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Drawing out associations between soil health, crop yield, environment and management – advanced data analysis and statistical modelling

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1. Abstract

As part of the work within the Soil Biology and Soil Health Research and Knowledge Exchange (SBSH) Partnership, this project aimed to deploy advanced data analysis and statistical modelling approaches to add further value to the Soil Health scorecard data collected in Projects 4 and 9. The project used the Grower Platform (developed within the AHDB Rotations Partnership project) to collate data on rotational management and outcomes. In particular, this project aimed to explore the associations between soil health indicators and crop yield, and to investigate the relationships with environmental and management variables.

78 Soil Health scorecards (with complete data) were collected on-farm as part of the SBSH Partnership by 33 different farmers between 2018-2020; these data were also combined with a larger dataset of 169 Soil Health scorecards collected, usually by researchers or agronomists, e.g., during the AHDB Monitor Farm programme. All sites collected data including: visual evaluation of soil structure (VESS), topsoil pH, extractable P, K & Mg, soil organic matter (SOM), earthworm numbers. This work was reported fully in Project 9. Rotational management data was collated within the Grower Platform for 6 years before the collection of the Soil Health scorecard data (45 Soil Health scorecard sites, 35 with field-scale yield records). Data for management of 336 crops/intervals was collated. Exploratory multivariate data analysis was carried out using principal component analysis.

Across the integrated Soil Health scorecard dataset, SOM, soil structure, pH and nutrient (P, K, Mg) availability were found to be the most important measures within the Soil Health scorecard in distinguishing between sites. However, less than 70% of the total variation was explained by the first three principal components, this is a relatively low percentage and confirmed that the Soil Health scorecard data distinguished sites from one another in a way that cannot be explained simply by consideration of the variables singly or in simple clusters. This confirmed that soil health is a complex multi-factorial characteristic that cannot be readily collapsed into a single score through weighted averaging or, perhaps, that some key soil measures were not yet included within the Soil Health scorecard.

Consideration of the on-farm data when separated by rotational land use showed grassland sites were largely distinguished from the cropping systems. Separation of the grassland sites was mainly due to higher SOM content and earthworm numbers and conversely, lower pH, P and K. The rotational cropping systems were more similar, although sites with rotations including late harvested crops generally had lower SOM and earthworm numbers. This suggests that rotational land use is part of the explanation of the differences in measured Soil Health scorecard data. When the data were considered by soil texture group, there was some weak evidence of separation between soils with light and heavy textures. Heavy soils had higher SOM, higher VESS scores (poorer structure), higher earthworm numbers and higher available Mg than light soils. While simple segmentation is

useful to support benchmarking, this cannot explain the variation in soil health fully, as there is a large variation in practice within cropping systems (including tillage, application of organic materials *inter alia*). Descriptive comparison of Soil Health scorecards and site data with the positioning of sites within the PCA biplot showed that soil health was characterised by an overall balance between physical, chemical and biological properties. It also showed the importance of site factors in determining the Soil Health potential and the consequent difficulty in providing reliable benchmarking at regional or national scale.

Soil Health scorecard data together with crop yield and grain quality measures were assessed in three long-term experimental sites evaluating the effect of repeated organic material additions, the experiments together with data analysis were described in full in Project 4. These long-term multi-site studies provided robust recording of management practices conducted over a long enough time period to allow for their effect to become measurable in the soil. Here we used ANOVA Simultaneous Components Analysis (ASCA), which first fitted an analysis of variance (ANOVA) model separately for each of the variables and partitioned the variance attributable to each of the treatment terms (site, treatment). The next stage then looks at the multivariate relationships among the Soil Health scorecard variables strictly within these separate effects. It can be thought of as doing a PCA on the treatment effects. ASCA provided evidence that the Soil Health scorecard variables were able to distinguish differences in soil health resulting from organic matter applications compared with no application, and also detected differences between the impacts of different materials (slurry, FYM, green compost). These data also highlighted the critical importance of site/ management interactions in determining the actual value of the measured indicators even though common trends in the directions of responses to treatments were seen across sites.

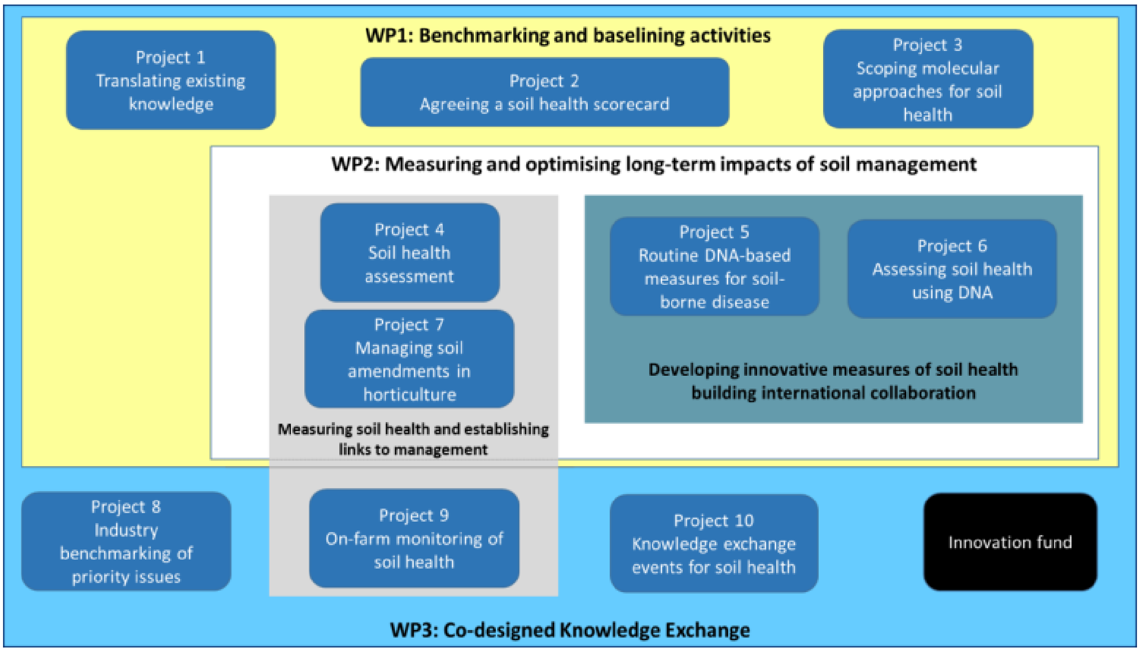
It proved impossible to develop simple rotational management indicators using PCA. When the number of response measures within the Soil Health scorecard, together with the range of other factors that might influence yield, was also taken into account, it was clear that the intended approach using computed factors could not be relied upon to give robust interpretation and so it was not pursued further. Simple indices of tillage intensity or organic matter balances are available in the USA / Europe. If these were calibrated for the UK, these may provide an opportunity to characterise farmer practice at rotational scale from routine farm records. However, it is important to note that developing ways to support effective record-keeping on-farm and also more streamlined ways to access and share farm management data would also be needed to enable a fuller analysis of rotational management data and its use to evaluate impacts on crop yield, soil health and/or other outcomes.

2. Introduction

This project (Project 13 of the Soil Biology and Soil Health Research and Knowledge Exchange (SBSH) Partnership) aimed to deploy advanced data analysis and statistical modelling approaches to explore the associations between soil health indicators, crop yield and investigate the relationships with environmental and management variables.

The SBSH Partnership had designed the studies in Projects 4 and 9 and planned data analysis effectively so that the main aims of the SBSH Partnership could be met, i.e., to evaluate soil biological measures and the overall Soil Health scorecard approach and explore linkages to farm management and to crop yield, especially in the replicated multi-site organic material addition trials in Project 4. However, it was recognised that there may be an opportunity to add significant further value by using advanced data analysis and statistical modelling approaches to improve mechanistic understanding of the interactions driving soil health and crop yield. This is a rapidly growing field of data analysis with new tools and approaches emerging. Hence the opportunity was not fully recognised at the application stage and hence no partner with this specific research expertise was initially included within the Partnership to guide the process. Therefore, this additional study with Biomathematics and Statistics Scotland (BioSS) was funded as one of the Innovation Fund projects.

Innovation Fund shown (in black) together with the integrated project delivery of the Soil Biology and Soil Health Research and Knowledge Exchange Partnership



The AHDB Rotations Research Partnership (Project 91140001; 2016-2021) also delivered an integrated programme of soil and water research to optimise the productivity and sustainability of crop rotations in UK farming systems. This included work to bring together data on rotational management and explore the linkages between management, soil physical conditions and economic and agronomic sustainability and the resilience of UK agricultural systems to external stresses. Data on rotational management and outcomes were collected and summarised through a Grower Platform developed by BioSS. This project therefore also provided an opportunity to link the approaches to data analysis as well as the datasets collected for the two Partnerships, with a view to increasing the value of these separate datasets.

2.1. Objectives

As part of the SBSH Partnership, this project worked with data collected in Projects 4 and 9, in particular for the sub-set of sites that also had detailed rotational management data information together with crop yield/ quality data. The overall aim of this project (Project 13) was to deploy advanced data analysis and statistical modelling approaches to explore the associations between soil health indicators, crop yield and investigate the relationships with environmental and management variables.

The specific objectives of Project 13 were:

1. Develop clear protocols to ensure that all recorded soil health and associated variables arising from a number of different research trials and on-farm monitoring sites were entered in a unified and consistent format into a single database aligned with that of the Grower Platform.
2. Carry out data analysis and statistical modelling to identify:
   a. Associations between environmental (crop, soil texture/type and climate) conditions and soil health, and between soil health and crop yield
   b. Patterns relating management options to soil health.
   c. How environmental conditions modify impacts of management on soil health.
3. Work with the Partnership project teams to disseminate the key conclusions from the statistical analysis in a clear and accessible manner to end-users.

2.2. Background

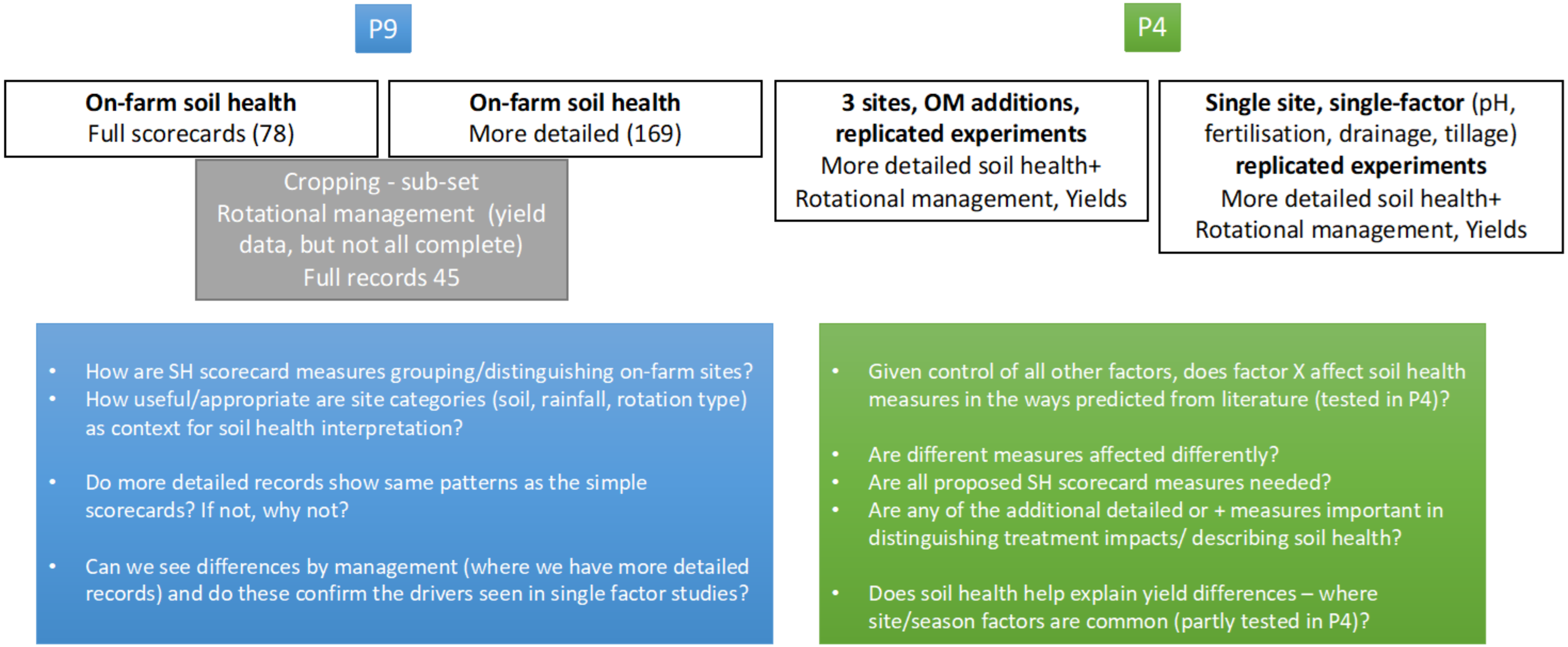
Sustainable soil management is central to the delivery of economically and environmentally sound, resilient and productive cropping. Improving/securing soil ‘health’ has therefore been increasingly discussed within the agricultural industry, with the assessment of soil health essential for informing decisions on soil and nutrient management in order to maximise crop yield and quality, whilst minimising production costs and environmental impacts. The assessment of soil health requires consideration of soil physical, chemical and biological properties and the SBSH Partnership has developed (Project 2) and evaluated (Projects 4 and 9) an integrated approach to quantify and benchmark soil health i.e. a Soil Health scorecard. The Soil Health scorecard aims to a give a ‘snapshot’ overview of soil health (akin to a car MOT or school report) on a rotational basis and thereby assist farmers and growers to identify soil constraints that are limiting crop production or exacerbating environmental risk so that they can target specific management practices to address any identified problem areas.

Studies of soil health (or quality) within realistic farm rotational contexts are relatively rare (e.g., Wander and Bollero, 1999, focussing on differences in tillage); this has been constrained by a lack of agreed metrics to quantify both soil heath and rotational management practices. Farmers’ field management is often dynamic, with multiple management practices implemented season to season over several decades based on a range of practical considerations, e.g., farm labour, machinery requirements etc. and tailored to specific fields. This diversity and seasonal variation in practice complicates the characterisation of farms / fields through the use of simple management indices. In contrast, field plot experiments tend to simplify farming systems to reduce the number of confounding factors, so that the influence of single management practices can be identified. However, a single management practice, such as the application of organic materials, can also have multiplicative impacts on a number of soil properties (physical, chemical and biological). This project sought to use advanced data analysis and statistical approaches to explore the associations between soil health indicators, and crop yield, and to investigate the relationships with environmental and management variables, especially for a sub-set of farm sites and cross-site field trials where detailed rotational management data and crop yield / quality data were available.

3. Materials and methods

3.1. Hypothesis mapping

At the outset of the project in spring 2020, the SBSH Partnership team (Elizabeth Stockdale, Christine Watson) met with the BioSS statisticians working as part of the Rotations Partnership (Katherine Preedy) and with the BioSS team leading the analysis for Project 13 (Ian Nevison, Colin Alexander) to discuss the SBSH Partnership project datasets (Figure 1, Table 1) and to consider how to frame the hypotheses to be explored through statistical testing. The statistics team are expert in the application of statistical methods to large data sets e.g. multivariate data from the ’omics field, and trials where multiple factors are measured e.g., sensory profiling. However, they had limited background knowledge about soil science and interactions / co-variation between soil properties. A key part of the information sharing was therefore to describe and discuss the Soil Health scorecard approach, the variables within the dataset and their possible interactions (Figure 2).



- How are SH scorecard measures grouping/distinguishing on-farm sites?
- How useful/appropriate are site categories (soil, rainfall, rotation type) as context for soil health interpretation?
- Do more detailed records show same patterns as the simple scorecards? If not, why not?
- Can we see differences by management (where we have more detailed records) and do these confirm the drivers seen in single factor studies?

- Given control of all other factors, does factor X affect soil health measures in the ways predicted from literature (tested in P4)?
- Are different measures affected differently?
- Are all proposed SH scorecard measures needed?
- Are any of the additional detailed or + measures important in distinguishing treatment impacts/ describing soil health?
- Does soil health help explain yield differences – where site/season factors are common (partly tested in P4)?

Figure 1 Main SBSH Partnership datasets where soil health measures (as Soil Health scorecards) had been collected and which had been identified as providing an opportunity to explore associations between environmental (crop, soil texture/type and climate) conditions and soil health, and between soil health and crop yield. Key questions associated with the datasets also shown. P9: Project 9 ‘Evaluating the soil health scorecard approach: monitoring innovations in management of soil biology and health already in place on farm’. P4: Project 4 ‘Quantifying the effects of management on soil health’

Table 1 Data reported in each dataset showing common variables across datasets as well as key differences together with notes on the measures.

	On-farm	More detailed	OM trials	Notes
Site code	✓	✓		Code – links to geolocation
Rainfall region	✓	✓		Category variable (low, mid, high) decided by expert group
Rotational cropping	✓	✓		Category variable (Grassland, Cropping – combinable, rotations with leys, rotations with late harvested crops e.g. potatoes, maize, sugar beet) decided by expert group
Soil texture class	✓	✓		Category variable (light, medium, heavy) decided by expert group
Site			✓	Name
Treatment			✓	Name/description - type of OM
OM loading			✓	Total OM applied
VESS	✓	✓	✓	Scorecard variable - 1 to 5 score where 1 and 2 are best; research trial scores to 0.1
pH	✓	✓	✓	Scorecard variable - pH optima around 6-6.5; less good for biological activity at lower and high pH; marked lower limit often observed at 5.5
P	✓	✓	✓	Scorecard variable - P optima for crops is at values >15; considered to be an environmental risk at >45
K	✓	✓	✓	Scorecard variable - K optima for crops is at values >120
Mg	✓	✓	✓	Scorecard variable - Mg optima for crops is at values >50; considered to be a risk of nutrient interaction causing limitation if >400
Earthworms	✓	✓	✓	Scorecard variable - more the better; generally grasslands have more (but not always) - hence there are different benchmarks for grassland soils; may correlate with OM
SOM	✓	✓	✓	Scorecard variable - in general, more is better - higher values are expected with increasing clay and with increasing rainfall, so benchmarks set differently for soil/rainfall categories. Very high values (> 15%) may indicate lack of biological activity (thatch layer).
PMN	Not 2018	Some missing	✓	More detailed measure - biological activity indicator; would expect to correlate with CO_2 burst and OM
CO_2 burst	x	✓	✓	More detailed measure - biological activity indicator; would expect to correlate with PMN and OM
Ca	✓	✓	✓	Largely a consequence of the underlying geology; but where low may be changed by addition of lime. <1000 ppm is probably restricting root growth and perhaps soil biology
Na	✓	✓	✓	Largely a consequence of the underlying geology; but where high >30 ppm may be leading to poor structural stability
Grain yield and quality measures	x	x	✓	More the better; influenced by seasonal weather and impacts of soil on water availability - but impact of "soil health" may be detectable in controlled trials

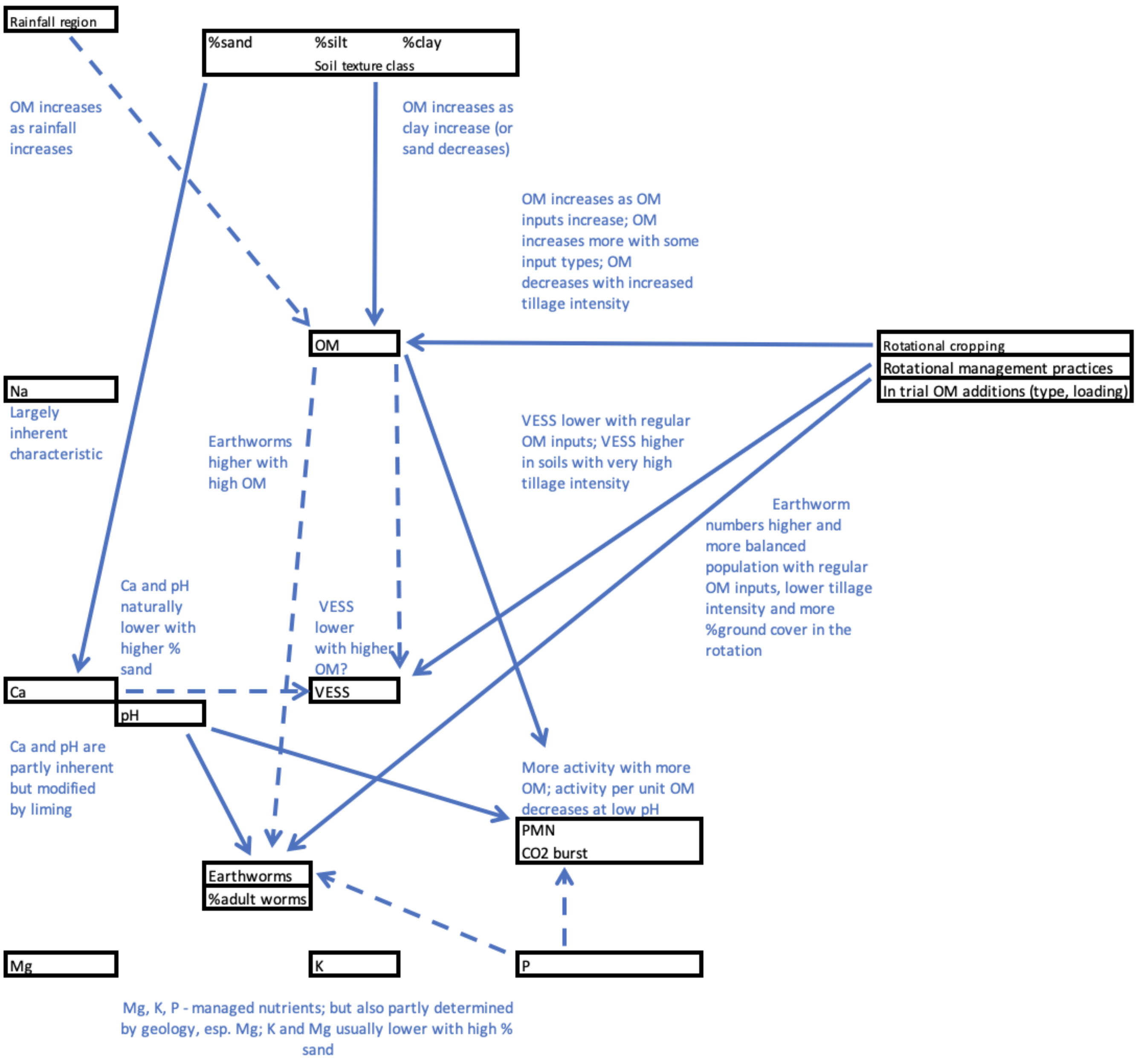


Figure 2 Outline of the dependencies and interactions between the site and soil variables collected in the Soil Health scorecard approach. Solid arrows show relationships between individual factors commonly reported with text explaining the most likely relationship. Dotted arrows show possible direct relationships which are less well described in the literature and may be indirect e.g. rainfall region affecting net primary productivity which influences OM inputs and SOM rather than affecting SOM directly.

3.2. Data collation

3.2.1. Soil health scorecard data

78 Soil Health scorecards (with complete data) were collected on-farm as part of the SBSH Partnership by 33 different farmers between 2018-2020; this work is reported fully in Project 9. The dataset includes simple site factor variables and the Soil Health scorecard measures describing physical, chemical and biological properties of soil (Table 1). Table 2 shows the coverage from each combination of rainfall region, soil texture class and rotational land use. Most of these (42 of the 78) were observed in mid rainfall regions with all but four of the possible combinations of soil texture and management observed in this rainfall region. The fields from high rainfall regions (26 of the 78) had representatives of each soil texture class and management; but not all combinations of these. For the low rainfall regions (East Anglia only) there were 10 fields and there were no sites on light soils or in grassland.

Table 2. On-farm Soil Health scorecards with complete data collected by farmers as part of Project 9. Numbers of sites with measurements from each combination of rainfall region, soil texture class and rotation cropping regime.

Rainfall region	**Low rainfall**			**Mid rainfall**			**High rainfall**		
Soil texture class	**Light**	**Medium**	**Heavy**	**Light**	**Medium**	**Heavy**	**Light**	**Medium**	**Heavy**
Combinable cropping	0	3	3	4	12	2	0	6	0
Rotation including late harvested crops	0	3	0	11	0	0	1	0	0
Rotation including leys	0	0	1	2	3	4	0	1	1
Grassland	0	0	0	0	4	0	6	11	0

A larger dataset of 169 Soil Health scorecards was collated from those collected, usually by researchers or agronomists, as part of associated work, e.g., during the AHDB Monitor Farm programme. These data were also summarised and described in Project 9. This dataset included laser measurements of soil particle size class and the PMN or CO_2 burst method for assessing microbial activity (Table 1). Table 3 shows the coverage from each combination of rainfall region, soil texture class and rotational land use. Most of these (129 of the 169) were observed in mid rainfall regions with all but two of the possible combinations of soil texture and management observed in this rainfall region. The fields from high rainfall regions (24 of the 169) had representatives of each soil texture class and management; but not all combinations of these. For the low rainfall regions (East Anglia only) there were 16 fields and there were no sites in grassland or in rotations with late-harvested crops.

Table 3. More detailed Soil Health scorecards collected in association with Project 9. Numbers of fields with measurements from each combination of rainfall region, soil texture class and rotation cropping regime.

Rainfall region	**Low rainfall**			**Mid rainfall**			**High rainfall**		
Soil texture class	**Light**	**Medium**	**Heavy**	**Light**	**Medium**	**Heavy**	**Light**	**Medium**	**Heavy**
Combinable cropping	7	6	0	8	37	36	5	5	8
Rotation including late harvested crops	0	0	0	6	0	0	1	0	1
Rotation including leys	0	1	2	3	11	12	0	2	0
Grassland	0	0	0	1	5	10	1	0	1

3.2.2. Rotational management data – Grower Platform

The Grower Platform collated data by ‘interval’ (usually a crop, Table 4). The interval for each crop runs from first cultivation or other operation associated with that crop until the final operation (usually harvest or destruction for a cover crop). For grassland, intervals are associated with livestock movements (entry/exit marking a grazing period) or cutting (e.g., for silage). Hence a winter cereal is one interval roughly August 31st to August 31st; the same period may be two or more intervals if a spring cereal is grown with a bare soil or cover crop ahead of the spring cereal. The crop management recorded in the Grower Platform largely mirrors the full records within farm management software with less detail in the Grower Platform for crop protection products. Compared with the first use of the Grower Platform in the Rotations Partnership, the data entry spreadsheet was simplified slightly for use in the project, so that the information requested about tractor passes (dates, duration etc) related solely to those for cultivation (soil-disturbing) operations for seedbed preparation and/or weed management (Table 5).

As part of Project 9, 28 participating farmers (94 Soil Health scorecard sites) agreed to share farm records, including rotational yield data with the project. Ultimately, 12 farmers returned complete records for 6 years before the collection of the Soil Health scorecard data (45 Soil Health scorecard sites, 35 with field-scale yield records) in a variety of formats, including paper notes, and with a range of levels of detail within farm management software. Where farm management software was used, there were usually good records of crop protection products and fertiliser use, but records were more patchy for tillage operations, organic material applications, residue management and yield. In some cases, the farms used separate spreadsheets to record some of this information and these were obtained on request. These data were coded and entered into the Grower Platform format as part of this project.

Table 4 Number of intervals coded by crop category; total number of intervals coded was 336; note that within the Grower Platform, use of the land for outdoor pigs is recorded as a ‘crop’.

Crop Category	Number of intervals
Wheat	124
OSR	49
Bare	35
Cover crop	31
Barley	33
Legumes (beans /peas)	21
Grass or grass/clover	16
Sugar beet	14
Oats / rye	3
Maize	4
Oats	4
Outdoor pigs	1
Potatoes	1
Field vegetables	0

Table 5 Original Grower Platform categories for tractor passes /cultivations and the new categories developed for this project showing how they were mapped. There was no equivalent of Roll in the initial data set and Harvest/chemical applications were not recorded as cultivations in this project.

Original Categories	New Categories
Bed-Form	Bed form / ridging
Bed-Till	Bed form / ridging
Destone	Destone
Broadcast/autocast	Direct drill / zero tillage
Direct drill into stubble	Direct drill / zero tillage
Drill/Plant	Direct drill / zero tillage
Plant/Drill	Direct drill / zero tillage
Apply amendments	
Harvest	
Sub-cast	
Apply fertiliser	
Non inversion tillage (deep > 10 cm)	Non inversion tillage (deep > 10 cm)
Non inversion tillage (shallow < 10 cm)	Non inversion tillage (shallow < 10 cm)
Plough	Plough
Plough & Press	Plough and press
	Roll
Rotavate	Rotavate
Rake/trash rake	Straw rake or equivalent
Single pass drilling ('strip tillage')	Strip tillage
Sub-soil	Subsoil

3.2.3. Designed experiments with Organic Material Additions

Soil Health scorecard data together with crop yield and grain quality measures were assessed in three long-term experimental sites evaluating the effect of repeated organic material additions, previously studied as part of the WRAP/Defra funded DC-*Agri* and Soil*QC* experimental programmes; full details of the experiments and monitoring within the SBSH Partnership are given in Project 4. At each site, four to five different organic materials were compared with a control treatment that received manufactured fertiliser additions only, with the number of years materials had been applied (up until autumn 2017) varying from 3 to 23 years, depending on the site and material. Each site had four common treatments: Control, Farmyard Manure (FYM), Green Compost and Slurry which were the focus of the analysis here (Table 6). Organic materials were applied at rates equivalent to *c.* 250 kg/ha total N (120-250 kg N/ha for slurries and digestates, depending on the total N content and dry matter), with supplementary manufactured fertiliser N applied at optimum rates to ensure both that nutrients were not limiting and that the only difference between treatments was the amount and form of organic matter applied. There were three replicates of each treatment at each experimental site.

Table 6: List of trial sites with trial treatments. 3 replicate plots of each treatment.

Experimental Site	Organic material additions	Soil texture (% clay)	Location Annual rainfall
Gleadthorpe	1. Manufactured fertiliser only 2. Green compost 3. Cattle FYM 4. Cattle slurry	Loamy sand (6% cl)	Nottinghamshire 577mm
Harper Adams	1. Manufactured fertiliser only 2. Green compost 3. Cattle FYM 4. Cattle slurry	Sandy loam (12% cl)	Shropshire 690 mm
Terrington	1. Manufactured fertiliser only 2. Green compost 3. Pig FYM 4. Pig slurry	Silty clay loam (28% cl)	Norfolk 630 mm

3.3. Statistical Analyses

3.3.1. Soil health scorecard data

Principal component analysis (PCA) is a statistical technique which summarises the overall variation among sample observations where multiple measurements have been taken for each sample. Here this covered at least VESS, pH, P, K, Mg, earthworms and SOM i.e., the measures from the Soil Health scorecard. PCA indicates the variables and relationships among them driving the variation in samples. For this experiment, PCA was used to summarise the variation among sites and the relationship among the variables driving this. PCA seeks, as far as possible, to reduce dimensionality by forming a few new variables (principal components, PCs) which capture the bulk of the variability within this multivariate dataset of soil health indicators. The variables were all $\log_{10}$ transformed before use in the PCA since their distributions were skewed. Without this transformation, the PCA would have been dominated by the larger values. PCA can use either the covariance or correlation matrix. Here the correlation matrix was used as this effectively standardises the variables so that differing measurement unit scales do not influence the analysis. The relationships between the first few principal components and the site factors (texture class, rainfall region, and rotational land use) was explored.

3.3.2. Rotational management data – Grower Platform

For the sites where rotational management data were stored within the Grower Platform, PCA was used to identify a couple of interpretable dimensions which could be used to describe the rotation i.e. indicators of rotational intensity/ practice) and which were able to account for the bulk of the variability within the data. It was then hoped to use exploratory data analysis to look for associations between this characterised management data and the within-cluster variability in the reduced dimensionality soil health data.

3.3.3. Designed experiments with Organic Matter Additions

ANOVA Simultaneous Components Analysis (ASCA; Smilde *et al.* 2005) is a statistical technique used with multivariate data collected from designed experiments which have a factorial structure of treatments and blocks. In essence, it comprises two stages. The first fits an analysis of variance (ANOVA) model separately for each of the variables. In the designed experiments with different organic material applications studied here, this is each of the scorecard variables in turn. This partitions the variance attributable to each of the treatment terms (here Site & Treatment etc). The next stage then looks at the multivariate relationships among the scorecard variables strictly within these separate effects. It can be thought of as doing a PCA on the treatment effects. This means that the associations among the scorecard variables can more effectively be observed without them being obscured by other treatments. ASCA was implemented using the R package *lmdme* (Fresno and Fernandez, 2014a, 2014b).

4. Results and discussion

4.1. Soil Health scorecard

Variation between sites in measured on-farm Soil Health scorecard data (78 sites) was examined with PCA. The first few principal components (PC) usually account for the majority of the variation in the dataset; here the first three PCs accounted for 67% of the variation. The relatively low percentage of the variation explained by these first components confirmed that the Soil Health scorecard data distinguished sites from one another in a way that cannot be explained simply by consideration of the variables singly or in simple clusters. PC1 (accounting for 27% of the variation) was most strongly associated with SOM and soil structure, PC2 (23%) was strongly associated with pH and nutrient availability. PC3, which also related to SOM and pH, accounted for 17% of the variation. This may suggest that soil health is a complex multi-factorial characteristic that cannot be readily collapsed into a single score through weighted averaging or, alternatively, that some key distinguishing measures were not yet included within the Soil Health scorecard.

Plots of the data against the first two PCs are shown in Figure 3 and 4. When the sites were coloured by rotation type (Figure 3), grassland sites were largely distinguished from the cropping systems. This suggests that rotational land use is part of the explanation of the differences in measured Soil Health scorecard data. Separation of the grassland sites was mainly due to higher SOM content and earthworm numbers and conversely, lower pH, P and K. The rotational cropping systems were more similar, although sites with rotations including late harvested crops generally had lower scores on PC1 (lower SOM and earthworm numbers). Amsili *et al.* (2021) also found lower pH and higher SOM levels in grassland systems on average and also lower soil health overall in intensive field vegetable systems. When the data were coloured by soil texture group (Figure 4) there was no strong evidence of separation, the soils of medium texture showed a wide range in the measured Soil Health scorecard indicators such that they overlapped with the soils of light and heavy textures. However, there was some weak evidence of separation between soils with light and heavy textures. Heavy soils had higher SOM, higher VESS scores (poorer structure), higher earthworm numbers and higher available Mg than light soils.

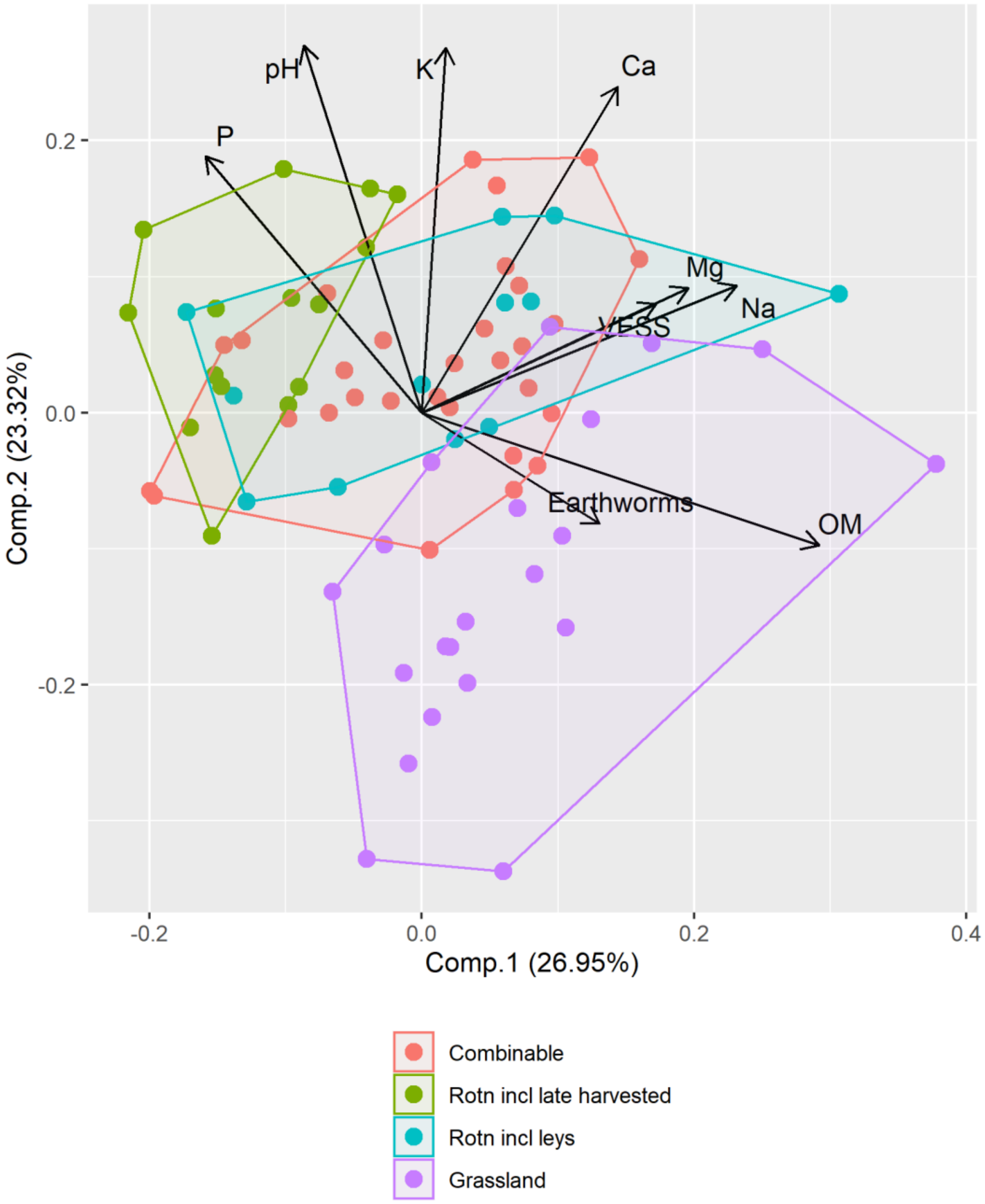


Figure 3. PCA biplot of PC 2v1 for Soil Health scorecard variables (plus Ca and Na) for on-farm sites. Sites coloured according to rotational land use. Arrows indicate the magnitude and sign of the variable loading associated with each principal component.

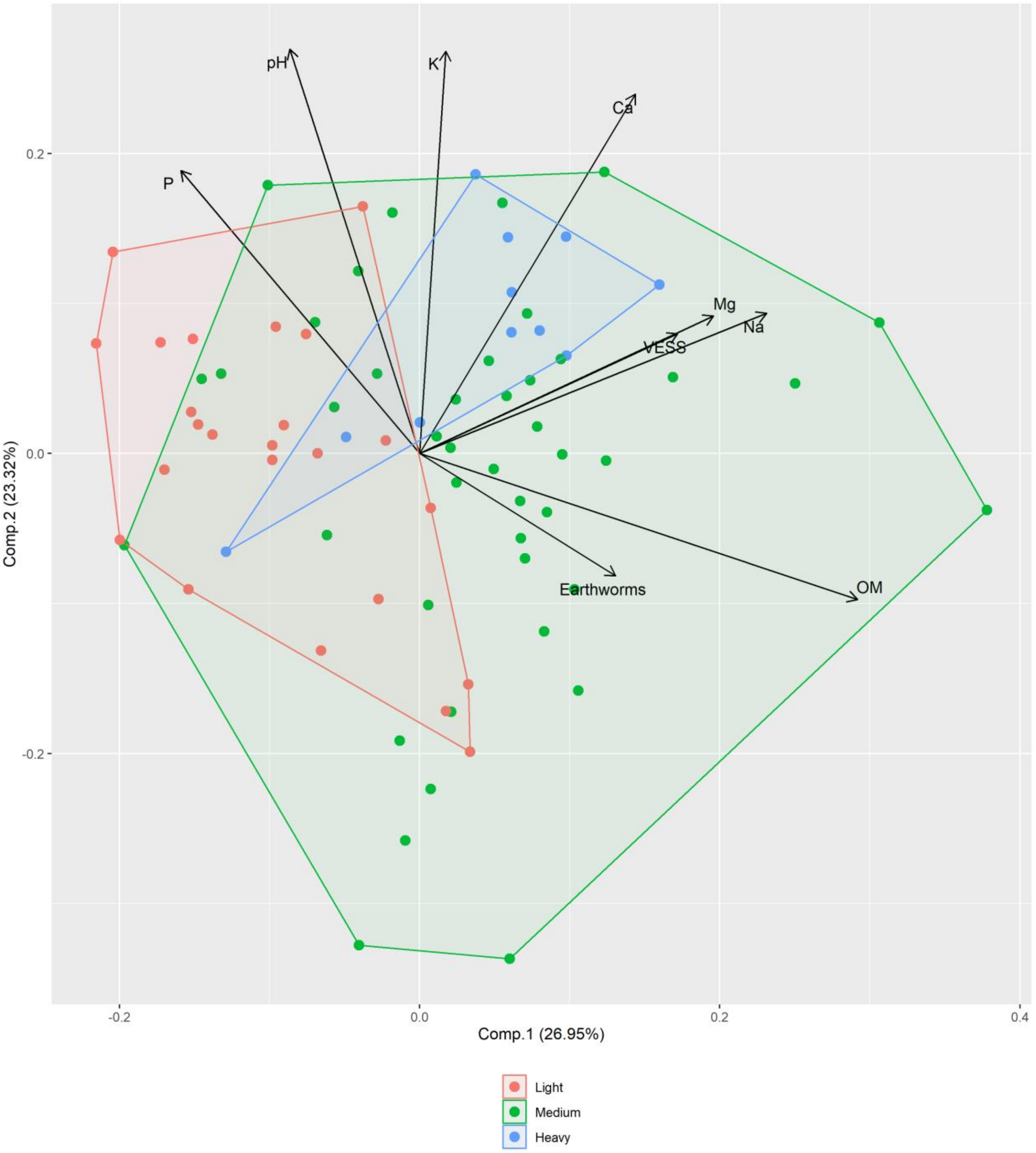


Figure 4. PCA biplot of PC 2v1 for Soil Health scorecard variables (plus Ca and Na) for on-farm sites. Sites coloured according to soil texture group. Arrows indicate the magnitude and sign of the variable loading associated with each principal component.

To look at the possible interactions between rotational land use and soil texture class, the biplot of PC2 versus PC1 was separated into four plots by rotational land-use, coloured by soil texture class (Figure 5). It was noticeable that sites where there were cropping rotations with late harvested crops were dominantly found on light soils. Sites in other cropping systems were measured across all soil texture classes; no grassland sites were measured on heavy soils. Given the small sample sizes that resulted from this segregation, it was not possible to make strong statements, however, broadly speaking there was some evidence that soil texture classes were distinguishable within the rotational land use types. This suggests that segmentation by both rotational land use and soil texture class is needed to support on-farm interpretation of Soil Health scorecard data. Amsili *et al.* (2021) also showed that both soil texture classes and cropping systems needed to be considered to support interpretation of soil health testing (Comprehensive Assessment of Soil Health, Cornell Soil Health laboratory). However, they noted that whilst simple segmentation is useful to support benchmarking, this cannot explain the variation in soil health fully, as there is a large variation in practice within cropping systems e.g. tillage intensity, organic material inputs.

Separation of the data by Rainfall Regions was shown to occur when PC3 is also considered; the plot of PC 3v2 is shown in Figure 6. There was a complete separation between the data collected in Low and High Rainfall regions with the Mid rainfall region sites lying between these. Here, separation was driven by higher values in the Low rainfall compared with the High rainfall sites for Ca, pH and to a lesser extent VESS; and lower values for SOM, earthworm numbers, Mg and P in the Low rainfall compared with the High rainfall sites. Whilst this suggested that segmentation by rainfall region is also needed to support on-farm interpretation of Soil Health scorecard data, care needs to be taken not to overinterpret the data as the data set included relatively few sites (and no grasslands) in the Low rainfall region whereas grasslands are the most common rotational land use for sites in the High Rainfall region, therefore the region and rotational land use were largely conflated in this dataset.

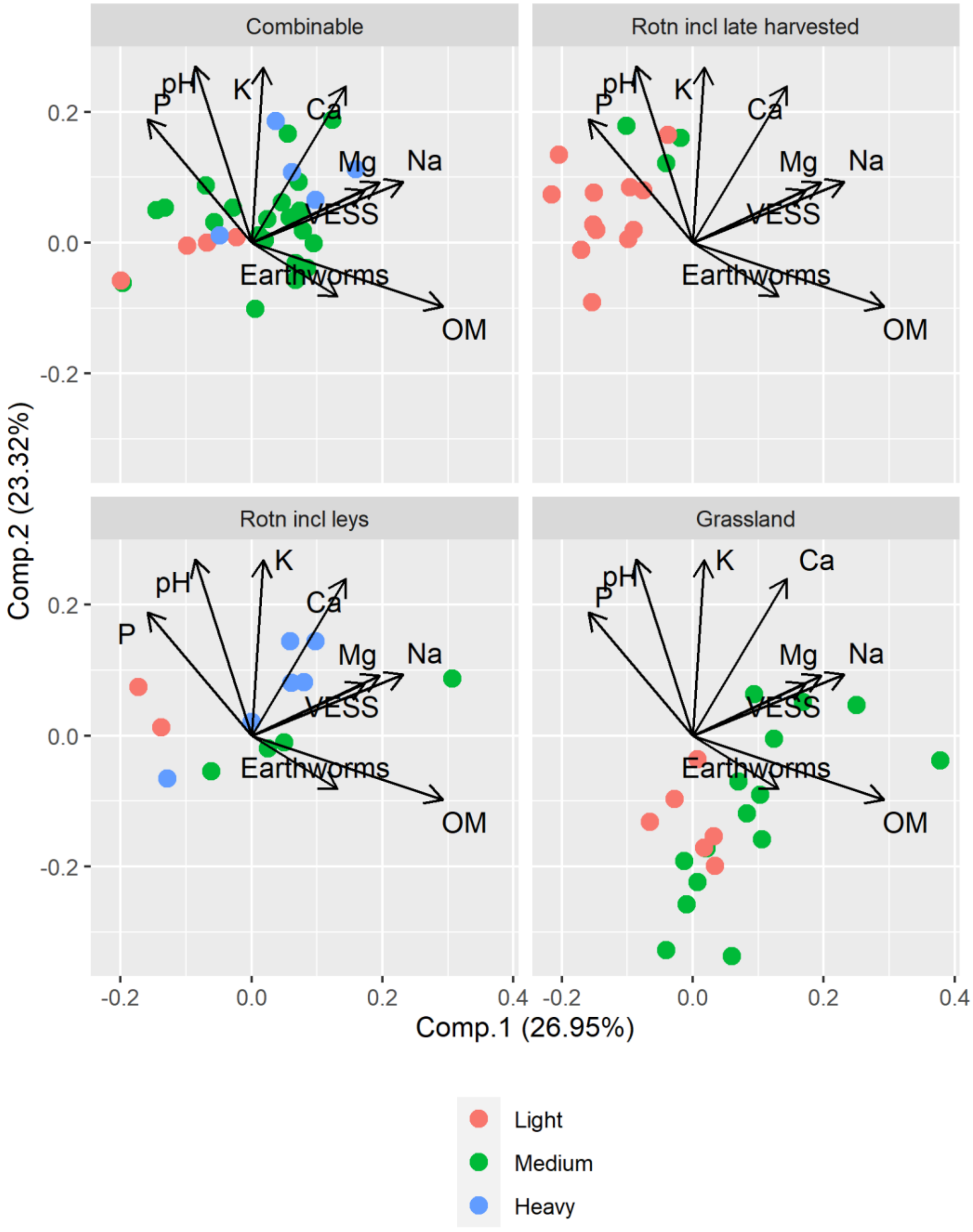


Figure 5. PCA biplots of PC 2v1 for Soil Health scorecard variables (plus Ca and Na) for on-farm sites. Data have been split into separate plots for each rotational land use type. Sites coloured according to soil texture group. Arrows indicate the magnitude and sign of the variable loading associated with each principal component.

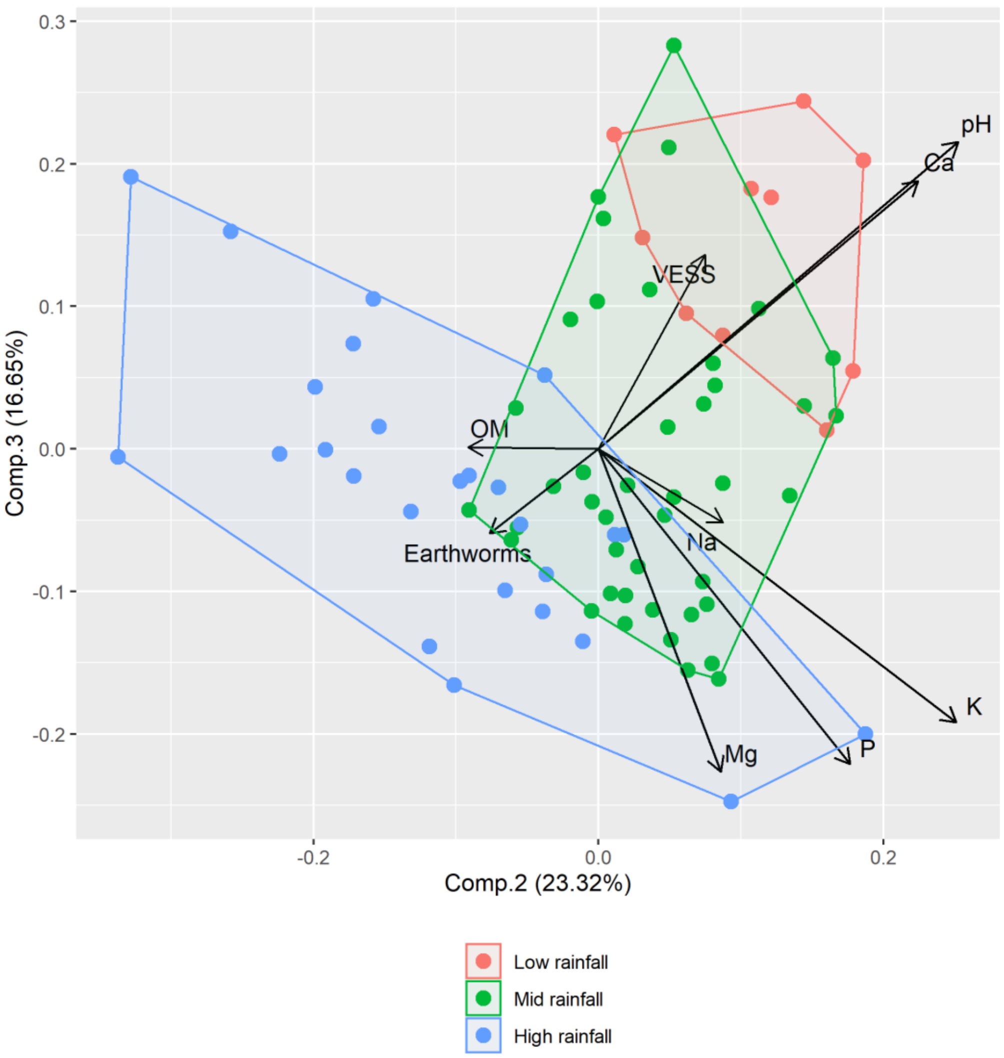


Figure 6. PCA biplot of PC 3v2 for Soil Health scorecard variables (plus Ca and Na) for on-farm sites. Fields are coloured according to Rainfall region. Arrows indicate the magnitude and sign of the variable loading associated with each principal component.

When both Soil Health scorecard datasets were combined (247 Soil Health scorecards), the percentage of the variation explained was also relatively low. PC1 (accounting for 27% of the variation) is most strongly associated with available Mg, SOM and soil structure, PC2 (18%) is strongly associated with pH, P and K availability (Figure 7). Across the wider dataset, this confirmed the importance of these measures in determining site differences. In this data set, there was little evidence of separation by soil texture class, rotational land use or rainfall region. However, the combined dataset was dominated by cropping systems (combinable, rotations with leys) in the Mid rainfall region (134 sites). A PCA was repeated for this subset alone and shows a similar allocation of the Soil Health scorecard measures to the PC axes, with only a slightly higher % of the variation accounted for (PC1 30.4%, PC2 22.1%; Figure 8).

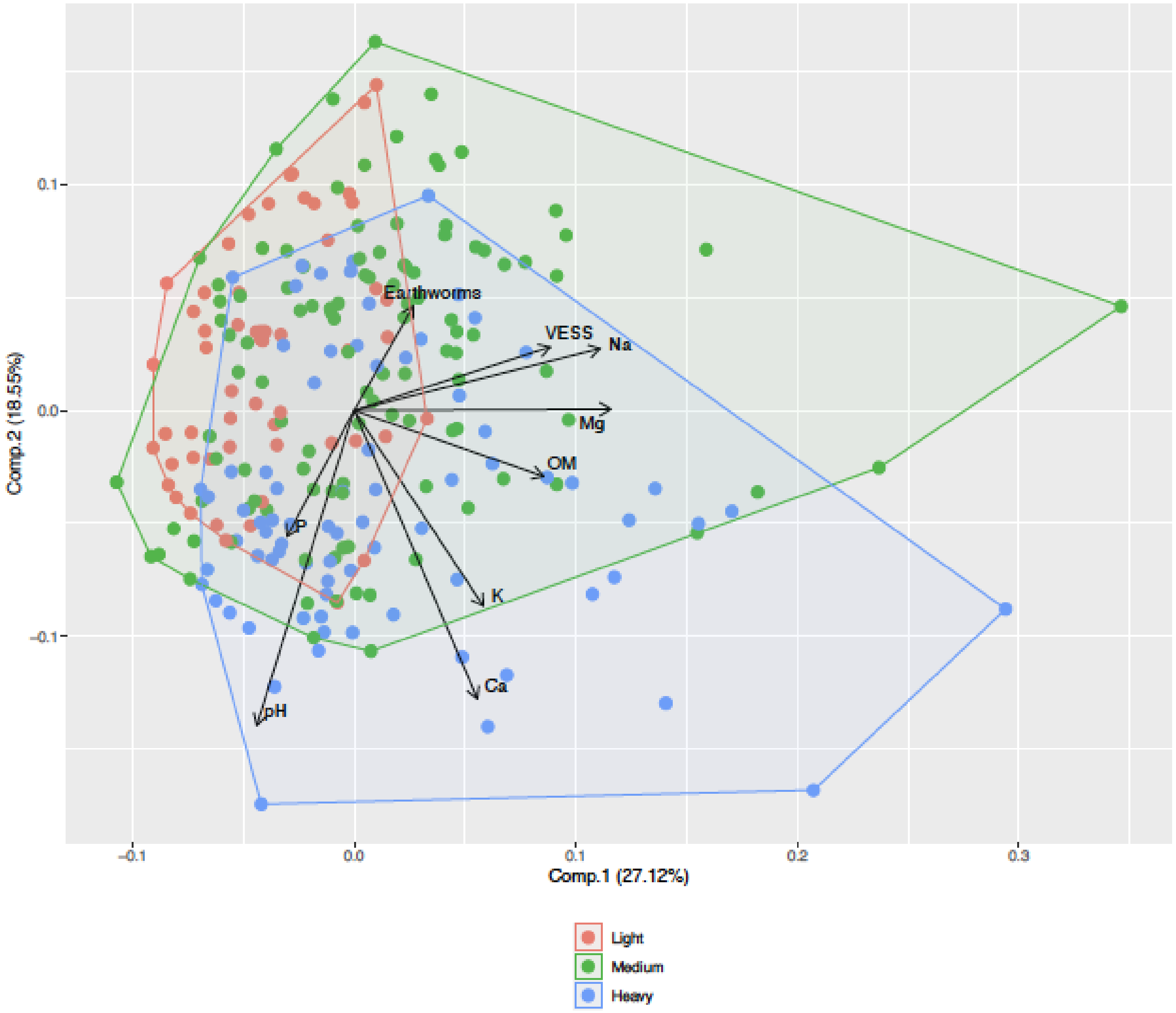


Figure 7. PCA biplot of PC 2v1 for Soil Health scorecard variables (plus Ca and Na) for the combined dataset. Fields are shaded by Soil texture class. Arrows indicate the magnitude and sign of the variable loading associated with each principal component.

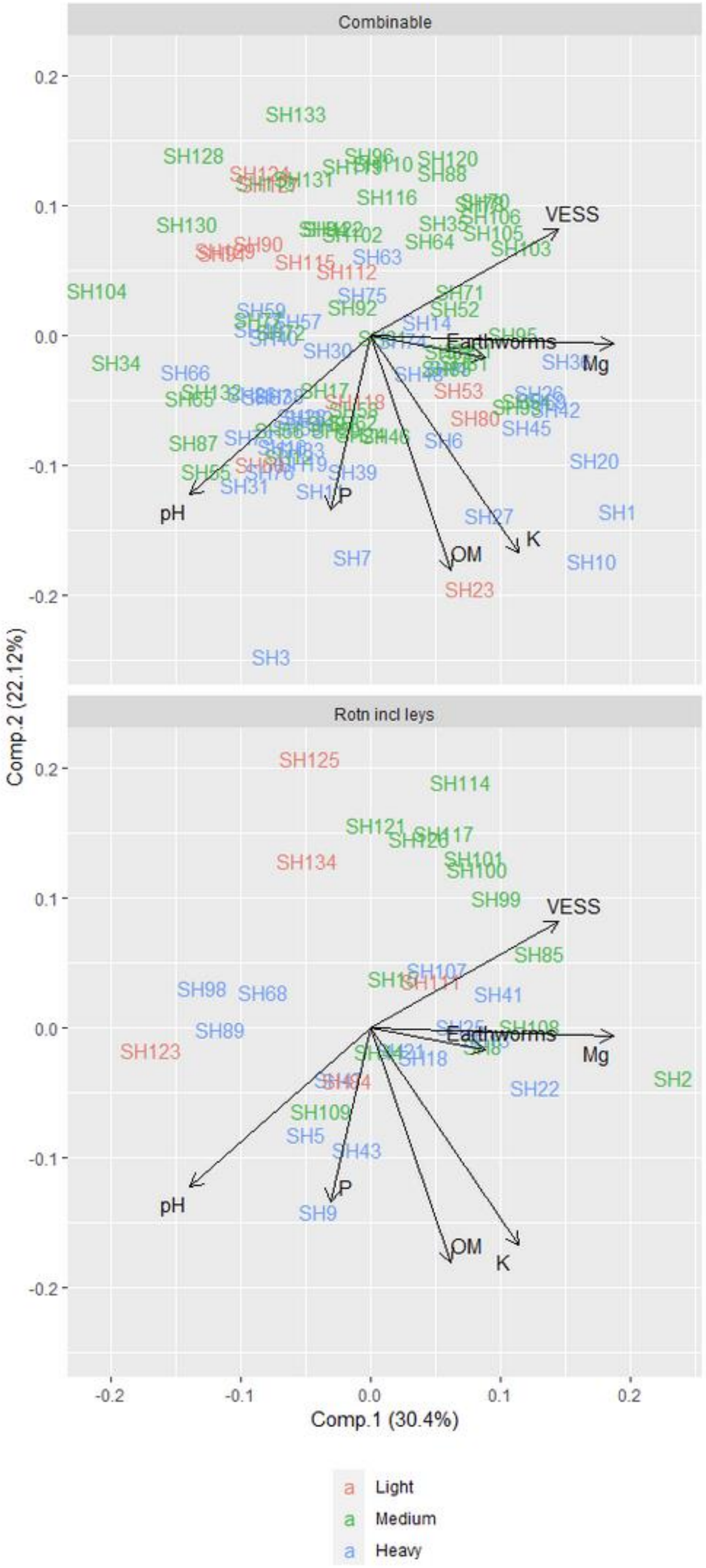


Figure 8. PCA biplots of PC 2v1 for Soil Health scorecard variables for soils in the Mid rainfall region in the main cropping systems with separate plots for each cropping system:combinable cropping, orrotations with leys. Site are coded and coloured according to soil texture group. Arrows indicate the magnitude and sign of the variable loading associated with each principal component.

There was some indication of a weak split by texture group with light and medium soils separating from heavy soils on PC2 (Figure 9). The co-location of the site SH23 (light soil with high P and K indices as a result of use of the site by outdoor pigs) with the heavy soils within the biplot suggests that this grouping may be as a result of the impact of increased clay content on CEC (hence available K) and P adsorption (hence available P) as well as on stabilisation of SOM.

We plotted the biplots using site codes so that we were able to cross-reference the site data and full Soil Health scorecards with the locations within the PCA biplot (Figure 9). Sites that are plotted around the periphery of the biplot have one or more extreme characteristics (Table 7). However, these did not always indicate poor soil productivity e.g. SH23 and SH3 had high soil P indicating a significant risk to the environment; these sites were suggested for sampling by the farmer as they were high yielding. In contrast the collated data for sites in the upper left and centre periphery suggested possible yield constraints (SH104, SH128, SH125, SH114). Sites that were most likely to have good soil health scores across the range of physical, chemical and biological characteristics within the Soil Health scorecard were clustered towards the centre right of the biplot (shown by the green square, Figure 9).

Table 7 Soil Health scorecard data for sites that are plotted around the periphery of the PCA biplot, shown in Figure 9. Soil Health scorecards are shown for sites appearing from centre top (SH125) clockwise around the periphery.

Site characteristics			Physical	Chemical				Biological		
Code	Rotational cropping	Soil texture class	VESS	pH	P	K	Mg	Earthworms	OM	PMN
SH125	Cropping - rotation including leys	Light	2	6.4	15	64	67	4	3.7	24.4
SH114	Cropping - rotation including leys	Medium	4	6.8	12	89	177	5	4.4	34.5
SH2	Cropping - rotation including leys	Medium	3	6.5	6	359	290	29	12.9	165.8
SH1	Cropping - combinable crops	Heavy	3	6.7	43	269	450	10	14.3	118.1
SH10	Cropping - combinable crops	Heavy	3	7.8	28	653	340	12	9.2	148.2
SH23	Cropping - combinable crops	Light	2	7.3	112	390	113	27	8.1	74.8
SH3	Cropping - combinable crops	Heavy	1	7.8	125	263	81	1	11.5	143.7
SH34	Cropping - combinable crops	Medium	1	8	34	71	29	1	7.7	102.5
SH104	Cropping - combinable crops	Medium	1	8.4	20	81	17	6	4.7	105.8
SH128	Cropping - combinable crops	Medium	3	8.5	12	106	28	1	3.2	50.0

This descriptive comparison also led to identification of clusters of soil types (overlaid as ovals to show their location in the biplot, Figure 9). This highlighted the importance of site factors in determining the Soil Health potential and the consequent difficulty in providing reliable benchmarking across sites/ soil types. However, for two of these clusters, up to six Soil Health scorecards had been collected across a range of management practices on a single farm (AHDB Monitor Farms) and the bold arrows within the ovals show the trend of improving soil health across those controlled sub-set of sites.

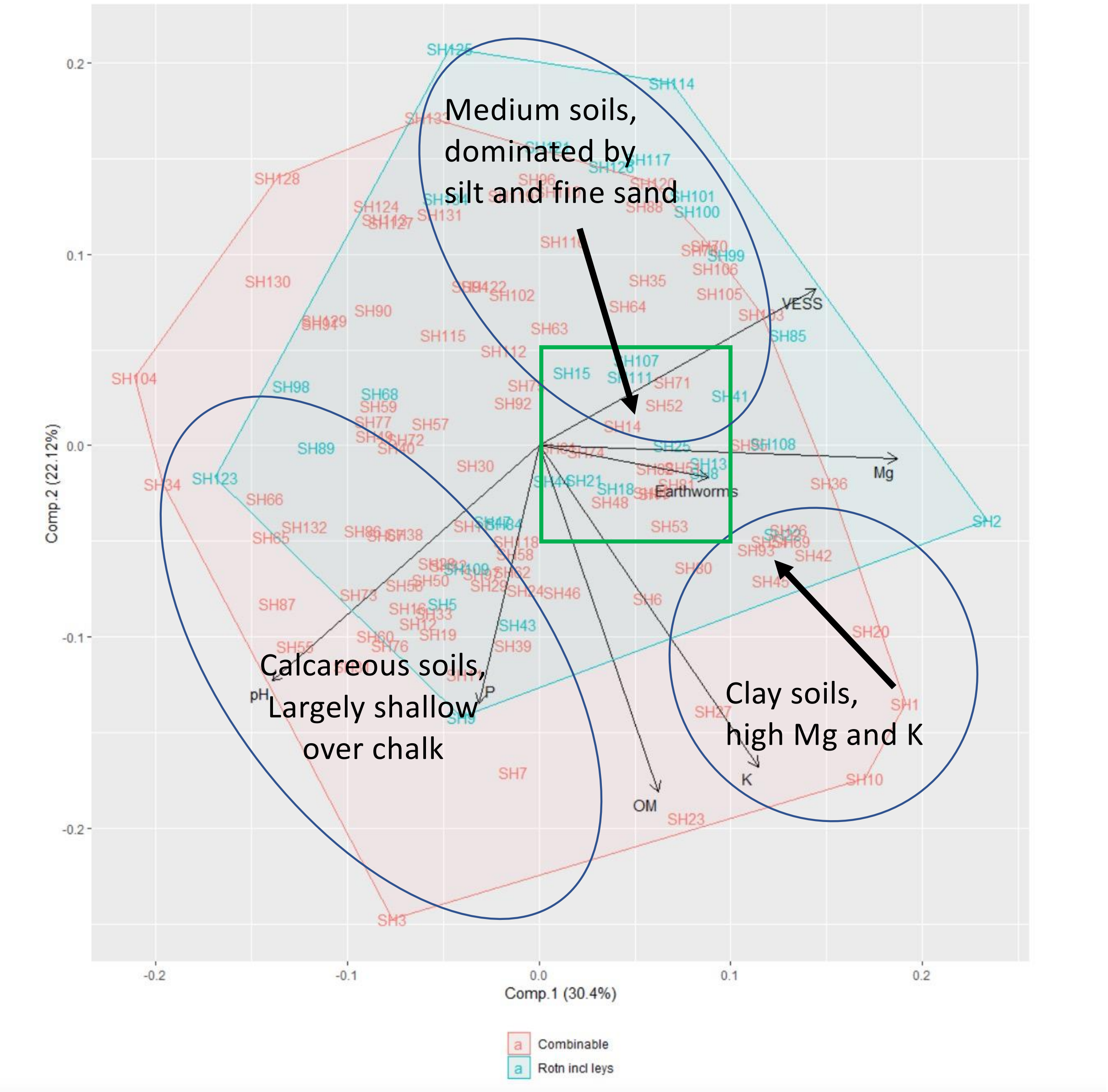


Figure 9. PCA biplots of PC 2v1 for Soil Health scorecard variables for soils in the Mid rainfall region in the main cropping systems with the Site Codes shown according to cropping system: combinable cropping, or rotations with leys. The magnitude and sign of the variable loading associated with each principal component are shown on the base diagram. The detailed records associated with the Soil Health scorecards for each site were cross-referenced with the PCA biplot. The location within the biplot of sites with good soil health scores across the range of physical, chemical and biological characteristics within the scorecard is shown by the green square. This descriptive comparison also led to identification of clusters of soil types (overlaid as ovals to show rough location in the PCA). For two of these clusters, up to six Soil Health scorecards had been collected across a range of management practices on a single farm (AHDB Monitor Farms) and the bold arrows within the ovals show the trend of improving soil health across those controlled sub-set of sites.

4.2. Rotational Management data

The rotational management data were collated for 45 Soil Health scorecard sites; these were all cropping systems of all rotational types and represented about 50% of the data initially promised. The rotational management information covered approximately 6 years ahead of the collection of the Soil Health scorecard data to characterise the preceding rotation giving 336 intervals in the Grower Platform format. In their study of links between management and soil health, Williams *et al.* (2019) developed a simple soil management index based on crop diversity (number of crop species grown in a 5-year period), frequency of mechanical tillage and number of applications of organic amendments (from beyond the field boundary). However, using the data analysis methods employed here, it proved impossible to characterise the rotations simply; no single pair of factors accounted for the bulk of the variation. The range of management practices used across the farms and between crops and seasons were very variable. When the number of response measures within the Soil Health scorecard, together with the range of other factors that might influence yield, was also taken into account, it was clear that the intended approach using computed factors could not be relied upon to give robust interpretation and so it was not pursued further. Because of the way in which the data had been collated, it was also not possible to retrofit simple descriptive indices for rotational management such as those used by Williams *et al.* (2019). If approaches such as the Soil Tillage Intensity Rating (NRCS, 2008) and Organic matter balances (Brock *et al.* 2013) were calibrated for the UK, these may provide an opportunity to characterise farmer practice at rotational scale from routine farm records. However, it is important to note that developing ways to support effective record-keeping on-farm and also more streamlined ways to access and share farm management data would also be needed to enable a fuller analysis of rotational management data and its use to evaluate impacts on crop yield, soil health and/or other outcomes.

4.3. Linking soil heath, management and yield from designed experiments

In Project 4, cross-site analysis of the organic material addition experiments showed that Site had a highly significant effect ($P<0.001$) on all of the properties measured. Here ANOVA Simultaneous Components Analysis (ASCA) shows the multi-variate nature of the effect of site on the Soil Health scorecard variables. Figure 10 shows the ASCA biplot for the Site factor showing the relationships driving the differences among the Sites. All sites were split on PC1; Terrington had the highest scores then Gleadthorpe and Harper-Adams (2020 data). The highest scores at Terrington were associated with lower CO_2 burst (which may be an artefact of the high pH soils, as discussed in Project 9) and lower available P together with poorer soil structure (higher VESS score), higher pH, higher available K, and Mg, and improved SOM with more earthworms and higher biological activity (PMN measure). On PC2, Gleadthorpe was separated from Harper-Adams and Terrington and this was driven by lower SOM, very low earthworm numbers and low biological activity (PMN measure). These site effects were driven by the soil type, underlying parent material and previous management.

For grain yield and grain nutrient content variables, ASCA was again used to look at the multivariate relationships present within each of the Site effects for these variables determined from ANOVA. Figure 11 shows the differences in Sites and the measurements associated with these. PC1 was largely driven by yield and a counter trend in lower grain N. There was a much smaller difference in yield between Gleadthorpe and Harper-Adams but there were differences in grain nutrient content: higher Mg associated with Gleadthorpe and higher K, S and P associated with Harper-Adams.

Figure 10. ASCA biplot of PC 1v2 for the Site effects showing relationships with Soil Health scorecard variables. Arrows show relationships among Soil Health scorecard variables driving the separation in Sites.

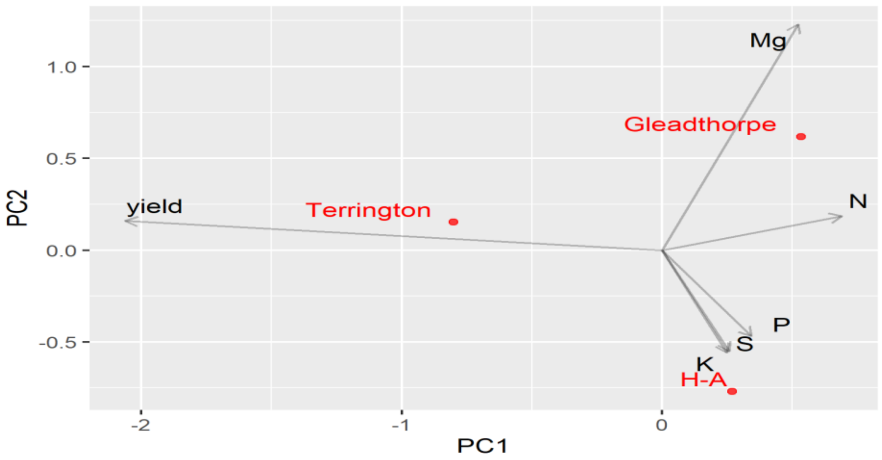


Figure 11. ASCA biplot of PC 1v2 for the Site effects on crop yield and grain nutrient content. Arrows show relationships among Yield and grain nutrient content variables driving the separation in Sites.

When considering the Treatment effects, the ASCA biplot (Figure 12) showed that the Soil Health scorecard variables distinguished differing impacts of the organic material additions. PC1 largely separated the control (no organic materials additions) from the treatments receiving organic materials; here the poorer soil structure (higher VESS score) had the main distinguishing effect. This was in contrast to the analysis in Project 4 which did not show a main effect of treatment on soil physical properties. PC2 highlighted the differences between FYM and Green compost treatments, with higher P and earthworm numbers associated with FYM additions. Green compost additions were associated with higher SOM and soil biological activity (PMN measure).

For grain yield and grain nutrient content variables, PC1 also mainly separated the control from the other treatments; the control treatment was associated with lower yields and higher grain S and N (Figure 13). PC2 highlighted the difference between FYM and slurry treatments; FYM had both higher yield and higher grain N, but lower grain K and Mg when compared with the slurry treatment.

These data from the organic material addition experiments confirmed the effectiveness of the Soil Health scorecard variables in characterising soils and in distinguishing among different management practices.

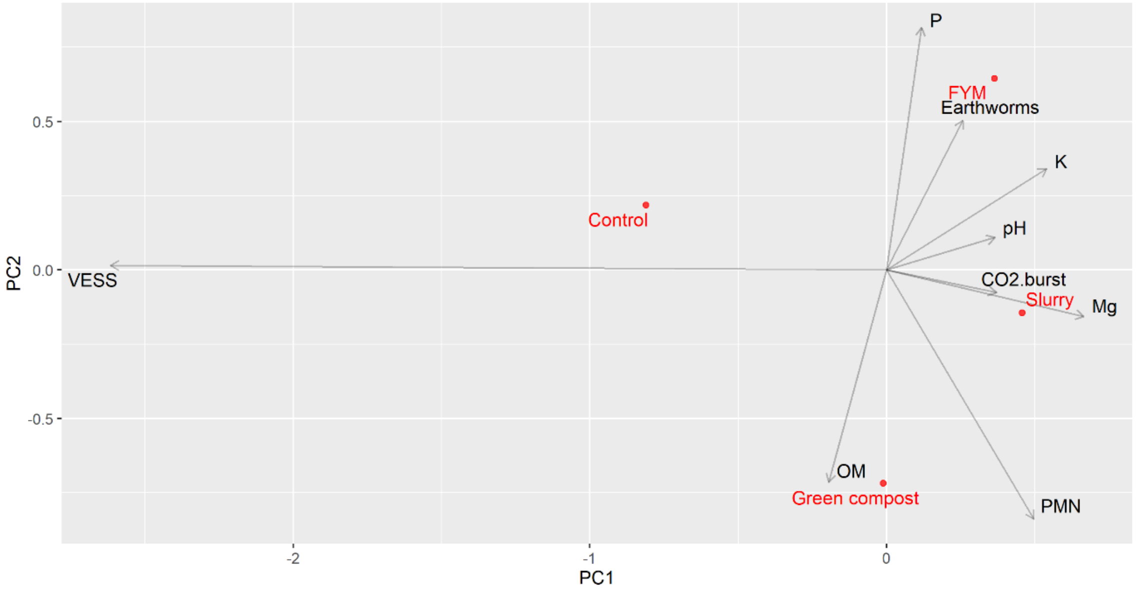


Figure 12. ASCA biplot of PC 1v2 for Treatment effects on Soil Health scorecard variables. Arrows show associations among Soil Health scorecard variables driving the separation in Treatments.

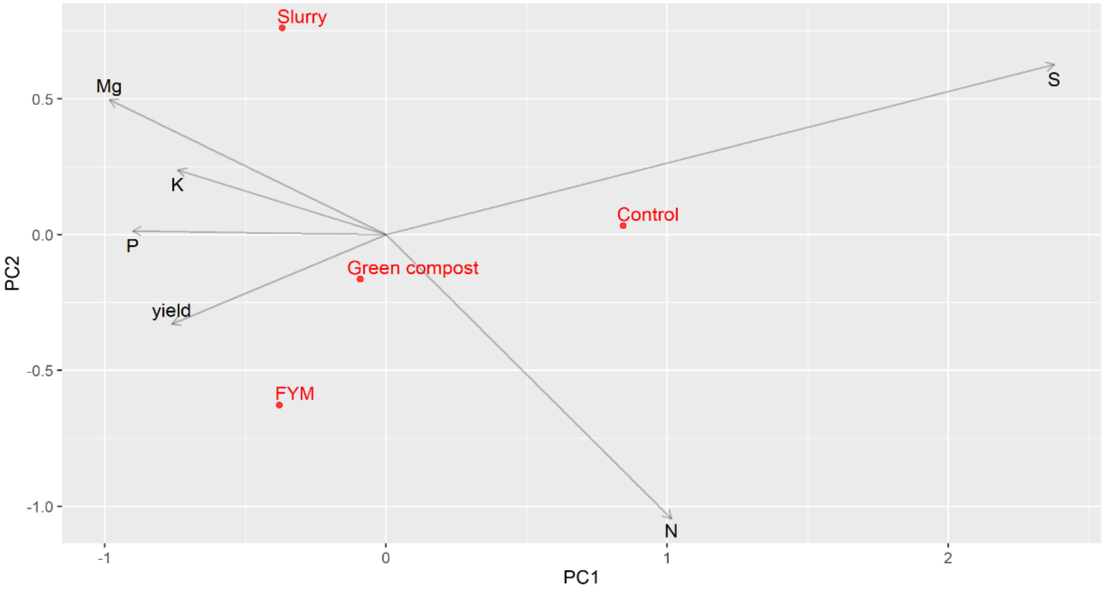


Figure 13. ASCA biplot of PC 1v2 for Treatment effects on crop yield and grain nutrient content. Arrows show relationships among Yield and grain nutrient content variables driving the separation in Treatments.

5. Conclusions

Together with the Countryside Survey data (https://countrysidesurvey.org.uk/science/soils), the Soil Health scorecard data is currently one of the largest datasets for soil health (topsoil physical, chemical and biological properties) in England. However, the nature of the SBSH Partnership data means that the sampling locations were self-selecting and did not seek to be regionally representative of soil types and/ or rotational land uses. In contrast, the Countryside Survey used a stratified randomised sampling approach. Consequently, when the data collected in this project were segmented by rainfall region, rotational land use, and soil texture class, the number of samples in any class was small and still highly variable, as a result of differences in on-farm management, including marked differences in practices known to have impact on soil health (including tillage, application of organic materials *inter alia*). Nevertheless, the on-farm Soil Health scorecard showed some evidence of differences among rotational land uses, soil types and rainfall supporting the use of these variables for segmentation ahead of benchmarking, although the variation was too large to draw strong conclusions.

The long-term multi-site studies of organic material inputs provided robust recording of management practices conducted over a long enough time period to allow for their effect to become measurable in the soil (Cusser *et al.* 2020). Using ANOVA Simultaneous Components Analysis (ASCA) provided evidence that the Soil Health scorecard variables were able to distinguish differences in soil health resulting from organic matter applications compared with no application, and also detected differences between the impacts of different materials (slurry, FYM, green compost). These data also highlight the critical importance of site/ management interactions in determining the actual value of the measured indicators even though common trends in the directions of responses to treatments were seen across sites.

Collation of data characterising farm management was not simple as farmers use a variety of recording systems and even where a common system is used, e.g. Gatekeeper, records are kept in different ways within the system and also stored outside it. These issues were also found in the AHDB Rotations Partnership project and within AHDB Horticulture Project (CP107d) Development of a Horticultural Soil Management Information System (SMIS). Whilst it seems to be obvious that the diverse and dispersed sources of management information held on farm should be able to be brought together to improve understanding and data-informed decision-making, this was still not easy to achieve in practice. There is little perceived value to record-keeping on farm and hence it is often not prioritised beyond that required for compliance e.g. agro-chemical application records. A data-driven approach to develop indicators to characterise crop rotations was not successful in this project. It may be that a more directed approach to develop a small number of indicators of key rotational practice (e.g. tillage intensity, crop/plant diversity, organic material additions) may be more successful. However, the data also clearly showed the over-riding importance of site in determining the current values for measured soil characteristics, as well as their potential. Hence, as for yield (e.g. , Sylvester-Bradley and Kindred 2014), soil health may need to be expressed in terms of site-specific potential.

6. Acknowledgements

The authors wish to thank all the farmers whose Soil Health scorecards are included here for their time and effort in sampling; and especially the farmers who compiled field records and responded patiently to our follow-up enquiries. Thanks are also due to Anne Bhogal and the teams responsible for data collection and collation on the long-term organic material addition experiments.

7. References

Amsili, J.P., van Es, H.M. and Schindelbeck R.R. (2021). Cropping system and soil texture shape soil health outcomes and scoring functions. *Soil Security* **4**, Article:100012.

Brock, C., Franko, U., Oberholzer, H.-R., Kuka, K., Leithold, G., Kolbe, J. and Reinhold, J. (2013). Humus balancing in Central Europe – concepts, state of the art, and perspectives review article. *Journal of Plant Nutrition and Soil Science* **176**, 3–11.

Cusser, S., Bahlai, C., Swinton, S.M., Robertson, G.P. and Haddad, N.M. (2020). Long-term research avoids spurious and misleading trends in sustainability attributes of no-till. *Global Change Biology* **26**, 3715-3725.

Fresno, C. and Fernandez, E.A. (2014a). lmdme: Linear Model decomposition for Designed Multivariate Experiments. *Journal of Statistical Software* **56**(7), 1-16.

Fresno, C. and Fernandez, E.A. (2014b). lmdme: Linear Model decomposition for Designed Multivariate Experiments. R package version 1.36.0. http://www.bdmg.com.ar/?page_id=38

Natural Resources Conservation Service, NCRS (2008) *Soil Tillage Intensity Rating (STIR)*. Published online at: www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1119754.pdf

Smilde, A.K., Jansen J.J., Hoefsloot, H.C.J., Lamer, R.A.N., Van der Greef, J. and Timmerman, M.E. (2005). ANOVA-simultaneous component analysis (ASCA): a new tool for analysing designed metabolomics data. *Bioinformatics* **21**, Article: 3043

Sylvester-Bradley, R. and Kindred, D. (2014). The Yield Enhancement Network: Philosophy and results from the first season. *Aspects of Applied Biology* **125**, *Agronomic Decision Making in an Uncertain Climate*, 53–62.

Wander, M.M. and Bollero, G.A. (1999). Soil quality assessment of tillage impacts in Illinois. *Soil Society of America Journal* **63**, 961-971.

Williams, H., Colombi, T. and Keller, T. (2020). The influence of soil management on soil health: an on-farm study in southern Sweden, *Geoderma* **360**: Article: 114010