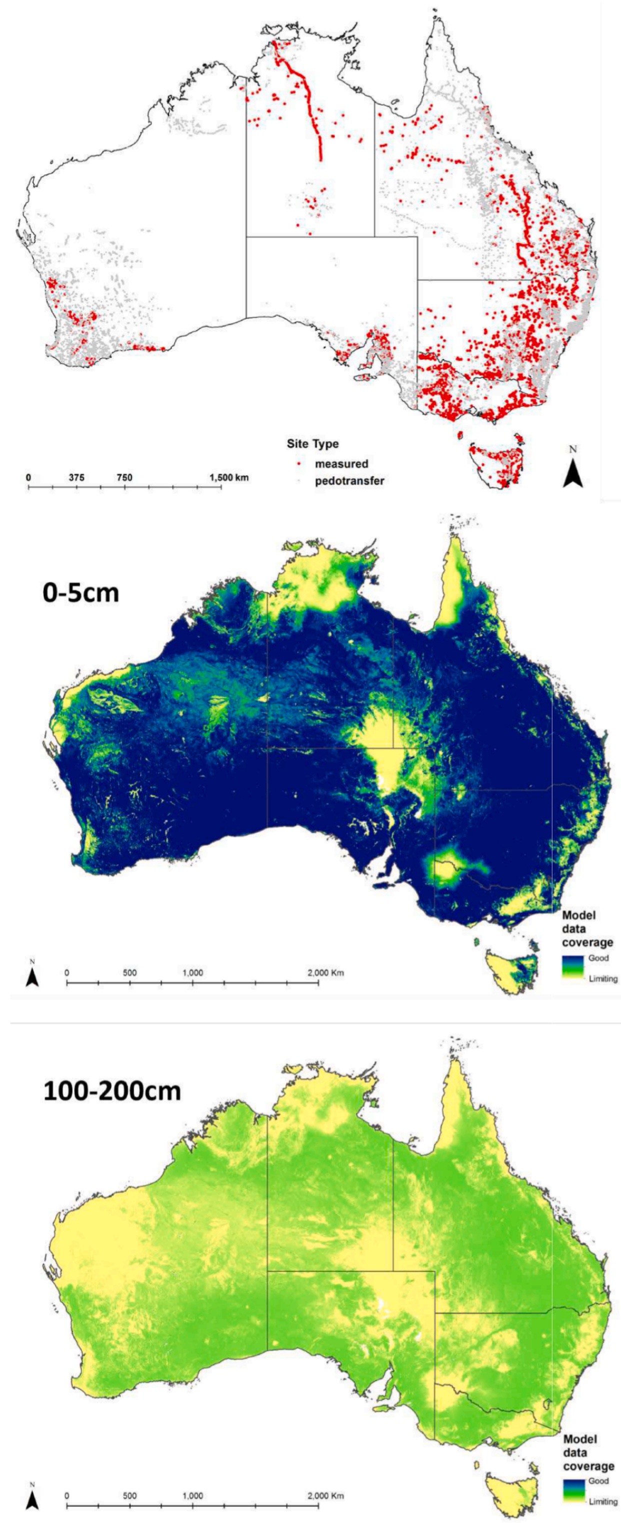

Fig. 2. Top map shows the distribution of site observations of measured (red dots) and inferred (grey dots) data about whole soil bulk density. Middle and bottom maps show the potential model extrapolation risk for the 0–5 cm and 100–200 cm depth layers respectively. The color ramp ranges from dark blue (low extrapolation risk) to yellow (high extrapolation risk). Extrapolation risk was quantified through combination of convex hull and distance measurement approaches. Low risk means available model data adequately covers landscape features, while high risk means few available data on hand to cover landscape variability, and therefore reliance on model estimates should be moderated. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.3.6. An improved soil carbon materials package to advance data-driven spatio-temporal modelling

SLGA Version 2 products, including updated SOC and whole soil bulk density mapping, along with new soil coarse fragment mapping, provide an enhanced data suite for national carbon accounting inventories. At regional and local scales, the development of 30 m resolution SOC mapping will complement baseline measurements for soil carbon auditing programs. Future national efforts to monitor soil carbon changes will be significantly informed by the new SOC fraction mapping. Additionally, the new microbial diversity mapping will serve as a foundation for investigations into the functional traits of microbial populations and their role in driving carbon and nutrient cycles across large spatial scales.

4.3.7. Soil moisture integration and prediction system

The SMIPS provides a systematic modelling and predictive platform offering daily estimates of plant-available soil moisture to a depth of 90 cm at a 1 km spatial resolution. This represents a significant advancement for the SLGA, enhancing its ability to deliver spatiotemporal soil information to end-users and marking the initial steps in a staged approach to soil system dynamics. Fig. 3 presents a snapshot of the interactive SMIPS data visualization and download tool.

The SMIPS system is primarily driven by a two-layered soil water balance model based on the methodology outlined in Wimalathunge and Bishop (2019). The model consists of two linked soil moisture stores: a shallow 10 cm upper store, which responds quickly, and a deeper 80 cm lower store, which responds more slowly. The soil water parameters—soil moisture at −33 kPa and −1.5 MPa soil water potential — developed for SLGA Version 2, provide the boundary conditions for plant-available water fluxes. The lower limit of soil moisture is defined by air-dry soil moisture, derived using SLGA cation exchange capacity data and the Shaw (1994) methodology, while the upper limit is set by soil saturation, derived using SLGA bulk density data and McKenzie et al. (2002). The total available soil moisture at all locations is further constrained by soil thickness estimates. Internal soil drainage, runoff, and deep drainage parameters are functions of soil texture and bulk density, calibrated through simulation experiments using soil moisture sensor data distributed across Australia (Stenson et al. 2018).

The SMIPS model incorporates precipitation and potential evapotranspiration data from the Bureau of Meteorology's AWRA (Australian Water Resources Assessment) model (Frost et al. 2016). To enhance model accuracy, the internal states of the upper layer are adjusted (with a 50 % weighting) using observational data from the European Space Agency's Soil Moisture and Ocean Salinity (SMOS) satellite mission. SMOS data are available at a 3-day temporal resolution across the entire country. The model processes for SMIPS are shown in Fig. 4.

Further refinements to SMIPS are currently underway, incorporating new climate forcing data and entailing more extensive evaluations of the model's predictive performance.

4.3.8. Establishing the basis for a national soil monitoring program

Soil monitoring networks are essential for establishing baselines, tracking the status and trends of soil resources, and facilitating early-warning systems that identify and delineate soil threats. At their core, soil monitoring is critical for supporting evidence-based policies aimed at incentivizing sustainable soil management (Van Leeuwen et al. 2017). Priority Action 1 of the Australian National Soil Action Plan (DAFF 2023) emphasizes the need for a national framework to support measurement, monitoring, mapping, reporting, and sharing of soil state and trend information, which in turn informs best practices, decision-

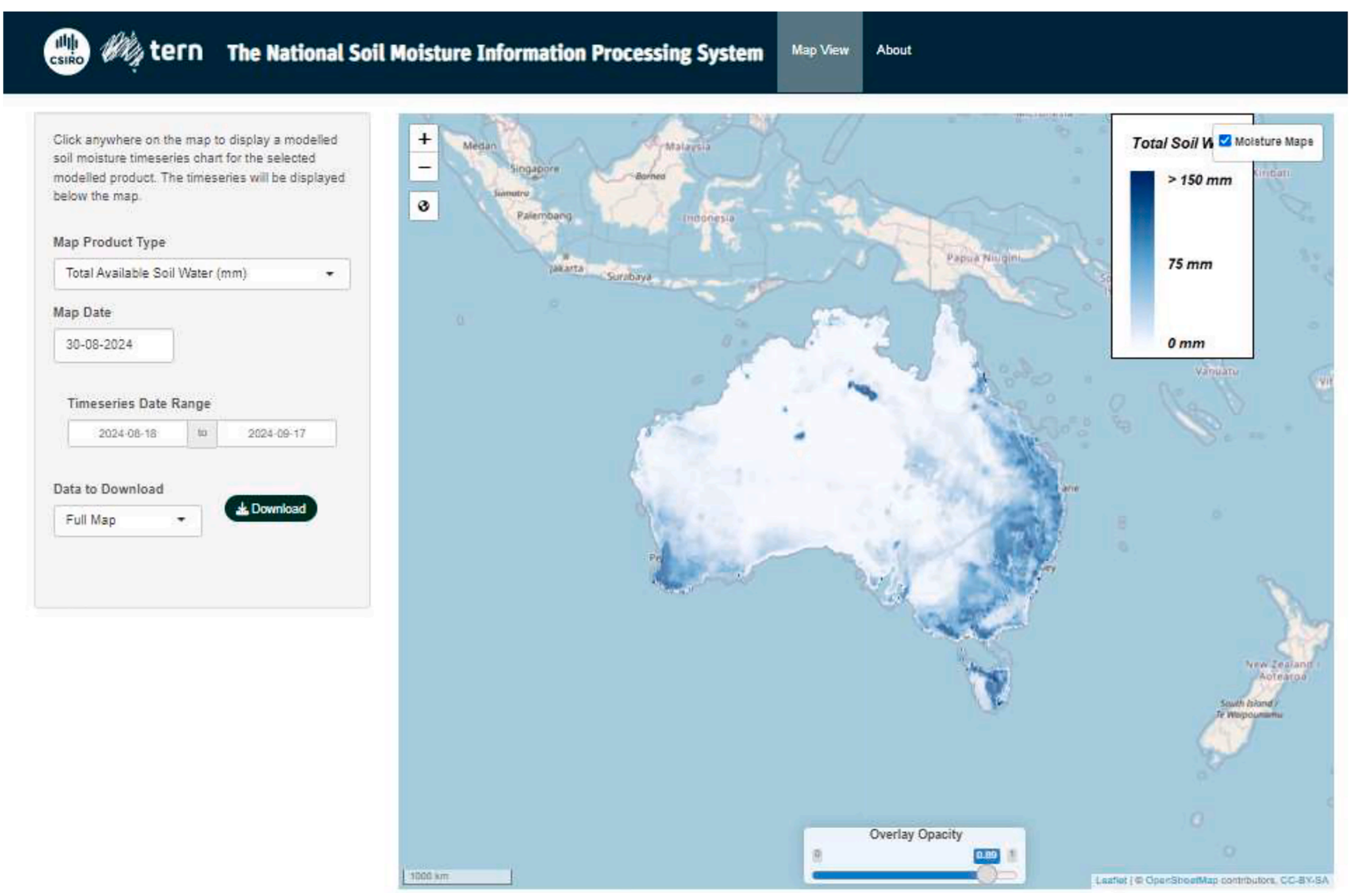

Fig. 3. Snapshot of the SMIPS data portal (https://shiny.esoil.io/SMIPS/) for basic visualization and download of daily soil moisture estimates across Australia for 0–90 cm depth and 1 km grid cell resolution.

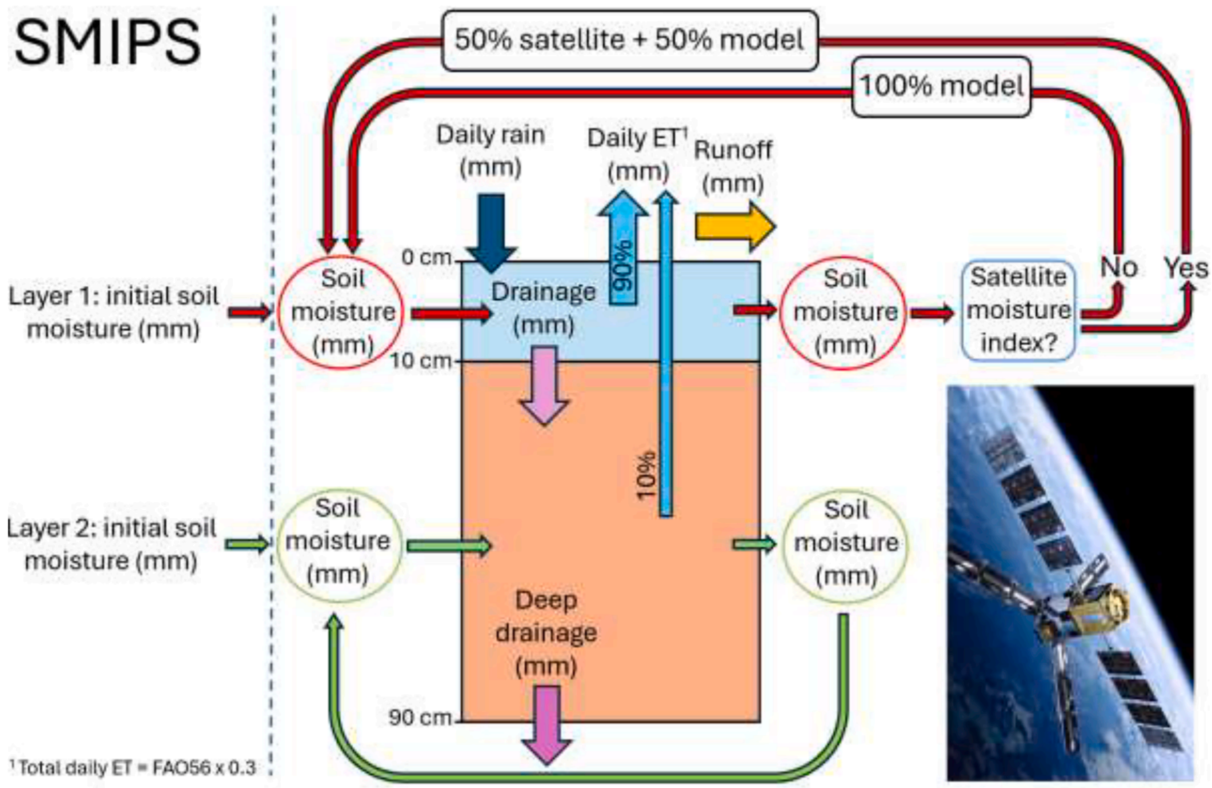

Fig. 4. SMIPS model flow chart showing processes modelled in each of the two layers.

making, and future investment. Given this context, the question arises: what should a national soil monitoring program for Australia look like?

There is no one-size-fits-all approach to establishing soil monitoring networks, but their design typically follows a set of established principles, shaped by the specific objectives they aim to achieve. Broadly, there is consensus that land management impacts on soils are not uniform, as they are influenced by both the inherent properties of the soil and variations in local settings. A key design principle is, therefore, to select sites based on shared soil and landscape attributes, regardless of land management practices, and compare these sites with others in the same setting that are considered undisturbed. Frameworks such as the Soil Security Assessment Framework (Evangelista et al. 2023), the Soil Health Assessment Protocol and Evaluation Tool (Nunes et al. 2021), and the more specialized 'Soil Health Gap' approach focused on soil carbon (Maharjan et al. 2020) all emphasize the need for establishing a reference condition. Román Dobarco et al. (2023a) introduced the concept of "Genosoils"—soils least affected by contemporary anthropogenic pressures—against which "Phenosoils" (soils impacted by land use and management) can be compared. The differences between these soils are primarily determined by land management practices, making it more realistic to infer changes and potential change trajectories when soils share common soil and landscape conditions.

A soil monitoring program built upon these assessment frameworks would begin with Pedogenon mapping (Román Dobarco et al. 2023a), followed by the delineation of Genosoils and Phenosoils within these Pedogenon Units. SLGA Version 2 enables the development of methods and mapping approaches to define these Pedogenon Units as a foundation for a future national soil monitoring program. Pedogenon classes aim to group homogeneous environmental variables that act as proxies for soil-forming factors at a given reference time (e.g., the time of European settlement in Australia). These units represent soil systems in quasi-steady state, shaped by the combination of soil-forming factors at the selected time (Román Dobarco et al. 2021). The assumption is that in large areas where soil-forming factors are consistent, pedogenetic processes would have been relatively uniform, leading to the development of soils with similar properties. Pedogenon classes can then be divided into subclasses along a gradient, from less anthropogenically impacted soils (Genosoils) to those more influenced by human activity (Phenosoils).

5. General discussion

At the start of the SLGA update program, scientists and practitioners from across Australia and internationally gathered to assess the progress and future of digital soil mapping. Kidd et al. (2020) examine the drivers that have transitioned digital soil mapping from a research-focused tool to an operational resource used by soil mapping agencies and private entities. The foundation for quantitative soil mapping began in the 1960 s with numerical soil taxonomy and multivariate analysis to study soil variation (Lee 1998). With vast land areas and limited soil data, geostatistical methods evolved into digital soil mapping (McBratney et al. 2003), utilizing data sources like digital elevation models and remote sensing.

Kidd et al. (2020) also review the SLGA alongside other digital soil mapping projects in Australia, highlighting the shared need for detailed soil information to address climate, ecosystems, and food production challenges. Grundy et al. (2020) extended this analysis by assessing seven case studies, including the SLGA, using an impact assessment framework to quantify the benefits of digital soil mapping. Their findings revealed that impact pathways for these projects are often complex, with the SLGA's openness enabling widespread data access while complicating the tracking of specific uses and benefits. Despite this, the high demand for soil data is evident through frequent downloads and widespread scientific applications. As digital systems integrate further into diverse sectors, the SLGA's influence is expected to grow.

Searle et al. (2021) surveyed soil scientists on the future of digital soil mapping, emphasizing the importance of technological advancements and the rising demand for soil experts with digital and data science skills. Emerging fields such as human health, climate change, food provenance, and ecosystem services are expected to drive an even broader user base for digital soil data.

As previously noted, this revision of the SLGA represents potentially the first update of digital soil mapping products at a continental scale. Conceived as a dynamic data system, the SLGA was designed to evolve as new data and methods became available. Realizing this vision requires long-term resource commitments. The recent SLGA revision was significantly supported by consistent funding from TERN, under the Australian Government's National Collaborative Research Infrastructure Strategy. This stable funding enabled researchers to maintain close collaborative working relationships, learn from previous iterations, share knowledge and experiences, and sustain a vibrant community of practice. These factors were crucial in improving this national data resource and ensuring its ongoing relevance.

6. Conclusions

The development of SLGA Version 2 builds on over 80 years of efforts to create national soil mapping products that benefit Australian society. Digital soil mapping has proven to be a valuable tool, providing quantitative insights into soil attributes at specific depths with greater granularity. One key advantage is the transparency of the process, allowing for continuous refinement and improvement. The update to SLGA Version 1 within 10 years highlights the advancements in enabling technologies and the ongoing commitment of TERN and the Australian soil information community to continuous improvement. SLGA Version 2 is not only broader in scope but also more efficient, setting the stage for future updates and enhancements. SLGA Version 3 is already underway.

CRediT authorship contribution statement

Brendan Malone: Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Ross Searle:** Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Matthew Stenson:** Writing – review & editing, Writing – original draft, Project administration, Investigation, Funding acquisition, Formal analysis. **David McJannet:** Writing – review & editing, Writing – original draft, Resources, Methodology, Formal analysis, Data curation. **Peter Zund:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Mercedes Román Dobarco:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alexandre M.J.-C. Wadoux:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Budiman Minasny:** Writing – review & editing, Writing – original draft, Resources, Conceptualization. **Alex McBratney:** Writing – review & editing, Writing – original draft, Resources, Funding acquisition, Conceptualization. **Mike Grundy:** Writing – review & editing, Writing – original draft, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Declaration of Generative AI in the writing process

In the preparation of this paper, ChatGPT-4 (https://chatgpt.com/), was employed to assist with improving the clarity, grammar, and overall quality of the English language. Following its use, the authors thoroughly reviewed and edited the content to ensure accuracy and alignment with the intended meaning. The AI's involvement was limited to language refinement, and no content generation, interpretation of data, or intellectual contributions were made by the AI. The responsibility for the scientific content lies entirely with the authors.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geoderma.2025.117226.

Data availability

Data will be made available on request.

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