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Genosoil and phenosoil mapping in continental Australia is essential for soil security

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ABSTRACT

The intensification of human pressures on soil can reduce pedodiversity and decrease soil multifunctionality impacting soil security. Mapping genosoils (least modified soils within a soil class or soil map unit by contemporary drivers of soil change) and phenosoils (variants resulting from land use history and management) can be a preliminary step for quantifying soil security dimensions and prioritising areas for soil preservation and regeneration. Genosoil properties can be used as a baseline for assessing the effects of management on soil condition for a particular pedological, climatic and landscape context. In this study, we stratified Australia into 1370 pedogenons (i.e., groups with relatively homogeneous environmental covariates, proxies of soil-forming factors) that represent soil classes prior to the European settlement from 1788 onwards. We overlayed the maps of global Human Modification and the Habitat Condition Assessment System for Australia for identifying areas with minimum human influence on terrestrial ecosystems and soils. Areas with very low human influence were defined as genosoils at the continental level. The percentage of land mapped as genosoils accounted for 56% of the continent and had a median area of 2550 km^2. There were 32 pedogenon classes that did not have any remaining genosoils while 218 pedogenon classes had less than 5% of their area as genosoils. The proportion of genosoils protected in conservation areas or managed resource protection varied widely, although almost 25% of the genosoils had at least half of their area under conservation. In addition to soil multifunctionality, the criteria for prioritising soil conservation areas could consider: 1) endangered genosoils and 2) genosoils closest (in the scorpan feature space) to the phenosoils without an existing reference soil.

1. Introduction

The soils we know today will be very different in some centuries from now. While soils evolve naturally, human activities have accelerated soil change to an unprecedented rate (Kuzyakov and Zamanian, 2019; Richter and Yaalon, 2012). The extent and intensity of human influence over soil systems have caused the reduction of the area occupied by certain soil classes, especially those soils and landscape positions most suitable for agricultural use (Amundson et al., 2003). Soil classes at the lowest taxonomic level, e.g., soil series in the Soil Taxonomy (Soil Survey Staff, 2022), can be compared to biological species in the sense that they designate entities with unique characteristics (Amundson et al., 2003). Several studies have tested the hypothesis of soil “species”-area relationships at global and continental scales (Guo et al., 2003; Ibáñez et al., 1998). The spatial distribution of soil types is controlled by the combination of conditions of soil-forming factors (Dokuchaev, 1883; Jenny, 1941) and the local pedogenetic processes over time. Whereas some soil classes occur naturally over large areas, other soil classes occupy small areas naturally (rare soils) or occur under specific conditions (endemic soils) (Amundson, 2022). The soil transformation and change driven by agriculture, extractive activities or urban expansion have led to a decrease in pedodiversity, with some soil classes becoming “endangered” or even “extinct” (Amundson et al., 2003). In an analogous way to the conservation of biological species and ecosystems, it is important to preserve soils’ diversity as the functions and ecosystem services they provide within an area are modified or reduced when

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pedodiversity disappears.

Soil microorganisms are fundamental actors of soil functions as they mediate multiple processes like nutrient cycling and bioavailability, mineralisation and stabilisation of soil organic carbon, or soil structure formation (Nannipieri et al., 2017). Guerra et al. (2022) identified areas across the world with high soil microbial species richness, community dissimilarity, and soil-based ecosystem services, showing that most hotspots are not located in conservation areas and are vulnerable to global change. Their findings highlight the need to set up soil reserves across different pedogenetic settings that consider the soil microbial biodiversity and functionality as well as a set of functions and services mediated by their physico-chemical soil attributes (Guerra et al., 2022). Evangelista et al. (2023b) proposed that "soil policy should consider soils and the planet as stakeholders in their own right". The protection of soil through a network of soil reserves would require to: 1) assess the pedodiversity by mapping soil classes, and 2) establish criteria to prioritise which soil classes should be protected. An anthropocentric approach to pedodiversity conservation could rely on soil multifunctionality mapping (Calzolari et al., 2016) and spatially-explicit decision-support tools (Debeljak et al., 2019; Terribile et al., 2015) to optimise the delivery of ecosystem services in an area of interest (e.g., watershed, region). A more ecocentric view would sustain that diverse soils should be equally protected and independent from the value perceived by society.

Evangelista et al. (2023a) proposed the Soil Security Assessment Framework (SSAF) for quantifying and mapping the ability of soils to perform several functions for each of the five dimensions of soil security. An anthropogenic approach for identifying soil reserves could apply the SSAF for locating the most multifunctional soils or hotspots of functions that only have high performance in a few soils. Some of the proposed indicators by the SSAF for estimating capacity and condition are calculated with the values of soil properties in genosoils (i.e., genetic soil classes least altered by human activities and that are used as the basis for detailed soil mapping) and phenosoils (i.e., soil classes whose characteristics and functions have been modified by management practices) (Rossiter and Bouma, 2018). Conversely, soil reserves could be also established to preserve as much variability of genosoils as possible according to a more ecocentric approach. Either way, genosoil mapping can be a valuable tool for soil conservation. Huang et al. (2018) and later Román Dobarco et al. (2021a) developed digital soil mapping frameworks for mapping genosoils and phenosoils. Román Dobarco et al. (2021a) proposed pedogenon mapping as a preceding step for delineating genosoils.

The assumptions for pedogenon mapping stem from the concept of genon (Boulaine, 1969) and the soil-forming factor models (Dokuchaev, 1883; Jenny, 1941). Pedogenon classes aim to define groups of homogeneous environmental variables, which act as proxies of the soil-forming factors for a given reference time. These units would represent soil systems in quasi steady-state for the combination of soil-forming factors at a selected time (Román Dobarco et al., 2021b). The assumption is that in an area sufficiently large where the soil-forming factors are homogeneous, the long-term pedogenetic processes would have been relatively similar and thus have developed soils with similar properties (Boulaine, 1969). Pedogenon classes can be divided into subclasses along a gradient from less (i.e., remnant pedogenons or genosoils) to more anthropogenic pressure on soils (i.e., pedophenons or phenosoils). The genosoils and phenosoils share some similarities with the concepts of *genoform* and *phenoform* (Droogers and Bouma, 1997; Rossiter and Bouma, 2018) but differ in that the latter use detailed soil (series) maps (which may not exist everywhere) and an established soil classification system (e.g., Soil Taxonomy, Soil Survey Staff (2022)). Droogers and Bouma (1997) defined genoform and phenoform as an analogy with the terms genotype and phenotype in biology. Genoform referred to pedons of the dominant genetic soil type (results from long-term pedogenesis) within a map unit, while phenoforms were areas within the genoform that had been sufficiently modified by management to alter soil functions. Later, Rossiter and Bouma (2018) defined genoform as "soil classes as identified by the soil classification system used as the basis for detailed soil mapping in a given area", and the degree of human modification on phenoforms is addressed as "persistent, non-cyclical variants of a soil genoform with sufficient physical or chemical differences to substantially affect soil functions".

Pedogenon mapping stratifies the landscape so it can be used for first-order soil mapping in areas lacking detailed soil data and mapping. The resulting mapping units can be modified after carrying out soil sampling and evaluation (Jang et al., 2022). Pedogenon classes, when divided into genosoils and phenosoils can also be used as the basis for estimating changes in soil condition due to recent land use changes and management practices (Román Dobarco et al., 2021a), quantifying and mapping the biophysical dimensions of soil security (capacity and condition), and mapping soil change with a space-for-time substitution approach (Jang et al., 2023). Genosoils can serve as reference soils to set targets for restoration (if contemporary land use has caused degradation of soil functions), but this will depend on the resilience of the soil, whether there is hysteresis in soil functions with respect to human pressure and land use intensification (Saiz et al., 2022), and if the soil system has reached a point of no return in degradation (Clunes et al., 2022). Conversely, many phenosoils have higher capability than their respective genosoils from the food and biomass production perspective. The role of genosoils for benchmarking can also be used to assess the positive effects of optimal management practices for several soil functions. Pedogenon classes, genosoils and phenosoils can serve as strata for soil monitoring. Long-term monitoring of genosoils will allow us to measure the effects of natural soil processes and indirect anthropogenic drivers of soil change (e.g., climate change, atmospheric N deposition) (Richter and Yaalon, 2012), and differentiate the soil change due to direct human activities on phenosoils. Thus, a continental map of pedogenon classes can provide an a priori estimate of pedodiversity and a way of finding areas for soil conservation, which in turn can be used for developing policies to protect unique soil entities and prevent their degradation and extinction.

This study has several objectives: 1) Produce a map of pedogenon and genosoil classes for continental Australia, 2) discuss ways of visualising and exploring the data, and 3) explore how genosoil mapping could be used to set up soil reserves.

2. Methods

2.1. Pedogenon mapping at continental extent

The methodology for pedogenon mapping was adapted from Román Dobarco et al. (2021b) to handle a greater sample size both during the clustering and the mapping steps. A set of 27 selected covariates (Table 1) were processed to cover the whole of Australia at the same extent, coordinate reference system and alignment. These covariates were proxies for the *scorpan* factors (McBratney et al., 2003) at the time of the European settlement in Australia (e.g., climate, relief, parent material, time). We did not include any proxy for *organisms* since the map of estimated pre-1750 major vegetation groups for Australia results from joining state maps with different methodology and has significant mismatches in the state borders (NVIS Version 6.0, 2023). Thus, we risk producing artefacts in the pedogenon map by including the pre-1750 vegetation map. However, future epochs of pedogenon mapping for Australia could incorporate updated versions of pre-1750 vegetation maps, and pre-1750 land use and management maps.

A regular sample (a grid of 840 m x 840 m) of 20,000,000 pixels was taken from the covariates, of which 9854,024 had data. The inverse Cholesky transformation was applied to decorrelate the covariates. The Euclidean distance of the decorrelated variables is equivalent to the Mahalanobis distance calculated on the original variables (Román Dobarco et al., 2021b). Subsequently, Euclidean distances could be used

Table 1
Covariates used to describe clorpt (Jenny, 1941) or scorpan (McBratney et al., 2003) factors and generate pedogenon classes. P: parent material; S: soil; T: time; R: relief; Cl: climate; O: organisms.

Covariate	Description	SCORPAN factor	Original resolution (m)	Reference
Sand	Sand content (%) for the depth intervals 30–60, 60–100 and 100–200 cm	S	90	Malone and Searle (2021)
Clay	Clay content (%) for the depth intervals 30–60, 60–100 and 100–200 cm	S	90	
ADM	Mean annual aridity index (annual precipitation/ annual potential evaporation)	Cl	270	Harwood et al. (2016a); Xu and Hutchinson (2013)
PTA	Annual precipitation (mm)	Cl	270	
PTS1	Precipitation: ratio of annual contrast in regional rainfall conditions between summer and winter solstice conditions.	Cl	270	
PTS2	Precipitation: ratio of annual contrast in regional rainfall conditions between spring and autumn equinox conditions.	Cl	270	
TNM	Minimum temperature (annual mean) (°C)	Cl	270	
TXM	Maximum temperature (annual mean) (°C)	Cl	270	
TRA	Annual temperature range (TXX – TNI) (°C)	Cl	270	
TRX	Maximum monthly mean diurnal temperature range (°C). High variation in temperature conditions (inland or continental locations).	Cl	270	
TRI	Minimum monthly mean diurnal temperature range (°C). Consistent temperature conditions (coastal locations).	Cl	270	
RSM	Short-wave solar radiation - annual mean (MJ/m2/day)	Cl	90	Gallant et al. (2014)
Dose	Radiometrics: Total dose	S, P	100	Wilford and Kroll (2020)
K	Radiometrics: filtered K element concentrations (%)	S, P	100	
Th	Radiometrics: filtered Th element concentrations (ppm)	S, P	100	
Th/K	Radiometrics: Ratio Th/K derived from the filtered Th and K grids	S, P	100	
WII	Weathering intensity index	P, T	100	Wilford (2012)
Gravity	Total Magnetic Intensity (TMI) Anomaly Grid of Australia	P	80	Lane et al. (2020)
Elevation	SRTM-derived 3 S Smoothed Digital Elevation Model	R	90	Gallant et al. (2009)
Slope	Slope (%)	R	90	
TWI	Topographic wetness index	R	90	Quinn et al. (1991)
MRVBF	Multi-resolution valley bottom flatness index	R	90	Gallant and Dowling (2003)
MRRTF	Multi-resolution ridge top flatness index	R	90	

in the k-means clustering process as a result of this data transformation. To reduce the computation time when working with more than 9 million observations, we applied a parallelised version of k-means (scalable k-means by Bahmani et al. (2012)) with the module *dask_ml.cluster* from the package Dask (https://ml.dask.org/modules/generated/dask_ml.cluster.KMeans.html). The algorithm was set for defining 1370 classes, with a maximum of 30,000 iterations, convergence tolerance set to 0.000001, and initialisation method k-means ++. We ran 50 different initialisations and retained the result with the lowest sum of squared distances of samples to their closest cluster centre (inertia). Mapping at 90 m resolution was carried out using the Google Earth Engine platform, assigning each pixel to the closest pedogenon centroid after rescaling the scorpan variables with the inverse Cholesky transformation.

Distinguishing between 1370 classes visually is challenging. We compared two methods of generating a colour legend and organising pedogenon classes by similarity with a map with random colours by class. The first method consisted of finding groups of similar pedogenons by hierarchical clustering using the Ward method and treating the pedogenon centroids as individuals. The optimal number of branches in the dendrogram was identified with the Silhouette method as well as the Dunn index. After visually inspecting the dendrograms, we repeated the hierarchical clustering excluding very dissimilar pedogenon classes. The second method consisted of first applying the Uniform Manifold Approximation and Projection (UMAP) (McInnes et al., 2018) to the pedogenon centroids, followed by clustering of the first two umap dimensions. UMAP is an algorithm for dimensional reduction that preserves both the local and global structure of the data. A density-based spatial clustering of applications with noise (DBSCAN) (Ester et al., 1996) was applied to the umap scores to identify groups of pedogenons. DBSCAN was applied with a minimum of 10 points to define a cluster and eps = 0.35 (distance for finding neighbours falling in the same cluster).

2.2. Genosoil mapping

We employed a genosoil mapping approach to identify suitable locations for establishing soil reserves (i.e., mapping the least affected areas by human activities within each pedogenon) rather than on a value-based perception of the soil functions and services. We used two indices for locating minimally modified ecosystems, the global Human Modification (HM) map (Theobald et al., 2020) and the Habitat Condition Assessment System (HCAS) (Harwood et al., 2016b).

2.2.1. Human modification map

Areas minimally affected by human influence were identified using the global Human Modification map at 300 m resolution for the year 2017 (Kennedy et al., 2019; Theobald et al., 2020). The cumulative degree of human modification of terrestrial ecosystems results from combining spatial data from multiple stressors: urban and built-up, crop and pasture lands, livestock grazing, oil and gas production, mining and quarrying, power generation stations, lines and towers, roads, railways, logging and wood harvesting, human intrusion, reservoirs, and air pollution. Each stressor is weighed by the amount of non-renewable energy required to maintain that activity and the proportion of the pixel occupied by that stressor (Theobald et al., 2020). The stressors are combined into an index with the fuzzy algebraic sum, which calculates the cumulative effect of the stressors while minimising the bias associated with correlated variables (Kennedy et al., 2019; Theobald et al., 2020). The HM index is continuous and ranges between 0 and 1, with 0 indicating no human influence and 1 corresponding to the maximum modification. Although this index is not explicitly defined for soil, it informs on the degree of human pressure on the environment. Several stressors represent direct pressures on soil systems (agriculture, mining), some may represent an indirect or diffuse pressure on soil functions (e.g., night lights as a proxy for human population density, air pollution), and a few do not represent pressure on soils (e.g., reservoirs). Thus, we consider it a good proxy for anthropogenic pressures on soils. We set the same thresholds as Kennedy et al. (2019) of HM ≤ 0.01 to identify areas with very low modification, and $0.01 < \text{HM} \leq 0.1$ for areas of low human modification.

2.2.2. Habitat condition assessment system

The HCAS is a remote-sensing algorithm for assessing the condition of habitats for native terrestrial biodiversity (Harwood et al., 2016b). HCAS was designed to differentiate when an ecosystem's condition results from natural dynamics to anthropogenic influence, taking into account the temporal and ecological variability of natural ecosystems (Harwood et al., 2016b). HCAS uses as input abiotic environmental data (soil, landform, climate, etc.), remote-sensing data, and reference sites condition data. The spatial ecological model is based on the notion that sites with similar abiotic environmental conditions would have a similar remote-sensing signal averaged over time. The reference sites are assumed to be the least modified for that habitat type, and are identified based on explicit knowledge (field observations) or inferred from multiple spatial data sources (land tenure, land cover, remote sensing) (Williams et al., 2021). We used the HCAS version 2.1 (2001–2018) at 9 arcsecond resolution (approximately 250 m grid) and Geocentric Datum of Australia (GDA94) (Harwood et al., 2021). The HCAS scores range between 0 (completely removed habitat) and 1 (habitat in best possible condition). While the HCAS score is not an index of anthropogenic pressure on soils (there would be a delayed response of soil systems to the replacement of natural vegetation, and the effects on soil properties would depend on the type of land use and management, e.g., cropping, grazing), it is useful for identifying genosoils under the assumption that the least modified ecosystems would be indicative of the least modified soils. The HCAS scores can be assigned to categories of the Vegetation Assets, States, and Transitions (VAST) classification (Thackway and Lesslie, 2006). The VAST class *residual* indicates that the "native vegetation community structure, composition, and regenerative capacity is intact, without significant perturbation from land use or land management practice" (e.g., old growth forest, native grassland that has not been grazed), whereas the class *modified* corresponds to "native vegetation community structure, composition and regenerative capacity intact, but perturbed by land use or land management practice" (e.g., native vegetation subject to sustainable grazing practices) (Thackway and Lesslie, 2006). Thus, we set a threshold of HCAS ≥ 0.8 (or VAST class *residual*) for very low modified ecosystems, and $0.6 \leq \text{HCAS} < 0.8$ for low human modification (Fig. 4).

The HM grid was resampled to 250 m with bilinear interpolation and aligned to the extent of the HCAS index. The pedogenon map was resampled to 250 m resolution with the mode as the aggregation method. Forest plantations and surface waterbodies were masked from the HCAS layer. The analyses were conducted at 250 m resolution because the HM index had been calculated using the proportion of different stressors occurring within 300 m pixels. We overlayed Australia's 2018 land use map (ABARES, 2022) to calculate the proportion of each pedogenon class with very low modification (according to HM and HCAS) located in conservation areas. The land use map was resampled from its original 50 m resolution to 250 m with nearest neighbour resampling. For comparison with other main land uses, we calculated the number of pedogenon classes, and the proportion of their area dedicated to cropping and grazing: dryland and irrigated cropping were designated as *phenosoil cropping*, dryland and irrigated grazing were designated as *phenosoil grazing*.

3. Results

3.1. Pedogenon mapping at the continental extent

The pedogenon map for continental Australia showed relatively spatially compact classes, where the pixels of the same class were mostly contiguous or in proximity (Fig. 1). However, it was common that different classes overlapped, and several classes occurred as neighbours. A focal filter can be applied to assign the dominant class and eliminate the "salt and pepper" effect with GIS. Assigning random colours allows one to distinguish individual classes (Fig. 1) but does not indicate the similarities between pedogenon classes.

We distinguished 21 branches in the dendrogram of the hierarchical agglomerative clustering after excluding 7 classes that were clear outliers (pedogenon classes 14, 95, 309, 472, 522, 576 and 799) (Fig. 2). The spatial distribution of the pedogenons organised by the dendrogram followed mainly a climatic gradient (Fig. 2c) but also reflected the influence of the parent material variables (gamma radiometrics and gravity). For example, the impact of the gravity anomaly is visible in the centre of Australia (Fig. 1 and 2a). The influence of the relief was more evident at the watershed and local scale.

The pedogenon classes were projected onto a two-dimensional plot after reducing the centroid coordinates from 27 scorpan variables to two UMAP dimensions (Figs. 3b and 3c). Pedogenon centroids that are more similar to each other are in similar regions of the plot. We trialled different settings for defining clusters of pedogenon classes with DBSCAN and plotted the results. We finally set the parameters to eps=0.35 and a minimum of 10 data points (centroids) to define the clusters (Fig. 3b). This defined 22 dense clusters, while 95 pedogenon classes were considered noise by DBSCAN. In this case, "noise" classes are those pedogenon centroids that were not close enough to other classes in the UMAP two-dimensional space to form a group (Fig. 3b), remaining as individual pedogenons. The groups of similar pedogenons differed between clustering algorithms (Fig. 2c and Fig. 3). However, some groups or regions were identified by both methods. For example, in the north of Australia (orange region in Fig. 2c and blue violet in Fig. 3a) which corresponds to a cluster of centroids on the left side of Figs. 3b and 3c (negative scores in the first UMAP dimension). Another region of similar pedogenons is in southeast Australia (sage green in Fig. 3a and two branches of the dendrogram —maroon and blue— in Fig. 2c). To determine which method of organisation is preferred, future studies should compare the correspondence between these two groupings and similarities between soil profiles based on their soil properties (Carré and Jacobson, 2009), e.g., which grouping has smaller average intra-dissimilarity and greater inter-dissimilarities.

3.2. Mapping genosoils and phenosoils

Both indices showed that areas within or close to the wheatbelt (southwestern, eastern and south Australia, or areas in grey in Fig. 4) had a higher degree of human influence on terrestrial ecosystems. Main areas of very low influence were in central, north, and western Australia, generally in semi-arid or tropical climate except for some areas in the Great Dividing Range in eastern Australia and Tasmania in temperate

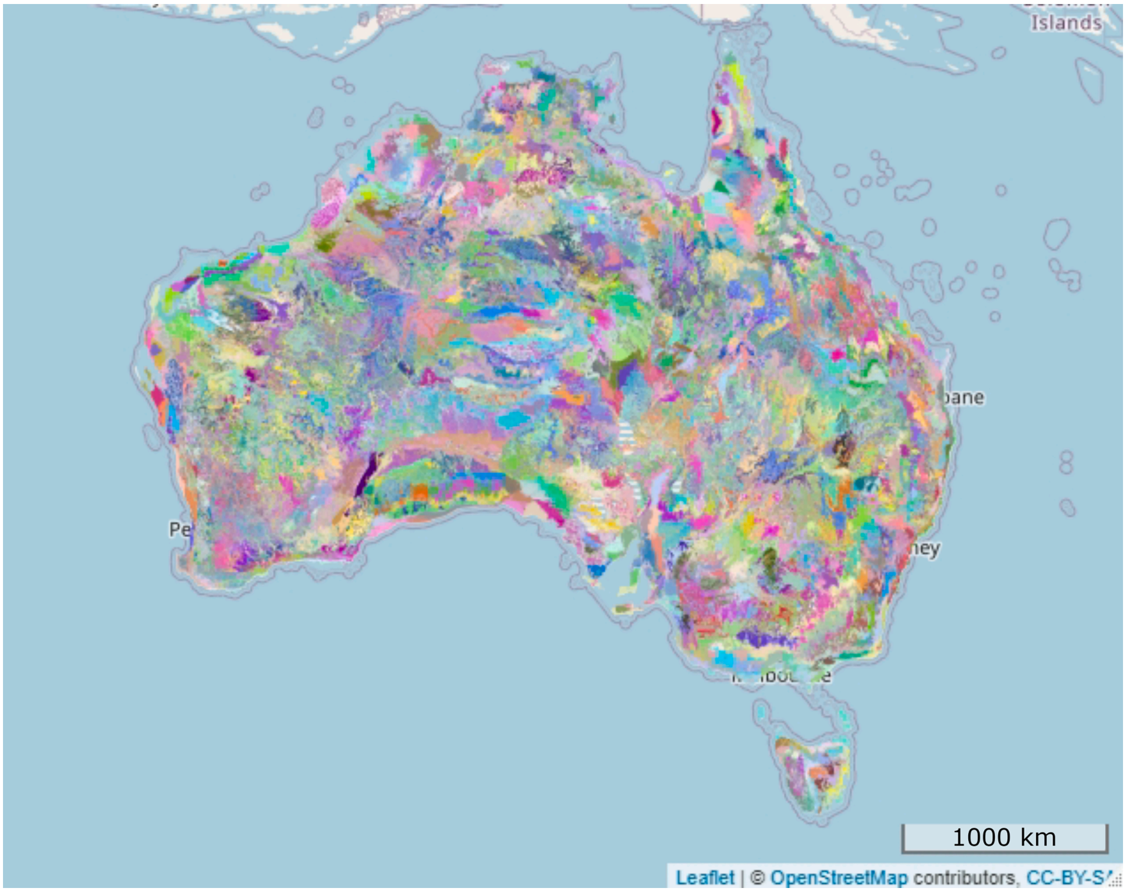

Fig. 1. Map of 1370 pedogenon classes for Australia. Colours were randomly assigned to each class.

climate. The HM index indicated a larger area assigned to very low impact areas (HM ≤ 0.01) than HCAS (HCAS ≥ 0.8), whereas the HCAS index assigned a higher area to low impact areas (0.8 > HCAS ≥ 0.6) than HM (0.1 > HM ≥ 0.01) (Fig. 4). The discrepancy between both indices are likely explained by being developed with different aims (pressure on terrestrial systems vs habitat integrity), methods (cumulative stressors vs. distance from reference) and scale (global vs continental). This resulted in a bimodal distribution of the percentage of pedogenon classes assigned to very low impact areas according to HM (Fig. 5), with 194 pedogenon classes having less than 10% and 819 classes having at least 90% of their surface in very low impact areas (genosoils), while 1009 classes had less than 10% of their surface in HM low impact areas (Fig. 5). Areas of very low impact according to HCAS, had a heterogeneous spatial distribution across Australia, resulting in 142 classes with up to 10% of their surface as potential genosoils, but 795 classes with at least 50% of their area, and 189 classes with at least 90% of their surface in very low impact areas (Fig. 5). The percentage of pedogenon classes assigned to low impact areas was generally smaller, with 1344 classes having up to 50% of their extent in low impact areas (Fig. 5).

We overlayed the land use map of Australia (ABARES, 2022) and quantified the proportion of pedogenon classes under nature conservation or managed resource protection. The percentage of pedogenon classes under conservation had a right-skewed distribution (Fig. 6a), with a median around 21% and a mean of 31%. The proportion of pedogenon classes that were both, assigned a very low human impact and under conservation was also right-skewed with a median around 13% and a mean of 24% (Fig. 6b) for HM and similar values for HCAS (median = 13% and mean = 22%). Conservation or managed resource protection covered a varied proportion of very low impact areas depending on the index (Fig. 6c). An important fraction of genosoils (~ 25%) had between 50 and 100% of their area under conservation (Fig. 6c).

Genosoils were identified by locating areas assigned to very low human impact by both indices (Fig. 7). There were 32 pedogenon classes with no genosoils while 218 pedogenon classes had less than 5% of their original area as genosoils (Fig. 6d). However, some pedogenon classes (n = 166) also had at least 90% of their area as genosoils (Fig. 6d). The histogram of the area occupied by genosoils was also strongly right skewed. The summary statistics indicated areas of 2 km^2, 22 km^2, and 396 km^2 for the 5th, 10th, and 25th percentile. The median genosoil area was 2550 km^2, reaching a maximum value of 26,212 km^2.

Most pedogenon classes had some area dedicated to agriculture (n = 1187). In 458 classes the area was smaller than 1 km^2. The number of pedogenon classes used for grazing was 856 (273 classes < 1 km^2). The median phenosoil cropping area was 1.6 km^2 (interquartile range (IQR) = 94 km^2) and for phenosoil grazing 0.2 km^2 (IQR = 28km^2), with mean areas respectively of 328 km^2 and 162 km^2 for cropping and grazing. In relative terms, phenosoil cropping and phenosoil grazing represented 7% and 4% of the pedogenon classes on average.

One application of genosoil and phenosoil mapping is using soil properties of genosoils as baseline for assessing how management affects soil condition and the performance of soil functions (Evangelista et al., 2023a). For pedogenon classes that no longer have genosoils or very low impact areas, the alternative is to either use the indicator value of the least affected phenosoil as a reference state or the closest genosoil (in the scorpan space). An example of a phenosoil (pedogenon class 288) and its closest genosoil (genosoil class 1149) is shown in Fig. 8, showing differences in pH between genosoil and phenosoil.

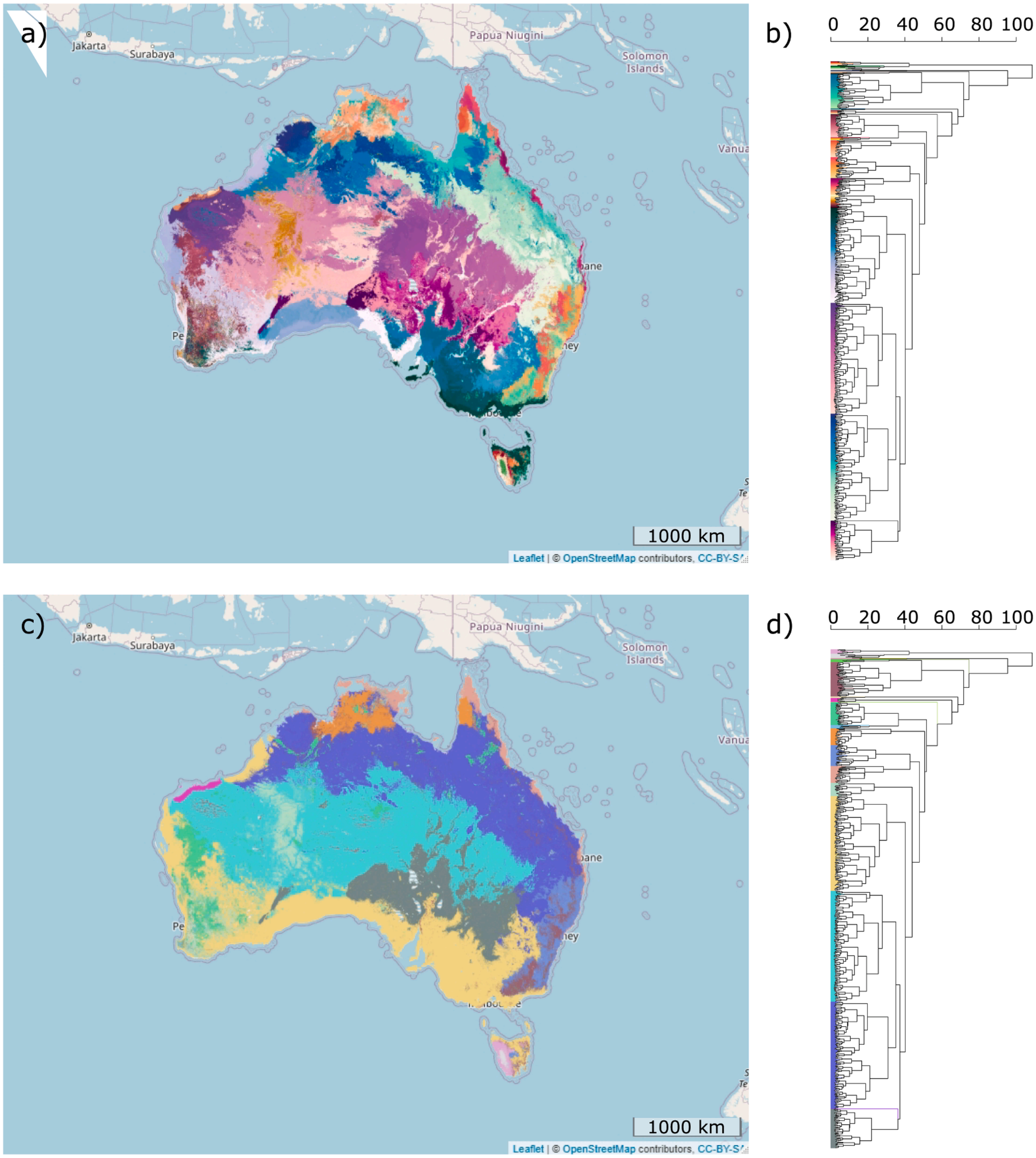

Fig. 2. Organisation and visualisation of pedogenon classes for Australia using agglomerative hierarchical clustering. a) and b) Pedogenon classes (n = 1370) coloured assigning a different sequential (multi-hue) palette to each branch of the dendrogram where we distinguished 21 main branches. c) and d) Each branch of the dendrogram (n = 21) has a colour assigned.

4. Discussion

Global maps of the human influence on terrestrial ecosystems started to be produced in the 1980s in the field of ecosystem and biodiversity conservation (Riggio et al., 2020). Riggio et al. (2020) compared four maps of human modification of terrestrial ecosystems produced with different methodologies (Anthromes (Ellis et al., 2010; Ellis and Ramankutty, 2008), global Human Modification (Kennedy et al., 2019), Human Footprint (Sanderson et al., 2002), and Low Impact Areas (Jacobson et al., 2019)), finding that around 48%–56% of the land had low impact and 20%–34% had very low impact. In Australia, the percentage of land mapped as genosoils (where both HM and HCAS indicated very low human impact) accounted for 56% of the continent. This value is larger than the global average and is likely related to the vast extent of semi-arid and arid areas that have not been transformed by agriculture (nor are they likely to be transformed). Finding genosoils in Australia is probably easier than in other areas of the world, noting that by genosoils we do not refer to pristine soils without human influence. In this context, **genosoils are soils representative of the legacies of natural and anthropedogenetic processes up to a reference time (pre-European settlement) which have been least affected by contemporary drivers of soil change** (Richter and Yaalon, 2012; Yaalon and Yaron, 1966). We set as reference time the transition from the agricultural systems practised by the First Nations Australians (traditional knowledge adapted to the environment and ecological conditions of the Australian landscape) (Gammage, 2011; Pascoe, 2014) into more intensive agricultural land use, following the cropping and grazing systems brought by the European settlers. Our analysis indicated that some pedogenon classes no longer have areas designated as genosoils (Figs. 6d and 7). These pedogenons have been transformed mainly by agricultural activities along the Australian wheatbelt. However, whether the genosoils are extinct will depend on the soils' vulnerability

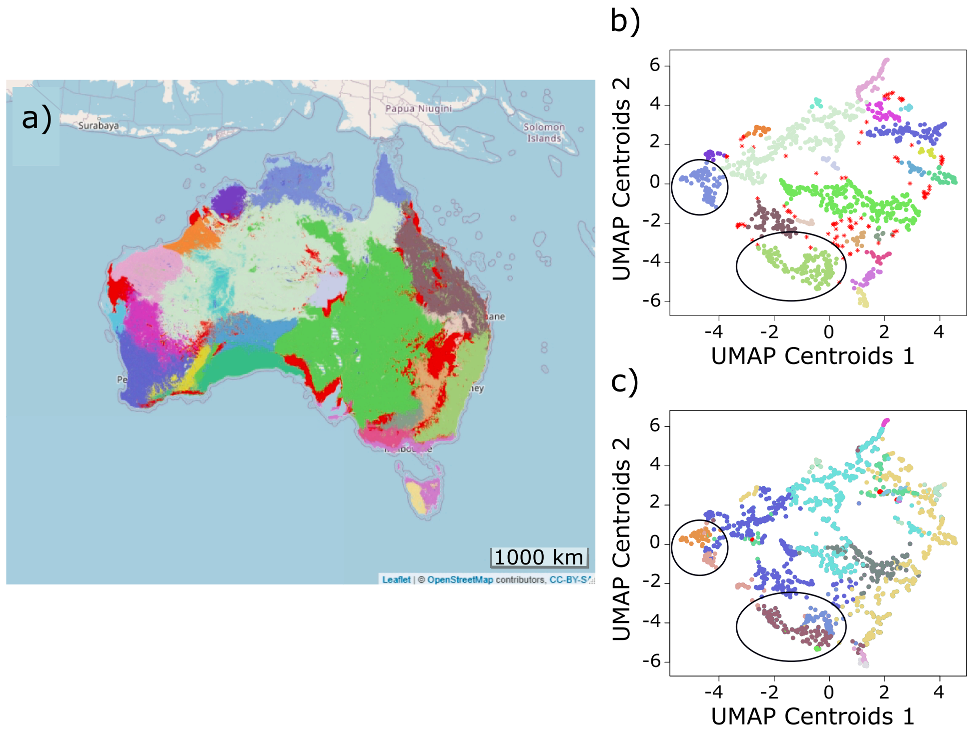

Fig. 3. a) Organisation of pedogenon classes by cluster defined by DBSCAN. In red, classes that remain individual (noise according to the DBSCAN clustering), b) clusters defined by DBSCAN on the UMAP scores of the pedogenon centroids. Red stars indicate those classes that were not grouped with others, c) UMAP scores of the pedogenon centroids with the same colour legend as by the agglomerative hierarchical clustering.

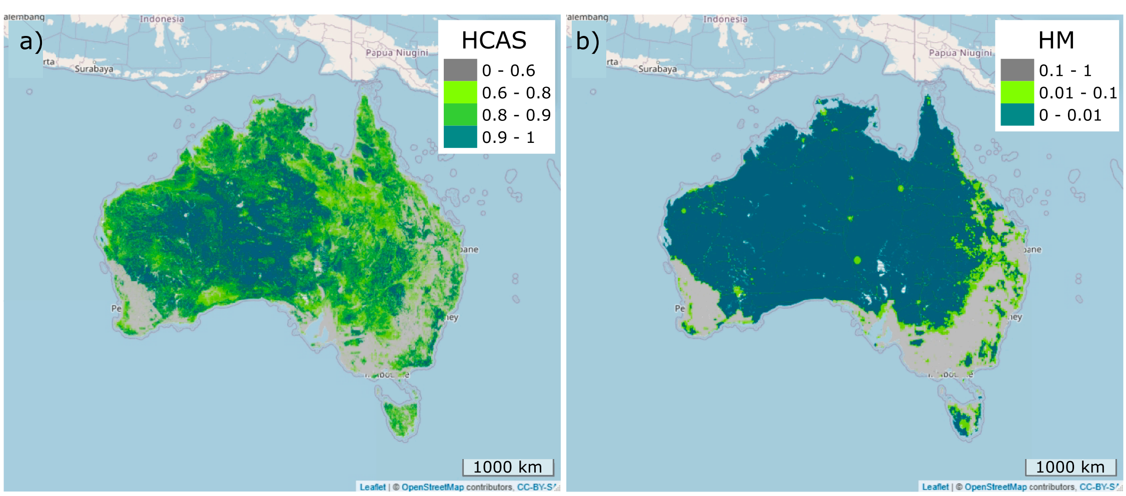

Fig. 4. a) Habitat Condition Assessment System and b) Global Human Modification index.

to human pressure and on the rate of soil change. The results presented here are a preliminary step but the analysis of soil change and genosoil specific vulnerability to anthropogenic change needs to be further assessed. Some pedogenetic processes modified by human activities will eventually be reflected on inherent soil properties after some decades or centuries while more dynamic properties may have been altered already (Yaalon and Yaron, 1966), e.g., loss of soil organic carbon. In this case, the least affected phenosoil from the same pedogenon class or the closest genosoil (Fig. 8) could be used as reference state.

Our approach for mapping genosoils and identifying areas where soil reserves could potentially be set up has several caveats. First, we need to validate the pedogenon classes and characterise that they describe distinct soil entities. This task is easier at the local scale (Jang et al., 2022), but efforts for sampling and characterising the soil properties of pedogenon classes at the continental scale are ongoing. The soil data of the sampled pedogenons can be used for merging classes based on taxonomic distances between soil profiles (Carré and Jacobson, 2009) and updating the map with an iterative process. The second is that the indices of human pressure were not designed for soil systems, but for terrestrial ecosystems or habitat conditions. In addition, the resolution of HM and HCAS is not high enough for locating genosoil profiles in the field. The global HM map does not represent some stressors for Australia, like grazing in relatively natural areas (Theobald et al., 2020). Grazing can be an important pressure on Australian rangelands, increasing the risk of soil loss by water and wind erosion (Aubault et al., 2015; Bartley et al., 2006). This may explain the high proportion of pedogenon classes assigned to very low impact areas by the HM map (Fig. 5). The HCAS index showed more detail in the spatial pattern than

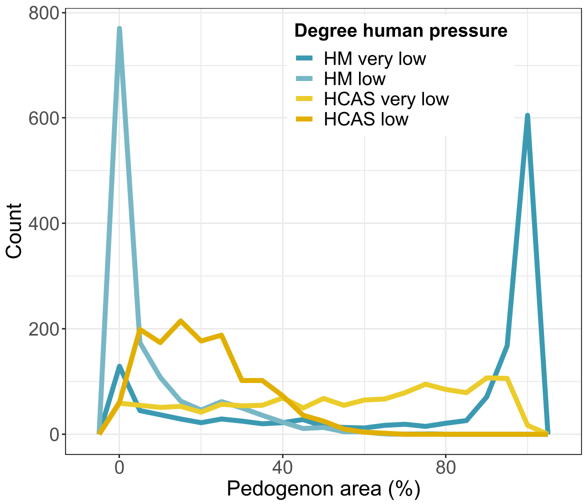

Fig. 5. Histogram of percentage of pedogenon classes assigned to very low impact and low impact areas by HM and HCAS indices.

HM. HCAS is not defined to identify pristine soils but to score the *capacity of an area to provide the structures and functions necessary for the persistence of all species naturally expected to occur in that area if it were in an intact (reference) state* (Williams et al., 2021). However, we assumed that terrestrial ecosystems that are intact or have high ecological integrity according to the HCAS framework would indicate the least affected soils, taking as reference time the European settlement in Australia. HCAS is defined as a reference to the environment prior to the arrival of Europeans to Australia and also considers that continued Indigenous land management practices are part of the ecosystem's dynamic reference state (Richards et al., 2020). Equating high ecological integrity to lack of pressures on soils is not exempt of uncertainty since plant biodiversity and soil properties often recover at different rates after anthropogenic disturbance depending on local conditions (An et al., 2019; van der Sande et al., 2023).

There are multiple examples of thematic maps of threats to soil, e.g., vulnerability to subsoil compaction (European Commission, 2008; Nazari et al., 2023). Orgiazzi et al. (2016) developed indices of potential threats to soil biodiversity by assigning weights to different stressors with a knowledge-based approach. Yet, a methodology for calculating an integrative index of pressures for all soil functions is missing. A cumulative index of pressure on soils following a similar methodology as for HM (Kennedy et al., 2019) could be developed for Australia but including proxies of the stressors at an adequate resolution for a continental assessment. Designing a method for assigning the weights to each stressor is challenging since their impact on soil properties and functions will vary geographically and with pedoclimatic conditions.

Generally, just a small proportion of genosoils in Australia were under conservation and 218 pedogenon classes had less than 5% of their area classified as genosoils. These genosoils could be considered at risk of becoming endangered (Amundson et al., 2003). Mapping them followed by field work to characterise their properties is essential for their protection. An increase in the anthropogenic and environmental pressure on soils and terrestrial ecosystems reduces the supply of soil-based ecosystem services (Rillig et al., 2023). Hence, policy and best management practices should be implemented for limiting the anthropogenic impact on genosoils and on multifunctional phenosoils. A value-based approach for identifying which soils should be protected in conservation areas could prioritise the soils that can satisfactorily perform more functions and those that can perform functions rarely fulfilled by applying digital soil assessment or multi-criteria decision support systems (Rabot et al., 2022; Vazquez et al., 2021).

Complementary criteria for prioritising soil conservation areas can consider: 1) endangered genosoils (i.e., they represent less than 5% of the pedogenon or the total genosoil area is less than a minimum, e.g., 5 km^2), 2) genosoils that are closest (in the scorpan feature space) to the

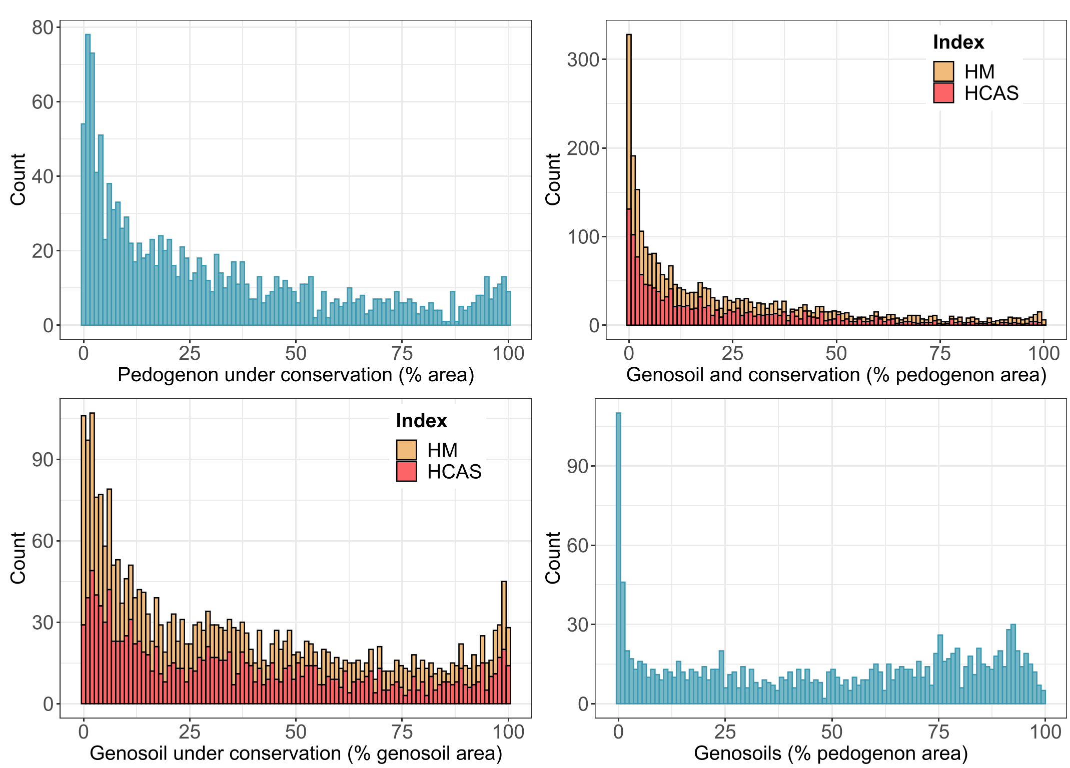

Fig. 6. a) Proportion of pedogenon area under conservation, b) proportion of pedogenon area under conservation and with very low human impact (genosoil), c) proportion of genosoils (very low impact areas) that are under conservation, and d) proportion of pedogenon classes found as genosoils according to both HM and HCAS.

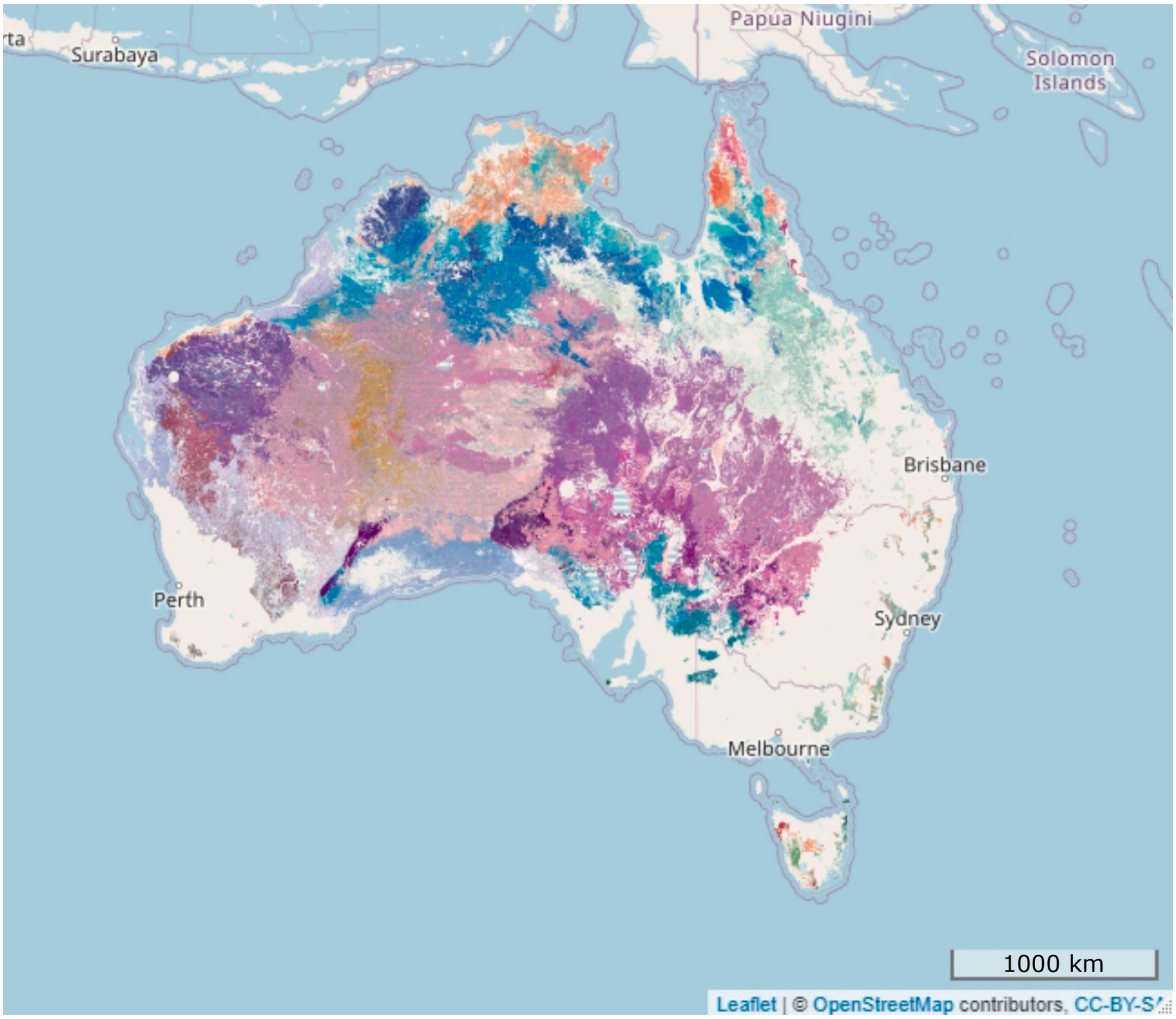

Fig. 7. Genosoil map of Australia. Genosoils are mapped here as very low human impact areas by HCAS and HM indices. Soil reserves could be set up within these genosoils.

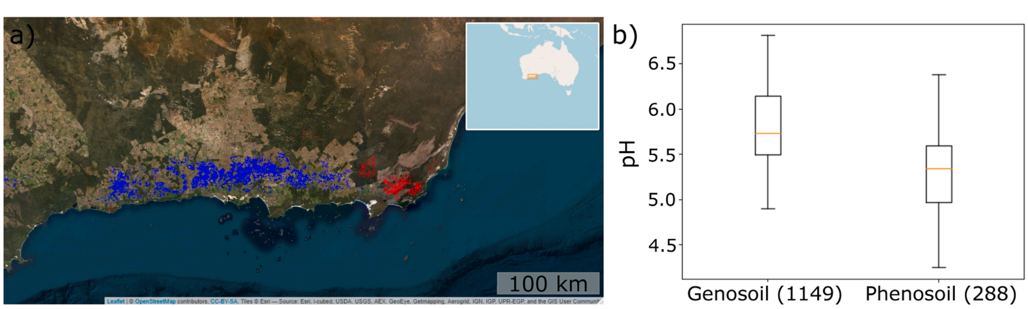

Fig. 8. a) A phenosoil class (in blue) from southwestern Australia that does not have genosoil area left. The closest genosoil (in red) in the scorpan feature space could be used as baseline for condition assessment. b) Topsoil pH from the genosoil and phenosoil.

phenosoils that do not have remnant genosoils, and 3) capability to perform different functions. The suggested threshold of 5 km^2 could be modified after genosoil delineation and verification with fieldwork. Nevertheless, the conservation of genosoils that occupy large areas should not be disregarded. McBratney (1992) proposed some criteria for setting up soil reserves and preserving endangered soils from extinction based on pedodiversity: 1) a set of potential soil reserves are ranked in terms of pedodiversity (weighed by soil taxonomic distance and proportional area soil units), 2) the area with the highest pedodiversity is selected, 3) areas that incorporate new soil classes are added subsequently. The proposal in the current paper is based on better data (environmental covariates) and is more concrete and sophisticated, but should also incorporate pedodiversity estimates from soil profile data (legacy data or from new field campaigns) as additional criteria.

Finally, monitoring genosoils could serve for assessing changes in soil condition with land-use changes (genosoil vs phenosoil assessment) (Román Dobarco et al., 2021a), but also for assessing temporal trends in capacity and condition due to natural pedogenesis and global change drivers (e.g., climate change, atmospheric deposition), as is often done with long-term soil monitoring networks (Arrouays et al., 2002; Keith et al., 2020).

Conclusions

- The mapping of genosoils and phenosoils based on disaggregating pedogenons has been demonstrated for the Australian continent.
- For wider application, the methods for mapping pedogenons and delineating genosoils and phenosoils need to integrate spatial data of land-use history and management at the appropriate temporal and spatial scales. This is challenging for areas lacking historical maps or georeferenced records of land management. Global datasets of historical population density, land use, and cultural biomes (Ellis et al., 2021; Klein Goldewijk et al. 2017) can be coarse resolution (~ 90 km^2) proxies of human influence in the *organisms* soil-forming factor. In Australia, products like HCAS or the map of estimated pre-1750 vegetation are amongst the best available datasets.
- The choice of methods for the hierarchical grouping of pedogenons remains somewhat subjective and needs to be contrasted with soil profile descriptions and laboratory data.
- Definitive criteria for setting up soil reserves should consider the remaining genosoil area, the representativity of combinations of soil-forming factors at the continental scale, and the diversity of soil classes and soil properties within a reserve unit.

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.

Data availability

Data will be made available on request.

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References

ABARES, 2022. Land use. Australian collaborative land use and management program (ACLUMP).
Amundson, R., 2022. Soil biogeochemistry and the global agricultural footprint. Soil Secur. 6, 100022.
Amundson, R., Guo, Y., Gong, P., 2003. Soil Diversity and Land Use in the United States. Ecosystems 6 (5), 470–482.
An, H., Zhang, B., Thomas, B.W., Beck, R., Willms, W.D., Li, Y., Hao, X., 2019. Short term recovery of vegetation and soil after abandoning cultivated mixedgrass prairies in Alberta, Canada. Catena 173, 321–329.
Arrouays, D., Jolivet, C., Boulonne, L., Bodineau, G., Saby, N., Grolleau, E., 2002. A new projection in France: a multi-institutional soil quality monitoring network. Comptes Rendus de l'Académie d'Agriculture de France (France).
Aubault, H., Webb, N.P., Strong, C.L., McTainsh, G.H., Leys, J.F., Scanlan, J.C., 2015. Grazing impacts on the susceptibility of rangelands to wind erosion: the effects of stocking rate, stocking strategy and land condition. Aeolian Res. 17, 89–99.
Bahmani, B., Moseley, B., Vattani, A., Kumar, R., Vassilvitskii, S., 2012. Scalable k-means ++. arXiv preprint arXiv:1203.6402.
Bartley, R., Roth, C.H., Ludwig, J., McJannet, D., Liedloff, A., Corfield, J., Hawdon, A., Abbott, B., 2006. Runoff and erosion from Australia's tropical semi-arid rangelands: influence of ground cover for differing space and time scales. Hydrol. Process. 20 (15), 3317–3333.
Boulaine, J., 1969. Sol Pedon et Genon Concepts et definitions. Bull. AFES 5, 7–10.
Calzolari, C., Ungaro, F., Filippi, N., Guermandi, M., Malucelli, F., Marchi, N., Staffilani, F., Tarocco, P., 2016. A methodological framework to assess the multiple contributions of soils to ecosystem services delivery at regional scale. Geoderma 261, 190–203.
Carré, F., Jacobson, M., 2009. Numerical classification of soil profile data using distance metrics. Geoderma 148 (3), 336–345. https://doi.org/10.1016/j.geoderma.2008.11.008.
Clunes, J., Valle, S., Dorner, J., Martinez, O., Pinochet, D., Zuniga, F., Blum, W.E.H., 2022. Soil fragility: a concept to ensure a sustainable use of soils. Ecol. Indic. 139.
Debeljak, M., Trajanov, A., Kuzmanovski, V., Schröder, J., Sandén, T., Spiegel, H., Wall, D.P., Van de Broek, M., Rutgers, M., Bampa, F., Creamer, R.E., Henriksen, C.B., 2019. A field-scale decision support system for assessment and management of soil functions. Front. Environ. Sci. 7.
Dokuchaev, V.V., 1883. Russian Chernozem. Selected works of V.V. Dokuchaev (translated in 1967), 1. Israel Program for Scientific Translations, Jerusalem.
Droogers, P., Bouma, J., 1997. Soil survey input in exploratory modeling of sustainable soil management practices. Soil Sci. Soc. Am. J. 61 (6), 1704–1710.
Ellis, E.C., Gauthier, N., Klein Goldewijk, K., Bliege Bird, R., Boivin, N., Díaz, S., Fuller, D. Q., Gill, J.L., Kaplan, J.O., Kingston, N., Locke, H., McMichael, C.N.H., Ranco, D., Rick, T.C., Shaw, M.R., Stephens, L., Svenning, J.-C., Watson, J.E.M., 2021. People have shaped most of terrestrial nature for at least 12,000 years. Proc. Natl Acad. Sci. 118, e2023483118 https://doi.org/10.1073/pnas.2023483118.
Ellis, E.C., Klein Goldewijk, K., Siebert, S., Lightman, D., Ramankutty, N., 2010. Anthropogenic transformation of the biomes, 1700 to 2000. Global Ecol. Biogeogr. 19 (5), 589–606.
Ellis, E.C., Ramankutty, N., 2008. Putting people in the map: anthropogenic biomes of the world. Front. Ecol. Environ. 6 (8), 439–447.
Ester, M., Kriegel, H.-P., Sander, J., Xu, X., 1996. A density-based algorithm for discovering clusters in large spatial databases with noise. In: Proceedings of the Second International Conference on Knowledge Discovery and Data Mining. AAAI Press, Portland, Oregon, pp. 226–231.
European Commission - Joint Research Centre, 2008. Map for Europe of natural susceptibility of soils to compaction, available from ESDAC.jrc.ec.europa.eu.
Evangelista, S.J., Field, D.J., McBratney, A.B., Minasny, B., Ng, W., Padarian, J., Román Dobarco, M., Wadoux, A.M.J.C., 2023a. A proposal for the assessment of soil security: soil functions, soil services and threats to soil. Soil Secur. 10, 100086.
Evangelista, S.J., Field, D.J., McBratney, A.B., Minasny, B., Ng, W., Padarian, J., Román Dobarco, M., Wadoux, A.M.J.C., 2023b. Soil security –strategising a sustainable future for soil (accepted for publication). Adv. Agron. 183.
Gallant, J., Austin, J., Van Niel, T., 2014. Mean monthly total shortwave radiation on a sloping surface modelled using the 1" DEM-S - 1" mosaic. v2. In: C.D. Collection (Ed.).
Gallant, J.C., Dowling, T.I., 2003. A multiresolution index of valley bottom flatness for mapping depositional areas. Water Resour. Res. 39 (12).
Gallant, J., Wilson, N., Tickle, P.K., Dowling, T., Read, A., 2009. 3 S SRTM derived digital elevation model (DEM) Version 1.0. Record 1.0. Geoscience Australia, Canberra.
Gammage, B., 2011. The Biggest Estate on Earth: How Aborigines made Australia /Bill Gammage. Allen & Unwin, Crows Nest, N.S.W.
Guerra, C.A., Berdugo, M., Eldridge, D.J., Eisenhauer, N., Singh, B.K., Cui, H., Abades, S., Alfaro, F.D., Bamigboye, A.R., Bastida, F., Blanco-Pastor, J.L., de los Ríos, A., Durán, J., Grebenc, T., Illán, J.G., Liu, Y.-R., Makhalanyane, T.P., Mamet, S., Molina-Montenegro, M.A., Moreno, J.L., Mukherjee, A., Nahberger, T.U., Peñaloza-Bojacá, G.F., Plaza, C., Picó, S., Verma, J.P., Rey, A., Rodríguez, A., Tedersoo, L., Teixido, A.L., Torres-Díaz, C., Trivedi, P., Wang, J., Wang, L., Wang, J., Zaady, E., Zhou, X., Zhou, X.-Q., Delgado-Baquerizo, M., 2022. Global hotspots for soil nature conservation. Nature 610 (7933), 693–698.
Guo, Y., Gong, P., Amundson, R., 2003. Pedodiversity in the United States of America. Geoderma 117 (1), 99–115.
Harwood, T., Donohue, R., Harman, I., McVicar, T., Ota, N., Perry, J., Williams, K., 2016a. 9s climatology for continental Australia 1976-2005: summary variables with elevation and radiative adjustment. v3. In: C.D. Collection (Ed.).
Harwood, T.D., Donohue, R.J., Williams, K.J., Ferrier, S., McVicar, T.R., Newell, G., White, M., 2016b. Habitat condition assessment system: a new way to assess the condition of natural habitats for terrestrial biodiversity across whole regions using remote sensing data. Methods Ecol. Evol. 7 (9), 1050–1059.
Harwood, T.D., Williams, K.J., Lehmann, E.A., Ware, C., Lyon, P., Bakar, S., Pinner, L., Schmidt, B., Mokany, K., Van Niel, T.G., Richards, A.E., Dickson, F., McVicar, T.R., Ferrier, S., 2021. 9 arcsecond gridded HCAS 2.1 (2001-2018) base model estimation of habitat condition for terrestrial biodiversity, 18-year trend and 2010-2015 epoch change for continental Australia. In: CSIRO (Ed.), Canberra, Australia.
Huang, J.Y., McBratney, A.B., Malone, B.P., Field, D.J., 2018. Mapping the transition from pre-European settlement to contemporary soil conditions in the Lower Hunter Valley, Australia. Geoderma 329, 27–42. https://doi.org/10.1016/j.geoderma.2018.05.016.
Ibáñez, J.J., De-Alba, S., Lobo, A., Zucarello, V., 1998. Pedodiversity and global soil patterns at coarse scales (with discussion). Geoderma 83 (3), 171–192.
Jacobson, A.P., Riggio, J., Tait, M., E. M, A., Baillie, J., 2019. Global areas of low human impact ('Low Impact Areas') and fragmentation of the natural world. Sci. Rep. 9 (1), 14179.
Jang, H.J., Dobarco, M.R., Minasny, B., Campusano, J.P., McBratney, A., 2023. Assessing human impacts on soil organic carbon change in the Lower Namoi Valley, Australia. Anthropocene 43, 100393.
Jang, H.J., Román Dobarco, M., Minasny, B., McBratney, A., Jones, E., 2022. Developing and testing of pedogenons in the lower Namoi valley, NSW, Australia. Geoderma, 116182.

Jenny, H., 1941. Factors of Soil Formation: A System of Quantitative Pedology. Dover Publications, New York.

Keith, A.M., Griffiths, R.I., Henrys, P.A., Hughes, S., Lebron, I., Maskell, L.C., Ogle, S.M., Robinson, D.A., Rowe, E.C., Smart, S.M., Spurgeon, D., Wood, C.M., Emmett, B.A., 2020. Monitoring soil natural capital and ecosystem services by using large-scale survey data. Soil Ecosyst. Serv. 127–155.

Kennedy, C.M., Oakleaf, J.R., Theobald, D.M., Baruch-Mordo, S., Kiesecker, J., 2019. Managing the middle: a shift in conservation priorities based on the global human modification gradient. Glob. Chang. Biol. 25 (3), 811–826.

Klein Goldewijk, K., Beusen, A., Doelman, J., Stehfest, E., 2017. Anthropogenic land use estimates for the Holocene – HYDE 3.2. Earth Syst. Sci. Data 9 (2), 927–953.

Kuzyakov, Y., Zamanian, K., 2019. Reviews and syntheses: agropedogenesis – humankind as the sixth soil-forming factor and attractors of agricultural soil degradation. Biogeosciences 16 (24), 4783–4803.

Lane, R.J.L., Wynne, P.E., Poudjom Djomani, Y.H., Stratford, W.R., Barretto, J.A., Caratori Tontini, F., 2020. 2019 Australian National Gravity Grids (data set).

Malone, B., Searle, R., 2021. Updating the Australian digital soil texture mapping (Part 2*): spatial modelling of merged field and lab measurements. Soil Res. 59 (5), 435–451.

McBratney, A., 1992. On variation, uncertainty and informatics in environmental soil management. Soil Res. 30 (6), 913–935. https://doi.org/10.1071/SR9920913.

McBratney, A.B., Santos, M.L.M., Minasny, B., 2003. On digital soil mapping. Geoderma 117 (1–2), 3–52.

McInnes, L., Healy, J., Melville, J., 2018. Umap: uniform manifold approximation and projection for dimension reduction. arXiv preprint arXiv:1802.03426.

Nannipieri, P., Ascher, J., Ceccherini, M.T., Landi, L., Pietramellara, G., Renella, G., 2017. Microbial diversity and soil functions. Eur. J. Soil Sci. 68 (1), 12–26.

National Vegetation Information System (NVIS) V6.0 ©, 2023. Australia - pre-1750 major vegetation groups – NVIS Version 6.0 (Albers 100m analysis product). Australian Government Department of Agriculture, Water and the Environment.

Nazari, M., Bickel, S., Arthur, E., Keller, T., Lamandé, M., 2023. Soil vulnerability to logging-associated compaction in forest ecosystems across global climatic zones, EGU General Assembly 2023, Vienna, Austria.

Orgiazzi, A., Panagos, P., Yigini, Y., Dunbar, M.B., Gardi, C., Montanarella, L., Ballabio, C., 2016. A knowledge-based approach to estimating the magnitude and spatial patterns of potential threats to soil biodiversity. Sci. Total Environ. 545–546, 11–20. https://doi.org/10.1016/j.scitotenv.2015.12.092.

Pascoe, B., 2014. Dark emu: Black Seeds: Agriculture or Accident? Magabala Books, Broome, Western Australia. Bruce Pascoe.

Quinn, P., Beven, K., Chevallier, P., Planchon, O., 1991. The prediction of hillslope flow paths for distributed hydrological modeling using digital terrain models. Hydrol. Process. 5 (1), 59–79.

Rabot, E., Guiresse, M., Pittatore, Y., Angelini, M., Keller, C., Lagacherie, P., 2022. Development and spatialisation of a soil potential multifunctionality index for agriculture (Agri-SPMI) at the regional scale. Case study in the Occitanie region (France). Soil Secur. 6, 100034.

Richards, A., Dickson, F., Williams, K., Cook, G., Murphy, H., Roxburgh, S., Doherty, M., Warnick, A., Metcalfe, D., Prober, S., 2020. The Australian Ecosystem Models Framework Project: A conceptual Framework. CSIRO, Australia.

Richter, D.d., Yaalon, D.H., 2012. "The changing model of soil" revisited. Soil Sci. Soc. Am. J. 76 (3), 766–778.

Riggio, J., Baillie, J.E.M., Brumby, S., Ellis, E., Kennedy, C.M., Oakleaf, J.R., Tait, A., Tepe, T., Theobald, D.M., Venter, O., Watson, J.E.M., Jacobson, A.P., 2020. Global human influence maps reveal clear opportunities in conserving Earth's remaining intact terrestrial ecosystems. Glob. Chang. Biol. 26 (8), 4344–4356.

Rillig, M.C., van der Heijden, M.G.A., Berdugo, M., Liu, Y.-R., Riedo, J., Sanz-Lazaro, C., Moreno-Jiménez, E., Romero, F., Tedersoo, L., Delgado-Baquerizo, M., 2023. Increasing the number of stressors reduces soil ecosystem services worldwide. Nat. Clim. Chang. 13, 478–483. https://doi.org/10.1038/s41558-023-01627-2.

Román Dobarco, M., McBratney, A., Minasny, B., Malone, B., 2021a. A framework to assess changes in soil condition and capability over large areas. Soil Secur. 4, 100011.

Román Dobarco, M., McBratney, A., Minasny, B., Malone, B., 2021b. A modelling framework for pedogenon mapping. Geoderma 393, 115012.

Rossiter, D.G., Bouma, J., 2018. A new look at soil phenoforms – definition, identification, mapping. Geoderma 314, 113–121.

Saiz, H., Neuenkamp, L., Penone, C., Birkhofer, K., Bluthgen, N., Boch, S., Bonkowski, M., Buscot, F., Felipe-Lucía, M., Fiore-Donno, A.M., Fischer, M., 2022. Land use intensification results in abrupt transitions between contrasting grassland states. Authorea Preprints. DOI: 10.22541/au.167025017.79918858/v1.

Sanderson, E.W., Jaiteh, M., Levy, M.A., Redford, K.H., Wannebo, A.V., Woolmer, G., 2002. The human footprint and the last of the wild: the human footprint is a global map of human influence on the land surface, which suggests that human beings are stewards of nature, whether we like it or not. Bioscience 52 (10), 891–904.

Soil Survey Staff, 2022. Keys to Soil Taxonomy, 13th ed. USDA-Natural Resources Conservation Service.

Terribile, F., Agrillo, A., Bonfante, A., Buscemi, G., Colandrea, M., D'Antonio, A., De Mascellis, R., De Michele, C., Langella, G., Manna, P., Marotta, L., Mileti, F.A., Minieri, L., Orefice, N., Valentini, S., Vingiani, S., Basile, A., 2015. A web-based spatial decision supporting system for land management and soil conservation. Solid Earth 6 (3), 903–928.

Thackway, R., Lesslie, R., 2006. Reporting vegetation condition using the vegetation assets, States and Transitions (VAST) framework. Ecol. Manag. Restorat. 7 (s1), S53–S62.

Theobald, D.M., Kennedy, C., Chen, B., Oakleaf, J., Baruch-Mordo, S., Kiesecker, J., 2020. Earth transformed: detailed mapping of global human modification from 1990 to 2017. Earth Syst. Sci. Data 12 (3), 1953–1972.

van der Sande, M.T., Powers, J.S., Kuyper, T.W., Norden, N., Salgado-Negret, B., Silva de Almeida, J., Bongers, F., Delgado, D., Dent, D.H., Derroire, G., do Espirito Santo, M. M., Dupuy, J.M., Fernandes, G.W., Finegan, B., Gavito, M.E., Hernández-Stefanoni, J.L., Jakovac, C.C., Jones, I.L., das Dores Magalhães Veloso, M., Meave, J. A., Mora, F., Muñoz, R., Pérez-Cárdenas, N., Piotto, D., Álvarez-Dávila, E., Caceres-Siani, Y., Dalban-Pilon, C., Dourdain, A., Du, D.V., García Villalobos, D., Nunes, Y.R. F., Sanchez-Azofeifa, A., Poorter, L., 2023. Soil resistance and recovery during neotropical forest succession. Philos. Trans. R. Soc. B: Biol. Sci. 378 (1867), 20210074.

Vazquez, C., de Goede, R.G., Rutgers, M., de Koeijer, T.J., Creamer, R.E., 2021. Assessing multifunctionality of agricultural soils: reducing the biodiversity trade-off. Eur. J. Soil Sci. 72 (4), 1624–1639.

Wilford, J., 2012. A weathering intensity index for the Australian continent using airborne gamma-ray spectrometry and digital terrain analysis. Geoderma 183, 124–142.

Wilford, J.R., Kroll, A., 2020. Complete radiometric grid of Australia (Radmap) v4 2019 with modelled infill (data set).

Williams, K.J., Harwood, T.D., Lehmann, E.A., Ware, C., Lyon, P., Bakar, S., Pinner, L., Schmidt, R.K., Mokany, K., Niel, T.G.V., Richards, A.E., Dickson, F., McVicar, T.R., Ferrier, S., 2021. Habitat Condition Assessment System (HCAS Version 2.1): Enhanced Method for Mapping Habitat Condition and Change Across Australia. CSIRO, Canberra, Australia. Technical report EP2021-1200.

Xu, T., Hutchinson, M.F., 2013. New developments and applications in the ANUCLIM spatial climatic and bioclimatic modelling package. Environ. Modell. Softw. 40, 267–279.

Yaalon, D.H., Yaron, B., 1966. Framework for man-made soil changes—an outline of metapedogenesis. Soil Sci. 102 (4), 272–277.