Received: 1 October 2019 | Revised: 25 February 2020 | Accepted: 6 March 2020

DOI: 10.1111/ejss.12958

SPECIAL ISSUE ARTICLE

European Journal of Soil Science WILEY

Soil health cluster analysis based on national monitoring of soil indicators

Fiona M. Seaton[1,2] | **Gaynor Barrett**[1] | **Annette Burden**[1] | **Simon Creer**[3] | **Eleonora Fitos**[1] | **Angus Garbutt**[1] | **Rob I. Griffiths**[1] | **Pete Henrys**[3] | **Davey L. Jones**[2,4] | **Patrick Keenan**[3] | **Aidan Keith**[3] | **Inma Lebron**[1] | **Lindsay Maskell**[3] | **M. Gloria Pereira**[3] | **Sabine Reinsch**[1] | **Simon M. Smart**[3] | **Bronwen Williams**[1] | **Bridget A. Emmett**[1] | **David A. Robinson**[1]

[1]UK Centre for Ecology & Hydrology, Environment Centre Wales, Bangor, UK

[2]School of Natural Sciences, Bangor University, Bangor, UK

[3]UK Centre for Ecology & Hydrology, Lancaster Environment Centre, Lancaster, UK

[4]SoilsWest, UWA School of Agriculture and Environment, The University of Western Australia, Crawley, Western Australia, Australia

Correspondence

Fiona M. Seaton, UK Centre for Ecology & Hydrology, ECW, Deiniol Road, Bangor, United Kingdom.
Email: fiona_seaton@outlook.com

Funding information

Natural Environment Research Council, Grant/Award Numbers: NE/M009106/1, NE/R016429/1; Welsh Government, Grant/Award Number: C147/2010/11

Abstract

A major challenge in soil science is to monitor and understand the state and change of soils at a national scale to inform decision making and policy. To address this, there is a need to identify key parameters for soil health and function and determine how they relate to other parameters, including traditional soil surveys. Here we present a national-scale dataset of topsoil sampled as part of a wider agri-environment monitoring scheme in Wales, UK. Over 1,350 topsoils (0–15 cm) were sampled across a very wide range of habitats and a range of physical, chemical and biological soil quality indicators were measured. We show consistent differences in soil physicochemical properties across habitat types, with carbon decreasing and pH increasing across the habitat productivity gradient from bogs through woodlands and grasslands to arable systems. The soils within our dataset are largely within the limits identified as important for supporting habitat function, with the exception of excessive phosphate levels in mesotrophic grassland. Cluster detection methods identified four soil functional classes based on measured topsoil properties, which were more related to habitat type than the genesis-based soil classification from soil maps. These soil functional classes can be interpreted as phenoforms within the soil genoforms found by traditional soil classification. This shows the importance of land-use management in determining the soil health and functional capacity of soils. Our work provides an account of the current state of soil health in Wales, its relationship to soil function and a baseline for future monitoring to track changes against agri-environment and other policy targets.

Highlights

- We measured soil physicochemical properties in ~1,350 sites in a variety of temperate habitats

- There was a strong gradient in soil carbon and pH, with other variables being correlated with these
- Mesotrophic grassland sites had phosphate levels above the identified limit for good functioning
- Soil classes from topsoil properties were more related to land use than soil map classifications

KEYWORDS

bulk density, carbon, cluster analysis, land use, nitrogen, pH, phenoform, phosphorus, soil health, texture

1 | INTRODUCTION

Soils underpin human existence through food, feed, fibre and timber production, as well as through earth system functions that support the delivery of other ecosystem services. Soil degradation affects 33% of all land globally according to the Intergovernmental Technical Panel on Soils (ITPS) (FAO & ITPS, 2015), and "52 % of the land used for agriculture is moderately or severely affected by soil degradation" as reported in Goal 15 of the United Nations (UN) sustainable development goals. In 2015, the first UN ITPS proposed four urgent actions to tackle and reverse degradation. The fourth was the development of robust soil monitoring systems to determine the current state and trend of soil health. Soil monitoring has become increasingly important in recent years, as nutrient loss, erosion and land-use change have implications not just for agriculture but for human activities as a whole. Land-use change impacts heavily upon soil function (FAO & ITPS, 2015), making integrated surveys for both soils and land management particularly important for understanding the impacts on land-use and climate change. The measurements we report here provide a baseline for the continuing monitoring of soil health and directly align with previous monitoring, allowing greater power to detect anthropogenic impacts on soil health.

Traditionally, soil genesis and development studies have focused on processes occurring on the centennial to millennial timescales (Walker & Syers, 1976). However, there is an increasing recognition of the importance of sub-decadal changes in response to land-use change, pollution and climate drivers (Varallyay, 1990). This in turn is leading to a greater recognition of the importance of soil change and determining the speed of this change (Richter Jr & Markewitz, 2001; Tugel et al., 2005), and, perhaps more importantly, its potential impact on earth system function (Amundson et al., 2015; Schmidt et al., 2011). This shift in thinking has led to a difficulty in integrating traditional methods and results in soil science, which emphasize soil development and classification, with more recent needs for measuring and interpreting change in soil function, which recognize the more urgent need for evidence and action. In addition to traditional pedogenic-based classification (e.g., taxonomy), several approaches to bring together soil classification based upon genesis trajectories and results based on soil functional properties have been proposed. These include the Food and Agriculture Organization (FAO) topsoil classification (Broll et al., 2006), soil varieties within the Genetic Soil Classification of China (Shi et al., 2010), and the genoform – phenoform concept (Droogers & Bouma, 1997; Rossiter & Bouma, 2018). Under the latter, soil classifications are seen as genoforms, which are time-invariant at human timescales (e.g., climate, long-term organisms, or land cover, relief and parent material acting through time). Soils that are sufficiently different within a genoform, and substantially affect soil function and are persistent over time, are classed as phenoforms (e.g., managed properties known to be important in soil function, such as pH and organic carbon). Genoforms act as fundamental controls on soil phenoforms and their function. This enables linkages between soil maps and function to be clearly expressed.

Soil functions are inherent capabilities of the soil that include biomass and food production, maintaining soil biodiversity, carbon and nutrient sequestration, water filtration and transformation, landscape and heritage, and being a source of raw materials (Blum, 2005). In order to track changes in soil functions, functional properties must be defined, which are required for monitoring at the national scale and need to be scalable to large areas and representative of functions across a variety of landscapes (Bünemann et al., 2018). This set of functional properties together represent a way to assess soil health. Here, we define soil functional properties as those that can be managed in a habitat-specific manner and are associated with the above functions. Therefore, we include carbon, pH, bulk density, nitrogen and phosphorus (Van Alphen & Stoorvogel, 2000). Soil carbon, pH, water content and bulk density are the most commonly proposed indicators for soil function due to their impacts on a wide range of soil functions (Bünemann et al., 2018). Bulk density, soil texture and associated water-related properties have been considered to be key indicators for monitoring of physical soil health (Corstanje et al., 2017). Soil carbon and nitrogen are key determinants of various soil functions, including greenhouse gas emissions, biomass production and influencing biological communities, but their exact impacts are often hard to evaluate (Gärdenäs et al., 2011). Other soil properties that have been found to be important in determining soil functions may be system dependent; for example, electrical conductivity and salinity have a large influence on soil functions when at the high levels that are more common in arid or intense arable systems, but are less important in other soil systems.

Wales, the location of our study, has recognized the role of soil in supporting wider ecosystem functions by inclusion of soil carbon as a key sustainability indicator within domestic legislation (Well-being of Future Generations (Wales) Act 2015). As awareness of the role of soils in supporting key ecosystem functions has increased, programmes to monitor and promote soil management have been put in place in various countries (e.g., Orgiazzi, Ballabio, Panagos, Jones, & Fernández-Ugalde, 2018), and in Wales this is integrated within the Glastir agri-environment land management scheme (Rose, 2011). In order to achieve these aims, current soils data are required to monitor changes in soil functions in response to wider ecosystem changes and their downstream effects. Data on soil properties that underlie health and function need to be collected using methods that are transferrable across the range of soils within Wales, but also the UK, Europe and globally, so comparisons can be made at large scales (Ribeiro, Batjes, Leenaars, Van Oostrum, & De Jesus, 2015). Frequency of data collection needs to be sufficient to detect changes within a politically relevant time period to allow for adaptive change of current policies as well as slower changes. The Glastir Monitoring and Evaluation Programme (GMEP) scheme meets these criteria in that it collects data on soil as part of an integrated monitoring programme covering vegetation, soil and water properties using a robust soil sampling methodology that has been used successfully across the variety of soils in Wales (Emmett et al., 2014). The GMEP scheme uses a methodology used in previous surveys in 1978, 1998 and 2007 to also allow for links to historical datasets. The GMEP soil measurements seek to address the need for data to understand the soil state and change at a national scale in order to inform policy.

Two approaches are commonly used to monitor long-term changes in soil properties: (a) localized monitoring of change in response to modifications of soil treatment, often in the form of field-scale manipulation experiments (Jenkinson & Rayner, 1977), and (b) large-scale "soil quality" surveys designed to inform land use and policy (Tóth, Jones, & Montanarella, 2013). Our approach is unique and differs from these in that national soil change and change in areas subject to management interventions are both measured through the same survey design. This enables the evaluation of land-management interventions for policy goals. The survey design is based on a stratified random approach developed for a Great Britain-wide integrated monitoring programme, the UK Centre for Ecology & Hydrology (CEH) Countryside Survey (Carey et al., 2008); an example map of site selection is shown in Figure 1. The soil monitoring programme also includes measurements not reported here relating to factors not routinely measured in large-scale soil surveys, such as a holistic evaluation of soil biodiversity (George et al., 2019). In addition, the survey allows for direct comparison between soil properties and aboveground factors, such as land-use change and plant species composition, as well as stream-water quality, due to the soil and aboveground surveys being co-located and adjacent streams and ponds being sampled. Here, we present results from the first iteration of this monitoring programme, a survey of topsoil (0–15 cm) health across Wales. We use these data to identify clusters of soils with similar topsoil properties and compare these classes with previously mapped soil groups. Our objectives are:

1. To present the topsoil results of a sub-decadal rolling agri-environment monitoring programme by habitat type
2. To determine if pH, Olsen P and bulk density values are within the nationally determined thresholds for habitat support
3. To evaluate the relationships between topsoil functional properties
4. To classify soils based on topsoil properties and compare these classes to land use and traditional soil classification methods

2 | METHODS

2.1 | Field measurement programme

Topsoil measurements were conducted through a 4-year field survey of 300 1-km squares across Wales (Figure 1), half of which are in areas prioritized by the Glastir agri-environment scheme to determine the impact of land management interventions. The 1-km squares were selected at random from 26 land classes in proportion to

FIGURE 1 Map of Wales and the locations of the 300 individual survey squares. Locations are randomly shifted to any point on land within 10 km of the original location to ensure data confidentiality

their extent following the methodology of the UK CEH Countryside Survey (Carey et al., 2008; Reynolds et al., 2013), ensuring good coverage of the Welsh landscape. The initial survey took place over the summers of 2013 to 2016, and it is these results we present here. Each year, ~75 squares were monitored, with each square having five soil sampling sites, each randomly located within a segment of the square. The soil sampling locations are centrally located within a 200-m^2 square quadrat that has a corresponding vegetation survey and habitat assigned by the surveyors according to the UK Biodiversity Action Plan broad habitat classification (Jackson, 2000). The soil cores for physicochemical analysis were taken with a corer of 5 cm diameter down to 15-cm depth after removal of vegetation and removal of any loose litter. The major soil group for each site was taken from the UK National Soil Map of England and Wales (Proctor, Siddons, Jones, Bellamy, & Keay, 1998).

Sites were selected by a random stratified sampling method, with half the squares being selected to provide a representative sample of the major land classes in Wales, whilst the remaining half were weighted towards habitats of particular interest. For the latter, each 1-km square had probability of being selected proportional to the score assigned to it under the Glastir Advanced Scheme by the Welsh Government. Models were used to estimate expected future Glastir scheme outcomes so that adjustments can be made to match Welsh Government priorities (climate change mitigation and water resources in years one and two) and scheme impact can be maximized. The national monitoring programme in Wales has evolved from the Countryside Survey soil sampling approach and methodology (Emmett et al., 2008). In total there are: 20 supralittoral sediment sites, 39 arable sites, 388 improved grassland sites, 300 neutral grassland sites, 205 acid grassland sites, 79 broadleaf sites, 84 conifer sites, 86 heathland sites, 41 bracken sites, 53 fen and other sites, and 92 bog sites. Improved grassland is composed of fast-growing grasses typically managed as pasture or for silage production with the addition of fertiliser and/or lime. Neutral grasslands are usually found on soils with pH 4.5 to 6.5 and lack plants with strong preference for base-rich or acid soils. Acid grassland is characterized by plants with strong preference for acidic soils. Of the 1,387 sites, 1,353 had complete measurements for pH, carbon, nitrogen, total phosphorus and bulk density.

2.2 | Laboratory methods

The analysis of soil variables was performed using the methods employed in the Countryside Survey (Emmett et al., 2008). In addition, soil surface water repellency was measured using the water drop penetration time method as described in Seaton et al. (2019). Details of the methodology are presented within the supporting information, and the full dataset is available from the Environmental Information Data Centre (EIDC) (Robinson et al., 2019).

2.3 | Statistics

The differences in soil physicochemical properties by habitat were examined by providing summary statistics by habitat, counts of number of sites outside nationally determined threshold levels per habitat type, plotting

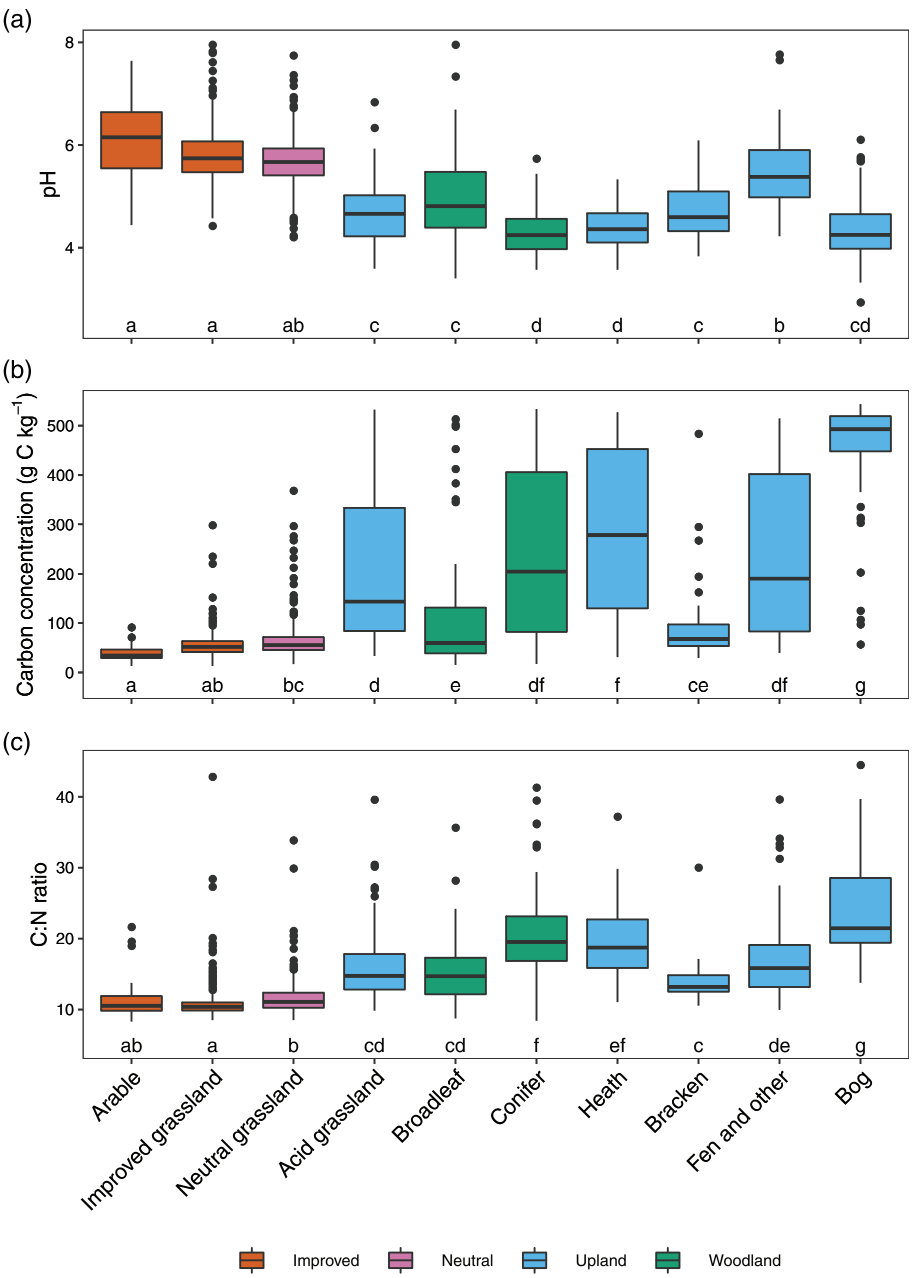


FIGURE 2 Differences in soil pH (a), soil carbon concentration (b) and C:N ratio (c) across the range of habitats found in our study across Wales. Habitats are coloured by which aggregated habitat group they belong to and arranged in decreasing plant productivity order. The line bisecting each box represents the median value, with the box extending to the first and third quartiles of the data. The whiskers extend to the furthest values no more than 1.5 times the interquartile range. Outliers are plotted individually. Habitats that are significantly different from each other are indicated by differing letters below the boxplots (at $p < .05$)

using the ggplot2 and egg packages (Auguie, 2019; Wickham, 2009) and mixed-effect models using the nlme package (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2019). Mixed-effect models were constructed with the square identity used as a random effect to account for spatial autocorrelation. Carbon, C:N, nitrogen, total phosphorus, Olsen P, rock volume and electrical conductivity were log transformed before modelling. Post-hoc comparison of habitats was performed using the emmeans package with Tukey adjustment of p values for significance (Lenth, 2020). The relationships between the different soil properties were examined using Spearman rank correlations. Classification of the soils was undertaken using cluster analysis upon the soil properties considered to affect soil functions, including pH, bulk density, carbon concentration, water content, soil surface water repellency and total nitrogen (N). Soil properties such as total and available phosphorus and electrical conductivity are considered to affect soil function but had such low variation in our dataset that they were not included in this analysis. Soil water repellency was $\log_{10}$-transformed before inclusion. The clusters were fit using hierarchical clustering with Ward's criterion using the hclust function in R and four clusters were selected as the most appropriate divide based on the hierarchical tree (Murtagh & Legendre, 2011). The correlation of the clusters with the habitat groups was calculated using the χ^2 test and the strength of the correlation presented using Crámer's V statistic. All statistical analyses and graphing were performed in R version 3.6.1 (R Core Team, 2019).

3 | RESULTS

3.1 | Soil properties across habitat types

Topsoil pH, carbon and nitrogen concentration vary across the different habitats found in Wales (Figure 2). Arable sites, improved grassland and neutral grassland tend to have the highest pH, lowest carbon concentration and lowest C:N ratios of the habitat types. The majority of all other habitat types have acidic soils (Figure 2a), with fen habitats having a slightly higher pH more similar to neutral grassland than the other habitats. Bog is an important carbon store, with a median carbon concentration of ~490 g C kg^{-1} (carbon stock ~6 kg C m^{-2}), with acid grassland, coniferous woodland, heathland and fen having large ranges in carbon concentration and some sites having around 500 g C kg^{-1} (carbon stock >15 kg C m^{-2}) (Figure 2b). C:N ratios are generally high across the different habitats, particularly in the high carbon habitats (Figure 2). Topsoil total nitrogen follows a similar variation across habitats to soil carbon, although total phosphorus and Olsen P show limited variation with habitat (Figure S1). Bulk density varies considerably across habitat types, being highest in arable sites followed by improved and neutral grasslands and lowest in bogs (Figure S2). Rock volume of soil and electrical conductivity show limited variation across habitat types (Figure S2).

The broad habitats identified by the surveyors were aggregated into four habitat groups (improved land, neutral land, upland and woodland) for ease of interpretation. The ranges of carbon concentration, pH, nitrogen and phosphorus for the habitat groups are presented in Table 1. We do not present results for Olsen P in upland or woodland sites due to its methodological unreliability within low pH soils (Emmett et al., 2010).

The soils were generally highest in silt-sized and sand-sized particles (Figure 3), with the majority being silty clay loam (n = 284) or clay loam (n = 232). There were also 145 sandy silty loams, 69 sandy loams, 19 silty

TABLE 1 Topsoil chemical properties: means ± SD, median, minimum and maximum, carbon concentration estimated from loss-on-ignition (LOI). Phosphorus measured as total phosphorus; Olsen-P results are only presented for improved land and neutral grassland

Habitat groups	Indicator	Unit	Mean	Median	Min	Max
Improved land N = 419	LOI carbon	g/kg dry soil	53.8 ± 25.1	51.3	13.2	300
	Carbon concentration	g/kg dry soil	50.1 ± 27.7	46.1	5.50	313
	pH	Unitless	5.83 ± 0.54	5.75	4.44	7.97
	Nitrogen	g/100 g dry soil	0.45 ± 0.18	0.45	0.02	1.77
	Phosphorus (total P)	g/kg dry soil	113.7 ± 50.9	112.1	9.6	398.2
	Olsen-P	g/kg dry soil	25.1 ± 17.4	19.6	2.22	104
Neutral grassland N = 300	LOI carbon	g/kg dry soil	65.3 ± 41.7	55.2	16.6	370
	Carbon concentration	g/kg dry soil	61.8 ± 43.0	49.6	13.3	370
	pH	Unitless	5.69 ± 0.50	5.67	4.22	7.76
	Nitrogen	g/100 g dry soil	0.52 ± 0.28	0.47	0.11	2.31
	Phosphorus (total P)	g/kg dry soil	100.6 ± 49.7	96.1	16.7	397.0
	Olsen-P	g/kg dry soil	17.2 ± 15.1	12.1	1.11	105
Upland grass and heathland N = 467	LOI carbon	g/kg dry soil	268 ± 181	219	29.6	544
	Carbon concentration	g/kg dry soil	262 ± 1,780	217	24.9	545
	pH	Unitless	4.66 ± 0.64	4.58	2.95	7.78
	Nitrogen	g/100 g dry soil	1.35 ± 0.78	1.27	0.16	3.31
	Phosphorus (total P)	g/kg dry soil	100.0 ± 45.6	92.6	11.5	317.2
Woodland N = 162	LOI carbon	g/kg dry soil	179 ± 166	101	15.0	534
	Carbon concentration	g/kg dry soil	173 ± 163	95.0	10.0	530
	pH	Unitless	4.63 ± 0.77	4.46	3.40	7.97
	Nitrogen	g/100 g dry soil	0.86 ± 0.67	0.58	0.10	2.66
	Phosphorus (total P)	g/kg dry soil	80.0 ± 42.6	72.6	3.0	237.1

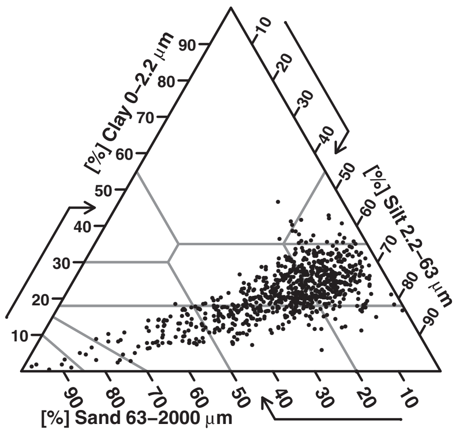


FIGURE 3 The clay, silt and sand percentages of a subset of the soils ($n = 781$) plotted on a ternary diagram

TABLE 2 Number of sites above the UK national guidelines set by the environment agency. For Olsen-P this is 10 mg/L for mesotrophic grassland; no results are presented for acid grassland and heathland. For pH this is <5 and >7 for mesotrophic grassland, >5 for acid grassland and heathland. For bulk density this is above 1.3 g/cm^3 for mesotrophic grassland and 1.0–1.3 g/cm^3 for acid grassland and heath

Habitat	Olsen-P	pH	Bulk density
Mesotrophic grassland	510 sites (75.3%)	39 sites (5.7%)	8 sites (1.2%)
Acid grassland	—	51 (25.6%)	3 (1.5%)
Dwarf shrub heath	—	4 (4.7%)	0 (0%)

clays, 15 silty loams, six loamy sands, six sands, four clays and one sandy clay loam. As the soil texture method involves organic matter removal prior to measurement it was only carried out on samples with lower loss-on-ignition carbon (LOI < 50%), so the carbon-rich soils are not included in these statistics.

3.2 | Thresholds

The majority of our sites are within the pH limits used as a national guideline for representing good support for the ecological habitat and biodiversity within specific habitat types (Bhogal, Boucard, Chambers, Nicholson, & Parkinson, 2008). We compare this to our new analysis of the Countryside Survey topsoil data, which compared the Welsh sites to the same thresholds (Table S1, Reynolds et al., 2013). Within the sites with mesotrophic grassland plant communities (i.e., improved and neutral grasslands), there are only 6% of sites that are outside the recommended pH range of 5–7 (Table 2). Two thirds of these 39 sites are deemed too acidic. This is considerably fewer mesotrophic grassland sites than have been identified as being too acidic in Wales in previous surveys such as the Countryside Survey (Table S1). However, in sites with acid grassland plant communities, 26% of our sites have pH above 5, which is considered to reduce their ability to support their distinct ecological communities (Bhogal et al., 2008). The previous Countryside Survey sites located in Wales found that the proportion of acid grasslands with pH above 5 increased over time from 1978 through 1998 to 2007 (Table S1). Countryside Survey soils in 2007 showed that 24% of acid grasslands had pH above 5, which is comparable to our result. A negligible proportion of our sites had bulk density above the identified threshold; however, the reliability of this threshold of bulk density as an indicator of soil status has yet to be fully tested due to a lack of data (Bhogal et al., 2008). Within mesotrophic grassland the extractable phosphorus (Olsen-P) was higher than the threshold for habitat support in three-quarters of the sites, which is similar to previous surveys (Table 2, Table S1).

3.3 | Relationships between soil variables

Soils across Wales show that soil carbon concentration, bulk density and total nitrogen are highly correlated with each other. The relationship between carbon concentration and bulk density follows the distinctive curved shape found in previous studies of UK soils (Figure 4a) (Emmett et al., 2010; Howard et al., 1995). Total nitrogen follows a positive linear relationship with carbon at low concentrations of carbon, with a gradual levelling off and increasing variance at high carbon concentrations ($R^2 = 0.87$, Figure 4e). High carbon content soils are found solely in conjunction with low pH (Figure 4c).

Plotting the Spearman correlations as a network shows the strong inner cluster of intercorrelated carbon, bulk density and nitrogen, which change in tandem across our sites (correlations ~ ±0.9, Figure 5). Highly correlated with these three are pH, water content and soil water repellency. The rock content of the soil, electrical conductivity and total phosphorus are poorly correlated with the other soil parameters and situated on the edge of the diagram. For the exact correlation values see Table S2.

3.4 | Alternative soil classifications

Using the key soil parameters identified in the previous section (carbon concentration, total nitrogen, bulk

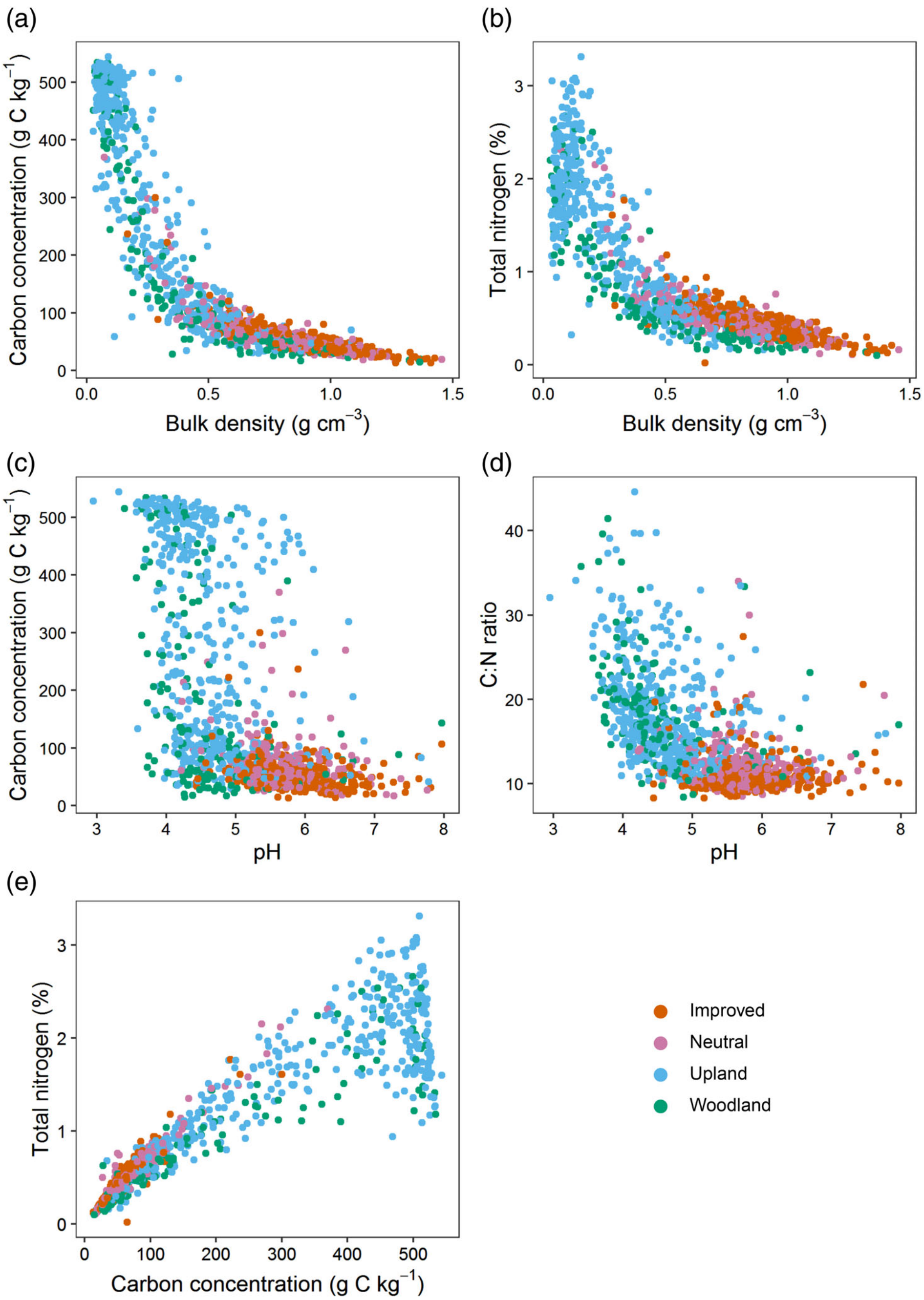


FIGURE 4 The major soil parameters plotted against each other and coloured by habitat group (n = 1,367, 1,363, 1,367, 1,362 and 1,364 for panels (a) to (e), respectively)

density, pH, water content and water repellency) we placed our soils into different categories. The cluster dendrogram from the k-means method of clustering usefully organized the hierarchical patterns of similarity in the dataset. This allowed the most ecologically informative clusters to be identified, striking a compromise between too few with too much internal variance versus too many similar groups, resulting in four approximately equally sized categories (Figure 6). We plotted these soil categories against the properties used to create these clusters and named the categories as organic, organo-mineral, acid mineral and neutral mineral soils (Figure S3, Table S3).

The classification of soils into our categories showed a stronger relationship with the aboveground habitat than the major soil group within the mapped classification by genesis did (Figure 7). Both soil classification systems were significantly associated with the aggregated habitat group (χ^2 test, $p < .001$); however, the relationship between the soil topsoil properties classification and habitat was stronger than the relationship between the soil genesis classification and habitat (Crámer's V was 0.455 and 0.301, respectively). The results for broad habitat were also significant and showed the same pattern of strength. The topsoil properties classification strongly separated out the bog, which was found only in the

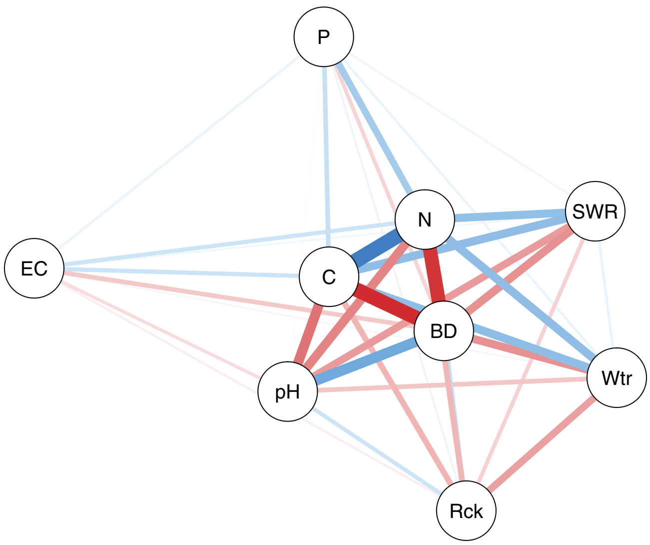


FIGURE 5 The Spearman's rank correlations between the variables plotted as a network. Each circle (node) is a variable and the lines between circles represent the correlation between those two variables across the entire network. The width of the line is proportional to the strength of the correlation and the lines are coloured with blue for positive correlations and red for negative correlations. The layout of the network is selected by an algorithm that attempts to put strongly related variables closer together. The node labels correspond to: BD, bulk density (log); C, carbon concentration; EC, electrical conductivity (log); N, total nitrogen; P, total phosphorus; pH; POI, Olsen-P; Rck, rock volume in soil; SWR, soil water repellency (log); Wtr, volumetric water content

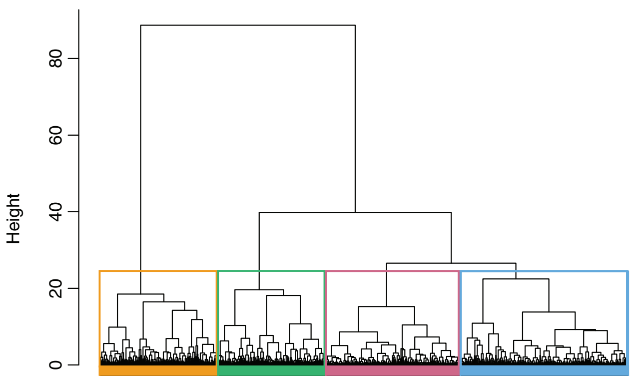


FIGURE 6 The results of the classification algorithm in dendrogram form. The tree diagram is truncated to remove individual data points. The groups identified by visual inspection are surrounded by coloured boxes, with the colours corresponding to the colours used in Figure 7. From left to right: group 1 (308 members, orange: improved grassland), group 2 (280 members, green: woodland), group 3 (350 members, pink: neutral grassland) and group 4 (437 members, blue: upland)

organic class, and the arable site, which was found almost solely on neutral mineral soils. All other habitats showed a definite trend with the topsoil properties classification. Improved and neutral habitats were more likely to be associated with acid and neutral mineral soils, or brown soils in the case of the mapped soil classes. There are differences in the proportions of topsoil properties clusters per each mapped soil unit (χ^2 test, $p < .001$, Crámer's V = 0.356), but every mapped classification had at least one example of every topsoil functional cluster, with limited differences in proportions across the three most numerous mapped soil classes (Figure S4).

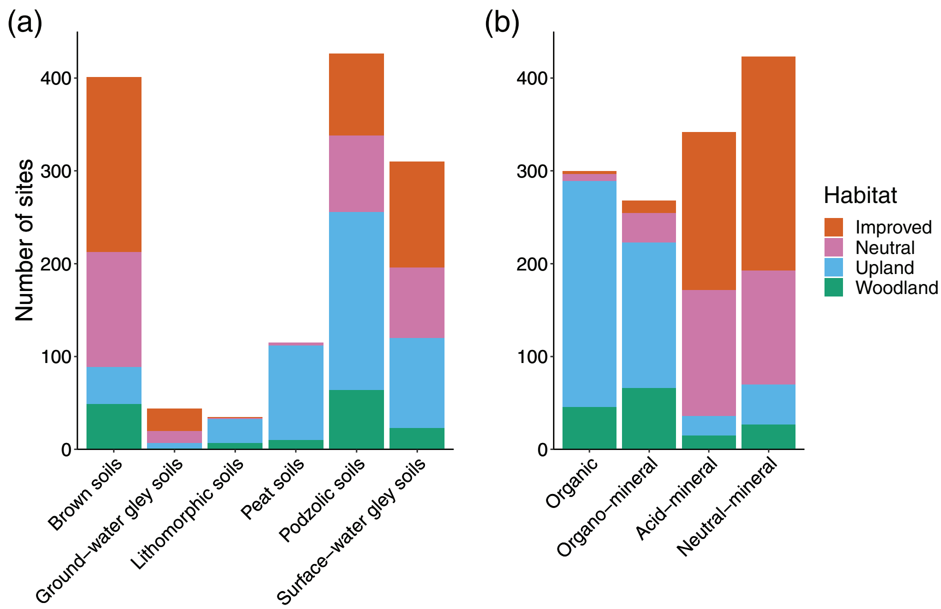
4 | DISCUSSION

4.1 | Key soil parameters status and correlations

The range and distribution of soil physicochemical properties found within this survey are in agreement with previous national-scale surveys of UK soils (Baxter, Oliver, & Archer, 2006; Bellamy, Loveland, Bradley, Lark, & Kirk, 2005; Reynolds et al., 2013). The trend in carbon and pH with habitat showed that arable and improved grassland habitats had the lowest carbon concentration and acidity, with these increasing in the lower productivity habitats such as bogs and heathland. Wales contains many carbon-rich, low-pH soils, which are not always included in other surveys due to their focus on soils of high agricultural production (e.g. Baxter et al., 2006). However, the improved lands included within our survey had pH levels consistent with previous studies of agricultural lands within Wales (Baxter et al., 2006; Reynolds et al., 2013). Compared to the rest of Europe, Welsh soils have on average higher carbon concentration and lower pH; this is also true when only comparing them with the soils from the Atlantic climatic region (Tóth et al., 2013). This may be related to the general dominance of an acid geology and the high precipitation, as globally there is lower pH in areas with greater precipitation, which is thought to be linked to acidity and slower decomposition, thus enabling a build-up of soil organic matter (Slessarev et al., 2016). Our soil texture results also support evidence from the National Soil Survey that Wales is lacking in finer-grained, clay mineral soils compared to the rest of the Atlantic region of Europe (Tóth et al., 2013). All of these properties will contribute to the generally low productivity of many Welsh soils and infrequent presence of arable farming systems.

The relationships between the different soil physicochemical variables are consistent with those found previously in the UK Countryside Survey, especially the strong correlation between carbon concentration and pH and other variables such as total nitrogen and bulk density (Reynolds et al., 2013). The distinctive curved negative association of carbon concentration with bulk density

FIGURE 7 The different habitats distributed across the different soil classification types; classification by genesis (a) and topsoil properties (b)



has been found by many studies across a variety of climatic zones (Emmett et al., 2010; Howard et al., 1995; Périé & Ouimet, 2011). There was limited correlation of total phosphorus, Olsen-P phosphate or electrical conductivity with the other variables in our dataset, which suggests phosphorus supply is not primarily linked to organic matter formation but rather the composition of the soil parent material and potentially in some cases the external supply of phosphorus from fertilisers.

The comparison of our soils to nationally set thresholds enables us to increase our understanding of soil health across Wales in a domain-specific manner. Some thresholds are relatively well established, such as those for pH and extractable phosphorus (i.e., Olsen-P), which have been identified for different environmental interactions and habitat support (Bhogal et al., 2008). Other indicators have been proposed, such as bulk density, soil carbon and C:N ratio, but often there is limited evidence and/or consistency across ecosystems in the impact of these (Bhogal et al., 2008). Bulk density, together with clay content, has been proposed as a soil quality indicator for British soils in relation to trends over time, rather than passing a pre-identified threshold (Corstanje et al., 2017). We have limited sites at the higher levels of bulk density, which makes it difficult to evaluate the threshold value, and overall there was little correlation between bulk density and soil biological indicators such as total mesofauna (George et al., 2017). Bulk density within our data strongly correlated with soil carbon, which may suggest that in these types of soil systems bulk density and carbon represent the same aspects of soil health. Instead of a single threshold, it has been suggested that evidence of decreasing soil carbon acts as a trigger value, in particular due to its relevance to carbon storage and biogeochemical cycling. The continuation of this survey in the coming years will allow clear identification of any habitats that may be losing carbon and thus should be targeted for land management interventions. Past surveys for Wales using the same methodology and some common locations in the Countryside Survey did not identify any consistent trends in C concentration or density between 1978, 1998 and 2007 (Reynolds et al., 2013). Other survey and modelling approaches have suggested soils for the UK are on average losing carbon (Bellamy et al., 2005; Jenkinson, Adams, & Wild, 1991; Jones et al., 2005) or are remaining stable (Reynolds et al., 2013; Smith et al., 2005). However, trends appear to be highly specific to land-use types (e.g. soil C loss in arable soils but gains in woodland soils) (Reynolds et al., 2013) and thus country-level trends perhaps mask important trends linked to specific management practices within land-use type. It is important to note also that this survey does not measure changes in subsoil carbon, which is critical for carbon storage and likely to be less influenced by land use than topsoil carbon, limiting the inferences that can be made about the overall soil carbon stock and changes (Harrison, Footen, & Strahm, 2011; Simo, Schulte, O'Sullivan, & Creamer, 2019).

We have found that three-quarters of our mesotrophic grassland sites with Olsen-P were above the trigger value related to habitat support, which is similar to the 60% and 90% of mesotrophic sites that we found to be above the trigger value in the Countryside Survey in 2007 and 1998, respectively. Globally, phosphate decreases in grasslands have been predicted from model data (Sattari, Bouwman, Martinez Rodríguez, Beusen, & van Ittersum,

2016) and have been previously reported in Wales from Countryside Survey data (DeLuca et al., 2015; Reynolds et al., 2013). This is linked to the 60% reduction in use of P fertilisers in the UK from the 1980s to 2010, which has since stabilized (The British Survey of Fertiliser Practice, 2019), and could be expected to have an impact across the landscape even on unimproved land due to reduced transfer of phosphate by hydrological or atmospheric pathways. Reduced grazing could be decreasing the removal of phosphate by preferential grazing on phosphorus-enriched areas and thus reducing its diversion away from grazing sites (Schütz et al., 2006; Statistics for Wales, 2016). High levels of phosphate have been linked to lower plant diversity (Critchley et al., 2002; Michalcová, Gilbert, Lawson, Gowing, & Marrs, 2011). Moreover, elevated phosphate levels can persist in the soil for long periods and have lasting impacts on the plant communities that can establish at a site (Horrocks et al., 2016).

The current proportion of sites that are outside the pH thresholds is comparable to the most recent surveys of the Welsh countryside by the Countryside Survey in 2007, which shows markedly less acidity overall than surveys within 1978 and 1998 (Reynolds et al., 2013). This can be interpreted as stabilization rather than continued recovery from historic acidification due to atmospheric acid deposition. This does not necessarily mean that Welsh soils are fully recovered from acidification, as there are some indications from model data that recovery from acidification is not yet complete (RoTAP, 2012). The stalling of recovery from acidification could indicate that the soils have entered into a lower pH stable state (Suding, Gross, & Houseman, 2004); thus, to enhance productivity some soils may require active remediation to return to pre-acidification pH. Similar results showing reductions in recovery from acidification are reported for woodland and other organic soils (Evans, Monteith, Reynolds, & Clark, 2008; Kirk, Bellamy, & Lark, 2010; Reynolds et al., 2013), and are attributed to vegetation uptake of base cations, nitrogen deposition or capture of acidic pollutants by the woodland canopy, which offsets SO_2 reductions. This does, however, raise the issue as to whether the assumption that a pH of less than 5 is required for habitat support in acid grassland and dwarf shrub heath will hold, as the impacts of anthropogenic acidification are reduced and soil pH values increase across the UK. The shifting baseline in soil pH may be altering our perception of what constitutes a good pH value for an acid grassland (Soga & Gaston, 2018). The thresholds for pH were established based largely on data from UK grasslands in the 1990s (Bhogal et al., 2008), which would represent sites that are in the process of recovery from intense acidification and therefore may not actually be similar to a true natural state. The pH trigger values for supporting metal retention and microbial function are actually contradictory to those suggested for supporting acid grassland and heathland habitats (<5 and >5, respectively), and recent results indicate microbial function may decrease below pH 5.5 rather than 5, exacerbating this difference (Jones, Cooledge, Hoyle, Griffiths, & Murphy, 2019). This shows the difficulties in designating appropriate boundaries when multiple functions and services are involved, especially when the different functions show differing responsiveness to change (Bhogal et al., 2008; Bünemann et al., 2018; Jarvis et al., 2019).

4.2 | Soil classification

The soil physicochemical clusters identified in this work have strong similarities with previous analysis of UK soils. Analysis of the soils collected as part of the Countryside Survey of the UK in 2007 found that there were three main clusters of soil physicochemical properties corresponding to mineral soils, organo-mineral soils and organic soils (Simfukwe et al., 2010). In our data we split the mineral soils into two groups; however, in other respects our classifications are similar. These results support the use of soil organic material in categorizing soils, as evidenced by the use of carbon classifications within multiple classification systems (Broll et al., 2006; Emmett et al., 2010).

Our analysis has shown that, as we hypothesized, the traditional soil classification methods, such as that used within the UK soil classification (Avery, 1980), are weakly correlated with differences in habitat type and land use, whereas those based on key topsoil manageable parameters are more strongly related. This is consistent with previous results showing that soil dissolved organic carbon is not well related to soil type in UK soils (Simfukwe, Hill, Emmett, & Jones, 2011). We have also found that there seems to be only a limited relationship between our identified topsoil class and the traditional classification, with the exception of peat soils. This suggests that there may be limited constraints from the soil genesis type upon the functional nature of the topsoil, indicating the importance of management decisions in determining soil function. The functional capacity of the subsoil, however, may be more constrained by the soil genesis type than land cover. Therefore, soil functions that are dominated by different soil horizons may have been influenced more or less strongly by the plant community versus the soil genesis type. One key limitation of this analysis is that the soil classification by genesis was taken from a map based largely on data collected from 1960 to 1970, which fails to capture changes in soil management and land use that have occurred since then. In addition, our survey locations were classified at the soil association rather than series level. Soil surveying to classify soil genesis is time consuming and labour intensive, often making funding of large-scale soil surveys unattractive. In practice, many key survey and modelling results are either based on previous soil mapping efforts or on topsoil sampling only, which is what we have compared here to land cover. Many ecosystem service maps use the soil classification maps, when actually soil function is more related to the plant communities and land-cover type.

The soil properties we have presented here are a selection of properties that are known to influence soil function and are both manageable and measurable at a national level. The soil properties that are often measured in the scientific literature to represent function (e.g., carbon mineralization rates) (Simfukwe et al., 2011) are usually difficult to scale up to large areas due to factors such as expense and limited generality across landscapes (Sanchez, Palm, & Buol, 2003). Many of these properties can also be only measured in a laboratory environment on highly processed soils, which means that they can fail to capture the conditions as they really exist, particularly the role of plants in regulating soil functioning (Carlyle, Nambiar, & Bligh, 1998; Oburger & Jones, 2009). Different functions can also respond differently to the soil properties considered here and even soil biodiversity can be represented by different aspects with different responses. For example, in our sites microbial diversity is highest in our habitats with high pH and low carbon (George et al., 2019), whereas mesofaunal abundance is highest in habitats with more intermediate pH and carbon (George et al., 2017). However, some properties, such as soil carbon, have been widely accepted to be indicators of soil function, influencing greenhouse gas emission, nutrient cycling, water filtration and biomass production, among others (Amundson et al., 2015; Bünemann et al., 2018; Environment Audit Committee, 2016; Rossiter & Bouma, 2018). It is these parameters – pH, carbon, nitrogen, bulk density and water – that we have found to be pivotal in determining the topsoil property classes of our Welsh soils; therefore, we term them functional clusters.

The clusters we have found behave differently in their functional attributes, reflecting their different land management regimes. The key functional attributes of soil vary depending upon their pedogenic characteristics and the overlying land use. We see the classes proposed by our analysis as a way of reducing complexity to enable comparison of like-for-like, and consequently, we do not apply the principles of functionality derived from lowland arable soils to upland peatlands. This comparison of appropriate classifications is particularly relevant for determining policy at the national scale, when balancing the need for provision of multiple functions across a heterogeneous landscape. There is no way to tell within our data whether differences in areas targeted for agri-environment interventions are due to the scheme or pre-existing conditions, and thus we have not evaluated that here. However, the dataset presented here offers an understanding of the current state of soil health in Wales that can be used as a baseline for future surveying to evaluate the response of soil health and function to land management interventions. The differences in soil health and function across habitats we have found show the importance of land management to soil function.

There have been objections to the principle of classifying soils into strictly defined categories since the advent of soil classification systems (Webster, 1968). In response, many authors have chosen to use fuzzy mathematical methods to classify soils (Burrough, 1989; Mazaheri, Koppi, & McBratney, 1995; Stevenson, McNeill, & Hewitt, 2015). This can allow any given soil to belong to more than one class, potentially better capturing the range of soils between different classes than the artificially abrupt boundaries between classes in a hierarchical classification system. Soils generally exist on a continuum in trait space, exhibiting different characteristics across a variety of landscapes. They can also change over time and under different management practices, particularly those already at the edge of the categorization boundaries. Results such as ours, which find certain categories of soils based on their properties, should be interpreted within this context. Although categorization is a useful tool for informing management and monitoring, it cannot represent the full breadth and flexibility of soil types.

The clusters of soils we have identified can be aligned to the phenoform concept, where the phenoforms are the functional clusters, which can be nested within the genoforms (i.e., the mapped soil classes by genesis). However, we have found that the genoform poses no major constraint upon the types of phenoform that can develop there, which suggests the nested nature of the genoform-phenoform concept may be an unnecessary complication in practice, at least with respect to topsoil. One issue with the comparison of our results to the genoform-phenoform concept is that the phenoform definition considers only soil properties that are persistent and require substantial management change to alter (Rossiter & Bouma, 2018). The properties often identified as being key to functional classification, such as carbon and pH, are experiencing ongoing change and are the target of key initiatives such as the 4 per mille initiative, which aims to increase global soil organic matter stocks by 0.4% per year (Minasny et al., 2017). There is a conflict in the application of the phenoform concept that hinges on the identification of what constitutes "substantial" management. This conflict reaches its peak when considering changes over time. If we were now to find that the 4 per mille initiative was successful then this would constitute enough change to alter the phenoform of all of our soils. But if all change in tandem, as occurred with the recovery from acidification in UK soils (Reynolds et al., 2013), then new attempts to define phenoforms on the basis of cluster analysis of soil properties will not show these changes and find the same phenoforms again. It may be unlikely that different areas will respond in tandem to external changes due to differences in the application of these changes, the inherent differences in responsiveness of different habitats, and the non-linearities of change directions as indicated in the fundamentally different direction of soil carbon losses within different land-use types reported by Reynolds et al. (2013). However, the direction and magnitude of change within soils is a key constraint on the application of the phenoform concept that requires further investigation. The value of repeated soil monitoring in establishing any trends in the health and presence of phenoforms cannot be overstated, as soil health is dynamic at management-relevant timescales.

5 | CONCLUSIONS

We present a national dataset, which provides a baseline for the survey of Welsh topsoils (0–15 cm), allowing for the quantification of the current health of the soil and enabling future surveys to track trends in these conditions. We show that there are consistent differences in soil properties across habitats. Few of our soils are outside established thresholds of pH and bulk density for ecosystem health, but high levels of phosphate in improved grasslands remain an issue. Several key soil properties, such as carbon, nitrogen and pH, are strongly correlated across our soils and can be used to create a classification of the soils. We propose that our conceptual classification of the topsoil is related to soil functionality, due to the known relationships between the key soil properties featured here and soil functions. Consequently, the functional classification of the topsoil developed in the present analysis is more related to land-use type than soil classes based on traditional methods.

ACKNOWLEDGEMENTS

We thank all the GMEP team who contributed to collecting all the data. The research was funded by the Welsh Government through the Glastir Monitoring and Evaluation Program (GMEP) with underpinning funding from the Natural Environment Research Council award number NE/R016429/1 as part of the UK – ScaPE Programme Delivering National Capability. Contract reference: C147/2010/11. NERC/Centre for Ecology & Hydrology (CEH Projects: NEC04780/NEC05371/NEC05782). F.M.S. is supported by the award of a studentship grant by the NERC and BBSRC funded STARS (Soils Training And Research Studentships) Centre for Doctoral Training and Research Programme; a consortium consisting of Bangor University, the British Geological Survey, the Centre for Ecology and Hydrology, Cranfield University, the James Hutton Institute, Lancaster University, Rothamsted Research and the University of Nottingham. Grant Ref: NE/M009106/1.

AUTHOR CONTRIBUTIONS

Study concept and design: B.A.E., P.H. and D.A.R. Field survey implementation: B.W., A.B., A.G., L.M., A.K., E.F. and S.M.S. Laboratory analyses: G.B., M.G.P., P.K. and I.L. Analysis and interpretation of data: F.M.S., S.R., S.M.S., D.L.J., D.A.R. and S.C. Drafting of the manuscript: F.M.S. Critical revision of the manuscript for important intellectual content: D.A.R., S.R., D.L.J., G.B., S.M.S., R.I.G. and S.C. Statistical analysis: F.M.S. Obtained funding: B.A.E. Study supervision: D.A.R. and B.A.E.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the Environmental Information Data Centre at http://doi.org/10.5285/0fa51dc6-1537-4ad6-9d06-e476c137ed09 (Robinson et al., 2019).

ORCID

Fiona M. Seaton https://orcid.org/0000-0002-2022-7451

REFERENCES

Amundson, R., Berhe, A. A., Hopmans, J. W., Olson, C., Sztein, A. E., & Sparks, D. L. (2015). Soil and human security in the 21st century. *Science*, *348*(6235), 1261071. https://doi.org/10.1126/science.1261071

Auguie, B. (2019). *Egg: Extensions for "ggplot2": Custom geom, custom themes, plot alignment, labelled panels, symmetric scales and fixed panel size*. R package version 0.4.5. https://CRAN.R-project.org/package=egg

Avery, B. W. (1980). *Soil classification for England and Wales: Higher categories*. Harpenden: Rothamsted Experimental Station.

Baxter, S. J., Oliver, M. A., & Archer, J. R. (2006). The representative soil sampling scheme of England and Wales: The spatial variation of topsoil nutrient status and pH between 1971 and 2001. *Soil Use and Management*, *22*(4), 383–392. https://doi.org/10.1111/j.1475-2743.2006.00047.x

Bellamy, P. H., Loveland, P. J., Bradley, R. I., Lark, R. M., & Kirk, G. J. D. (2005). Carbon losses from all soils across England and Wales 1978-2003. *Nature*, *437*(7056), 245–248. https://doi.org/10.1038/nature04038

Bhogal, A., Boucard, T., Chambers, B. J., Nicholson, F. A., & Parkinson, R. (2008). Road testing of 'trigger values' for assessing site specific soil quality. Phase 2 – other soil quality indicators. Science Rep. SC050054SR2. pp 59.

Blum, W. E. H. (2005). Functions of soil for society and the environment. *Reviews in Environmental Science and Bio/Technology*, *4* (3), 75–79. https://doi.org/10.1007/s11157-005-2236-x

Broll, G., Brauckmann, H.-J., Overesch, M., Junge, B., Erber, C., Milbert, G., ... Nachtergaele, F. (2006). Topsoil characterization - recommendations for revision and expansion of the FAO-Draft (1998) with emphasis on humus forms and biological features. *Journal of Plant Nutrition and Soil Science*, *169*(3), 453–461. https://doi.org/10.1002/jpln.200521961

Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R. E., De Deyn, G., de Goede, R., ... Brussaard, L. (2018). Soil quality – a critical review. *Soil Biology and Biochemistry*, *120*, 105–125. https://doi.org/10.1016/j.soilbio.2018.01.030

Burrough, P. A. (1989). Fuzzy mathematical methods for soil survey and land evaluation. *Journal of Soil Science*, *40*(3), 477–492. https://doi.org/10.1111/j.1365-2389.1989.tb01290.x

Carey, P. D., Wallis, S., Chamberlain, P. M., Cooper, A., Emmett, B. A., Maskell, L. C., ... Ullyett, J. M. (2008). *Countryside survey: UK results from 2007*. Lancaster: NERC/Centre for Ecology & Hydrology.

Carlyle, J. C., Nambiar, E. S., & Bligh, M. W. (1998). The use of laboratory measurements to predict nitrogen mineralization and nitrification in *Pinus radiata* plantations after harvesting. *Canadian Journal of Forest Research*, *28*(8), 1213–1221. https://doi.org/10.1139/x98-091

Core Team, R. (2019). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.

Corstanje, R., Mercer, T. G., Rickson, J. R., Deeks, L. K., Newell-Price, P., Holman, I., ... Waine, T. W. (2017). Physical soil quality indicators for monitoring British soils. *Solid Earth Discuss*, *8* (5), 1003–1016. https://doi.org/10.5194/se-8-1003-2017

Critchley, C. N. R., Chambers, B. J., Fowbert, J. A., Sanderson, R. A., Bhogal, A., & Rose, S. C. (2002). Association between lowland grassland plant communities and soil properties. *Biological Conservation*, *105*(2), 199–215. https://doi.org/10.1016/S0006-3207(01)00183-5

DeLuca, T. H., Glanville, H. C., Harris, M., Emmett, B. A., Pingree, M. R. A., de Sosa, L. L., ... Jones, D. L. (2015). A novel biologically-based approach to evaluating soil phosphorus availability across complex landscapes. *Soil Biology and Biochemistry*, *88*, 110–119. https://doi.org/10.1016/j.soilbio.2015.05.016

Droogers, P., & Bouma, J. (1997). Soil survey input in exploratory modeling of sustainable soil management practices. *Soil Science Society of America Journal*, *61*(6), 1704–1710. https://doi.org/10.2136/sssaj1997.03615995006100060023x

Emmett, B. A., Abdalla, M., Anthony, S., Astbury, S., August, T., Barrett, G., ... Wright, S. (2014). *Glastir monitoring & evaluation programme. First year annual report to Welsh government (contract reference: C147/2010/11)*. NERC/Centre for Ecology & Hydrology (CEH project: NEC04780). Lancaster: NERC/Centre for Ecology & Hydrology.

Emmett, B. A., Frogbrook, Z. L., Chamberlain, P. M., Griffiths, R., Pickup, R., Poskitt, J., ... Wood, C. M. (2008). Countryside survey. Tech. Rep. No. 03/07.

Emmett, B. A., Reynolds, B., Chamberlain, P. M., Rowe, E., Spurgeon, D., Brittain, S. A., ... Woods, C. (2010). Countryside survey: Soils report from 2007.

Environment Audit Committee. (2016). *Soil health*. HC 180 2016–2017. England: Stationery Office.

Evans, C. D., Monteith, D. T., Reynolds, B., & Clark, J. M. (2008). Buffering of recovery from acidification by organic acids. *Science of the Total Environment*, *404*(2–3), 316–325. https://doi.org/10.1016/j.scitotenv.2007.11.003

FAO & ITPS. (2015). *Status of the world's soil resources (SWSR) - main report*. Rome, Italy: Food and Agriculture Organization of the United Nations and Intergovernmental Technical Panel on Soils.

Gärdenäs, A. I., Ågren, G. I., Bird, J. A., Clarholm, M., Hallin, S., Ineson, P., ... Stendahl, J. (2011). Knowledge gaps in soil carbon and nitrogen interactions – from molecular to global scale. *Soil Biology and Biochemistry*, *43*(4), 702–717. https://doi.org/10.1016/j.soilbio.2010.04.006

George, P. B. L., Keith, A. M., Creer, S., Barrett, G. L., Lebron, I., Emmett, B. A., ... Jones, D. L. (2017). Evaluation of mesofauna communities as soil quality indicators in a national-level monitoring programme. *Soil Biology and Biochemistry*, *115*, 537–546. https://doi.org/10.1016/j.soilbio.2017.09.022

George, P. B. L., Lallias, D., Creer, S., Seaton, F. M., Kenny, J. G., Eccles, R. M., ... Jones, D. L. (2019). Divergent national-scale trends of microbial and animal biodiversity revealed across diverse temperate soil ecosystems. *Nature Communications*, *10* (1), 1107. https://doi.org/10.1038/s41467-019-09031-1

Harrison, R. B., Footen, P. W., & Strahm, B. D. (2011). Deep soil horizons: Contribution and importance to soil carbon pools and in assessing whole-ecosystem response to management and global change. *Forest Science*, *57*(1), 67–76.

Horrocks, C. A., Heal, K. V., Harvie, B., Tallowin, J. B., Cardenas, L. M., & Dungait, J. A. J. (2016). Can species-rich grasslands be established on former intensively managed arable soils? *Agriculture, Ecosystems & Environment*, *217*, 59–67. https://doi.org/10.1016/j.agee.2015.10.015

Howard, P. J. A., Loveland, P. J., Bradley, R. I., Dry, F. T., Howard, D. M., & Howard, D. C. (1995). The carbon content of soil and its geographical distribution in Great Britain. *Soil Use and Management*, *11*(1), 9–15. https://doi.org/10.1111/j.1475-2743.1995.tb00488.x

Jackson, D. L. (2000). *Guidance on the interpretation of the Biodiversity Broad Habitat Classification (terrestrial and freshwater types): Definitions and the relationships with other classifications, JNCC Report 307*. England: JNCC.

Jarvis, S. G., Henrys, P. A., Keith, A. M., Mackay, E., Ward, S. E., & Smart, S. M. (2019). Model-based hypervolumes for complex ecological data. *Ecology*, *100*(5), e02676. https://doi.org/10.1002/ecy.2676

Jenkinson, D. S., Adams, D. E., & Wild, A. (1991). Model estimates of CO_2 emissions from soil in response to global warming. *Nature*, *351*(6324), 304–306. https://doi.org/10.1038/351304a0

Jenkinson, D. S., & Rayner, J. H. (1977). The turnover of soil organic matter in some of the Rothamsted classical experiments. *Soil Science*, *123*(5), 298–305.

Jones, C., McConnell, C., Coleman, K., Cox, P., Falloon, P., Jenkinson, D., & Powlson, D. (2005). Global climate change and soil carbon stocks; predictions from two contrasting models for the turnover of organic carbon in soil. *Global Change Biology*, *11*(1), 154–166. https://doi.org/10.1111/j.1365-2486.2004.00885.x

Jones, D. L., Cooledge, E. C., Hoyle, F. C., Griffiths, R. I., & Murphy, D. V. (2019). pH and exchangeable aluminum are major regulators of microbial energy flow and carbon use efficiency in soil microbial communities. *Soil Biology and Biochemistry*, *138*, 107584. https://doi.org/10.1016/j.soilbio.2019.107584

Kirk, G. J. D., Bellamy, P. H., & Lark, R. M. (2010). Changes in soil pH across England and Wales in response to decreased acid deposition. *Global Change Biology*, *16*(11), 3111–3119. https://doi.org/10.1111/j.1365-2486.2009.02135.x

Lenth, R. (2020). Emmeans: Estimated marginal means, aka least-squares means. R package version 1.4.4. https://CRAN.R-project.org/package=emmeans

Mazaheri, S. A., Koppi, A. J., & McBratney, A. B. (1995). A fuzzy allocation scheme for the Australian Great Soil Groups classification system. *European Journal of Soil Science*, *46*(4), 601–612. https://doi.org/10.1111/j.1365-2389.1995.tb01356.x

Michalcová, D., Gilbert, J. C., Lawson, C. S., Gowing, D. J. G., & Marrs, R. H. (2011). The combined effect of waterlogging, extractable P and soil pH on α-diversity: A case study on mesotrophic grasslands in the UK. *Plant Ecology*, *212*(5), 879–888. https://doi.org/10.1007/s11258-010-9871-1

Minasny, B., Malone, B. P., McBratney, A. B., Angers, D. A., Arrouays, D., Chambers, A., … Winowiecki, L. (2017). Soil carbon 4 per mille. *Geoderma*, *292*, 59–86. https://doi.org/10.1016/j.geoderma.2017.01.002

Murtagh, F., & Legendre, P. (2011). Ward's hierarchical clustering method: Clustering criterion and agglomerative algorithm. *Journal of Classification*, *31*(October), 274–295. https://doi.org/10.1007/s00357-014-9161-z

Oburger, E., & Jones, D. L. (2009). Substrate mineralization studies in the laboratory show different microbial C partitioning dynamics than in the field. *Soil Biology and Biochemistry*, *41*(9), 1951–1956. https://doi.org/10.1016/j.soilbio.2009.06.020

Orgiazzi, A., Ballabio, C., Panagos, P., Jones, A., & Fernández-Ugalde, O. (2018). LUCAS soil, the largest expandable soil dataset for Europe: A review. *European Journal of Soil Science*, *69*(1), 140–153. https://doi.org/10.1111/ejss.12499

Périé, C., & Ouimet, R. (2011). Organic carbon, organic matter and bulk density relationships in boreal forest soils. *Canadian Journal of Soil Science*, *88*(3), 315–325. https://doi.org/10.4141/cjss06008

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & R Core Team (2019). Nlme: Linear and nonlinear mixed effects models. R package version 3.1–142. https://CRAN.R-project.org/package=nlme

Proctor, M. E., Siddons, P. A., Jones, R. J. A., Bellamy, P. H., & Keay, C. A. (1998). LandIS - a land information system for the UK. In *Developments for planning the sustainable use of land resources: Land Information Systems. European Soil Bureau Research Report 4*. Luxembourg: Office for Official Publications of the European Communities.

Reynolds, B., Chamberlain, P. M., Poskitt, J., Woods, C., Scott, W. a., Rowe, E. C., … Emmett, B. a. (2013). Countryside survey: National "soil change" 1978–2007 for topsoils in Great Britain—acidity, carbon, and total nitrogen status. *Vadose Zone Journal*, *12*(2), 1–15. https://doi.org/10.2136/vzj2012.0114

Ribeiro, E., Batjes, N. H., Leenaars, J. G. B., van Oostrum, A., & de Jesus, J. M. (2015). *Towards the standardization and harmonization of world soil data: Procedures manual ISRIC World Soil Information Service (WoSIS version 2.0)*. Wageningen: ISRIC - World Soil Information.

Richter, D. D., Jr., & Markewitz, D. (2001). *Understanding soil change: Soil sustainability over millennia, centuries, and decades*. Cambridge: Cambridge University Press.

Robinson, D. A., Astbury, S., Barrett, G., Burden, A., Carter, H., Emmett, B. A., … Wood, C. (2019). *Topsoil physico-chemical properties from the Glastir Monitoring and Evaluation Programme, Wales 2013–2016*. England: NERC Environmental Information Data Centre. https://doi.org/10.5285/0fa51dc6-1537-4ad6-9d06-e476c137ed09

Rose, H. (2011). *An introduction to Glastir and other UK agri-environment schemes*. Cardiff: Members Research Service, National Assembly for Wales.

Rossiter, D. G., & Bouma, J. (2018). A new look at soil phenoforms – definition, identification, mapping. *Geoderma*, *314*, 113–121. https://doi.org/10.1016/j.geoderma.2017.11.002

RoTAP. (2012). *Review of transboundary air pollution: Acidification, eutrophication, ground level ozone and heavy metals in the UK. Contract report to the Department for Environment, Food and Rural Affairs*. England: Centre for Ecology & Hydrology.

Sanchez, P. A., Palm, C. A., & Buol, S. W. (2003). Fertility capability soil classification: A tool to help assess soil quality in the tropics. *Geoderma*, *114*(3–4), 157–185. https://doi.org/10.1016/S0016-7061(03)00040-5

Sattari, S. Z., Bouwman, A. F., Martinez Rodríguez, R., Beusen, A. H. W., & van Ittersum, M. K. (2016). Negative global phosphorus budgets challenge sustainable intensification of grasslands. *Nature Communications*, *7*(1), 10696. https://doi.org/10.1038/ncomms10696

Schmidt, M. W. I., Torn, M. S., Abiven, S., Dittmar, T., Guggenberger, G., Janssens, I. A., … Trumbore, S. E. (2011). Persistence of soil organic matter as an ecosystem property. *Nature*, *478*(7367), 49–56. https://doi.org/10.1038/nature10386

Schütz, M., Risch, A. C., Achermann, G., Thiel-Egenter, C., Page-Dumroese, D. S., Jurgensen, M. F., & Edwards, P. J. (2006). Phosphorus translocation by red deer on a subalpine grassland in the central European alps. *Ecosystems*, *9*(4), 624–633. https://doi.org/10.1007/s10021-006-0091-4

Seaton, F. M., Jones, D. L., Creer, S., George, P. B. L., Smart, S. M., Lebron, I., … Robinson, D. A. (2019). Plant and soil communities are associated with the response of soil water repellency to environmental stress. *Science of the Total Environment*, *687*, 929–938. https://doi.org/10.1016/j.scitotenv.2019.06.052

Shi, X. Z., Yu, D. S., Xu, S. X., Warner, E. D., Wang, H. J., Sun, W. X., … Gong, Z. T. (2010). Cross-reference for relating genetic soil classification of China with WRB at different scales.

Geoderma, *155*(3–4), 344–350. https://doi.org/10.1016/j.geoderma.2009.12.017

Simfukwe, P., Hill, P. W., Emmett, B. A., & Jones, D. L. (2011). Soil classification provides a poor indicator of carbon turnover rates in soil. *Soil Biology and Biochemistry*, *43*(8), 1688–1696. https://doi.org/10.1016/j.soilbio.2011.04.014

Simfukwe, P., Griffiths, R. I., Emmett, B. A., Jones, D. L., Hill, P. W., Cooper, D. M., … Reynolds, B. (2010). *Is current soil classification relevant to soil function and soil diversity?* England: Centre for Ecology & Hydrology.

Simo, I., Schulte, R., O'Sullivan, L., & Creamer, R. (2019). Digging deeper: Understanding the contribution of subsoil carbon for climate mitigation, a case study of Ireland. *Environmental Science & Policy*, *98*, 61–69. https://doi.org/10.1016/j.envsci.2019.05.004

Slessarev, E. W., Lin, Y., Bingham, N. L., Johnson, J. E., Dai, Y., Schimel, J. P., & Chadwick, O. A. (2016). Water balance creates a threshold in soil pH at the global scale. *Nature*, *540*(7634), 567–569. https://doi.org/10.1038/nature20139

Smith, J., Smith, P., Wattenbach, M., Zaehle, S., Hiederer, R., Jones, R. J. A., … Ewert, F. (2005). Projected changes in mineral soil carbon of European croplands and grasslands, 1990-2080. *Global Change Biology*, *11*(12), 2141–2152. https://doi.org/10.1111/j.1365-2486.2005.001075.x

Soga, M., & Gaston, K. J. (2018). Shifting baseline syndrome: Causes, consequences, and implications. *Frontiers in Ecology and the Environment*, *16*(4), 222–230. https://doi.org/10.1002/fee.1794

Statistics for Wales. (2016). *Welsh agricultural statistics 2016*. Cardiff: Office for National Statistics.

Stevenson, B. A., McNeill, S., & Hewitt, A. E. (2015). Characterising soil quality clusters in relation to land use and soil order in New Zealand: An application of the phenoform concept. *Geoderma*, *239*, 135–142. https://doi.org/10.1016/j.geoderma.2014.10.003

Suding, K. N., Gross, K. L., & Houseman, G. R. (2004). Alternative states and positive feedbacks in restoration ecology. *Trends in Ecology & Evolution*, *19*(1), 46–53. https://doi.org/10.1016/j.tree.2003.10.005

The British Survey of Fertiliser Practice. (2019). *Fertiliser use on farm crops for crop year 2018*. United Kingdom: Department for Environment, Food & Rural Affairs.

Tóth, G., Jones, A., & Montanarella, L. (2013). The LUCAS topsoil database and derived information on the regional variability of cropland topsoil properties in the European Union. *Environmental Monitoring and Assessment*, *185*, 7409–7425. https://doi.org/10.1007/s10661-013-3109-3

Tugel, A. J., Herrick, J. E., Brown, J. R., Mausbach, M. J., Puckett, W., & Hipple, K. (2005). Soil change, soil survey, and natural resources decision making. *Soil Science Society of America Journal*, *69*, 738–747. https://doi.org/10.2136/sssaj2004.0163

Van Alphen, B. J., & Stoorvogel, J. J. (2000). A functional approach to soil characterization in support of precision agriculture. *Soil Science Society of America Journal*, *64*(5), 1706–1713. https://doi.org/10.2136/sssaj2000.6451706x

Varallyay, G. Y. (1990). Influence of climatic change on soil moisture regime, texture, structure and erosion. *Developments in Soil Science*, *20*, 39–49. https://doi.org/10.1016/S0166-2481(08)70480-X

Walker, T. W., & Syers, J. K. (1976). The fate of phosphorus during pedogenesis. *Geoderma*, *15*(1), 1–19. https://doi.org/10.1016/0016-7061(76)90066-5

Webster, R. (1968). Fundamental objections to the 7th approximation. *Journal of Soil Science*, *19*(2), 354–366. https://doi.org/10.1111/j.1365-2389.1968.tb01546.x

Wickham, H. (2009). *ggplot2: Elegant graphics for data analysis*. New York: Springer-Verlag.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Seaton FM, Barrett G, Burden A, et al. Soil health cluster analysis based on national monitoring of soil indicators. *Eur J Soil Sci*. 2021;72:2414–2429. https://doi.org/10.1111/ejss.12958