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25 Year Environment Plan Outcome Indicator E7: Healthy soils – proposed method for a soil health indicator for England

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Summary

This report outlines a proposed method for a soil health indicator for England. It is planned that this method will be used to produce results for use against the 25 Year Environment Plan's Outcome Indicator Framework, to be published by JNCC as an Official Statistic in Development. Such results are not presented within this document itself, as the field data required to feed into the models are not yet publicly available. The planned approach is published here to facilitate early user input and feedback. An updated version of this document (including any further method changes made between this proposal and final methods used to calculate the indicator) will be published as the accompanying technical document alongside the ultimate Official Statistic in Development publication.

Many ecosystem services (ES) rely on healthy soils for their delivery. The importance of monitoring and managing soil health is highlighted in a number of recent policy documents and government work areas, such as the Environmental Improvement Plan, the 'State of the Environment: Soil' report and the Net Zero Strategy. Understanding progress against such policies requires the ability to measure and track changes in soil health over time. This project therefore aims to outline a proposed method for an indicator of soil health in England. It builds on a previous proof-of-concept project (Harris *et al.* 2023), but aims to apply the concepts developed there to produce a national statistic, rather than a mapped output aimed at local scale stakeholders. The next step will be to publish an initial, interim statistic, which can be improved on iteratively.

For the purposes of this project, soil health is defined as "soils' contributions to ecosystem service delivery". Models have been developed to describe soils' contribution to three ecosystem services: climate regulation, water regulation, and sustainable production of food/fibre.

It is proposed that results will be shown on a 'gauge' style visualisation (see Figure 2, Section 2), which allows the user to gain an understanding of both modelled probability of absolute ES delivery being high and the potential to increase that probability. This is because, for example, a sandy soil in good condition will store less carbon than a peaty soil in poor condition; so understanding both overall performance and performance against what is possible is important.

Contents

1. Introduction

This report starts by outlining the background and context for developing a national-scale indicator of soil health, explaining why this is important and how it links to current national policies, and elaborating on the aims and scope of the current work (Section 1). It then describes the general concept being proposed, including the definition of soil health that is being used in the context of this work and descriptions of what an indicator is, how a national-scale indicator differs from a local-scale tool, planned visualisations for presentation of the indicator, and the process that has been used to develop the method (Section 2). Following this, technical detail is provided on the method proposed for each of the three aspects of soil health (soils' contribution to water regulation, soils' contribution to long-term carbon storage, and soils' contribution to sustainable food/fibre provision) that will be reported on initially, as well as early comments about ongoing work to develop a soil biodiversity indicator (Section 3). Finally, conclusions and next steps are outlined (Section 4) and a glossary is provided, before three appendices give supplementary information on each of the three models proposed.

1.1. Background and context

Many ecosystem services (ES) rely on healthy soils for their delivery. For example, soils are an essential part of the water regulation system, contributing to runoff reduction and drought resilience (Keesstra *et al.* 2021). Soils store three times as much carbon as the atmosphere does, playing a crucial role in carbon cycling and climate regulation (Ontl & Schulte 2012). Soils are also key for the provision of food and fibre, with an estimated 95% of the global food supply produced, directly or indirectly, on soils (FAO 2015).

The importance of monitoring and managing soil health is highlighted in a number of recent policy documents and government work areas, including:

- The Government's 25 Year Environment Plan (Defra 2018), and its first revision, the Environmental Improvement Plan (Defra 2023), which commit to including an indicator on "healthy soils" as one of 66 indicators of environmental change in their associated Outcome Indicator Framework (Defra 2021);
- The 'State of the Environment: Soil' report (Environment Agency 2021), which stated that "there are insufficient data on the health of our soils";
- The Sustainable Farming Incentive (Defra 2022), which rewards famers for various actions that improve soil health;
- The Net Zero Strategy, which refers to soils' potential to help meet climate targets, especially peat soils (UK Government 2021);
- The State of Natural Capital Report for England 2024 (Lusardi *et al.* 2024) which highlights the importance of soil health in reducing a range of risks to natural capital;
- The latest Office for Environmental Protection report which highlights that "there is uncertainty around delivering sustainable soils due to the lack of an available soil health indicator" (OEP 2025).

Understanding progress against such policies requires the ability to measure and track changes in soil health over time. However, assessing and monitoring soil health presents a significant challenge due to its complex nature, encompassing physical, chemical, and biological properties. England's soils also have a diverse range of soil types, climates, and land uses. Consequently, a national soil health indicator is currently lacking.

This report therefore aims to outline a proposed method for a national-scale indicator of soil health in England, addressing these complexities. It will act as a first step towards fulfilling the clear policy need for a soil health indicator. The commitment to publishing an indicator as part of the Outcome Indicator Framework is the work's primary policy driver.

1.2. Aims and scope

The aim of the current work is to produce a national-scale indicator for use in Defra's Outcome Indicator Framework. It seeks a way to provide a nationally representative baseline statistic estimating soil health for England as a whole, with the view to repeating the same analysis in future to track change over time. As such, the indicator will not provide a mapped output, but rather a numerical score indicating soil health for the country as a whole, and for subsets of the data related to each land cover and soil type combination. The purpose of this is to be used by those designing and implementing national scale policy, rather than by landowners and local scale decision makers.

The current report aims only to present the proposed method for the indicator; presentation of results is out of scope at this stage. It is planned that an initial, interim statistic will be published in 2026.

It should be noted that this scope differs significantly from JNCC's previous soil health indicator work (Harris *et al*. 2023), which aimed to produce a local-scale decision support tool, rather than a nationally representative indicator. However, it does build on this work in terms of aligning with the definitions and modelling frameworks that were developed.

2. The concept

2.1. Defining soil health

For the purposes of this project, soil health is defined as “soils’ contributions to ecosystem service delivery,” as proposed in Harris *et al*. 2023. Three ecosystem services were selected for consideration: climate regulation through soils’ contribution to long-term carbon storage, water regulation through soils’ contribution to runoff reduction, and food/fibre provision through soils’ contribution to sustainable production of food/fibre. Metrics relating to soil biodiversity are also under development, but are at an earlier stage due to data availability and so are not presented within this proposal. The final indicator will present results from these four themes separately. This will allow users to understand soil health from a variety of perspectives and more effectively target action.

Also core to the project’s concept of soil health is the idea that not all soils will have the same inherent capability of delivering ecosystem services. For example, a sandy soil in good condition will store less carbon than a peaty soil in poor condition (BSSS 2021). It is therefore important to report on how the soil is performing relative to its potential, rather than only in absolute terms. This concept is explained further in Section 2.4 below.

2.2. What is an indicator?

An indicator is a statistic that describes change through time. This change may relate to a driver (e.g. how are human population levels and demand for food production changing through time?), a pressure (e.g. how are tillage practices changing through time?), a state (e.g. how are the physical, chemical and biological properties of the soil changing through time?), an impact (e.g. how are soils’ contributions to ecosystem services changing through time?), or a response (e.g. how many farmers are taking up soil actions under agri-environment schemes?). Indicators aim to be representative, for example aggregating data from a random selection of samples, or from a selection of samples that are stratified to ensure that samples from all groups of interest (e.g. habitats for environmental indicators, socio-demographic groups for social science indicators) are included in a representative proportion. Indicators can be either measured (e.g. presenting information aggregated directly from a sample of earthworm counts) or modelled (e.g. bringing these earthworm data together with other data sources to predict the impact of these factors on soils’ contribution to water regulation). In both of these cases, the results are based on assumptions that must be clearly understood when interpreting them.

For the purposes of this project, the water, food/fibre and one of the two carbon metrics presented will be based on modelled impact indicators. In the case of the other carbon metric, and eventually the biodiversity metrics, state indicators will be used instead.

The primary focus on impact indicators is linked to the definition of soil health stated above (soils’ contribution to ecosystem service delivery). This definition arose from the fact that state indicators (e.g. the physical, chemical and biological properties of soil) can be difficult to interpret in the context of ‘health’ (i.e. is it good or bad that this variable is at that level?). In contrast, bringing these factors together alongside pressure variables (e.g. management options) to provide a prediction of ultimate impact on ecosystem service delivery against a potential, can be more meaningfully understood.

The modelled approach was chosen because it is difficult to measure soils’ contribution to ecosystem service delivery directly. For example, it is possible to measure flooding over time, but it is not possible to measure how much of this flooding was linked to soil health specifically, compared to other factors.

In the case of biodiversity, a state indicator approach was considered more appropriate, as data are currently being collected on biodiversity directly. In the case of carbon storage, both a state indicator reporting current carbon content of the soil and a model predicting the impact of other factors on how likely that delivery of this ecosystem service will continue into the future are proposed. This makes use of measured carbon data, whilst also responding to warnings in the literature that current carbon levels may have little relevance to stability and therefore long-term ecosystem service delivery.

In the case of this project, the initial aim is to produce a baseline statistic. It will not be possible to describe change through time until the analyses have been re-run with additional data cycles to be collected into the future. This baseline statistic will be national in scope aiming to be representative for England as a whole, based on bringing together field data from the Natural Capital and Ecosystem Assessment (NCEA) programme's England Ecosystem Survey (EES) and National Forest Inventory Plus survey (NFI+; the equivalent for forested locations), with averages taken from other national data sources (e.g. spatial data such as GIS layers and farmer surveys).

2.3. Scaling up

The current phase of work has focused on scaling up the modelling approach that was developed in the proof-of-concept (Harris *et al.* 2023) to be nationally, rather than locally, applicable. One key change that has resulted relates to the data sources used. A national-scale indicator will not be able to rely on local knowledge and management decisions to input into the model, as was done in the proof-of-concept study. It will require data that are applicable to the entire country, but the data do not need to be as detailed as in a land parcel scale indicator. For example, instead of knowing whether a certain management practice is taking place in a particular field, the national model needs to know what proportion of the country that management practice is taking place in. Much of the work related to scaling up the concept has therefore been around identifying and assessing potential data sources for these factors (see Appendices 1 to 3).

Much of these data will be provided through surveys that are currently underway as part of Defra's NCEA programme, which will allow for nationally representative analyses to be undertaken. These include the NCEA's EES and the NFI+ surveys. However, other data sources have also been identified, such as the use of soil moisture data from Copernicus and farm survey data for management practices (see Figure 1 for a visual representation of data sources used, and Appendices 1 to 3 for a detailed list of data sources against each variable that is included). A key requirement in identifying these data sources was for them to be openly available, to ensure transparency.

Section 3.1.1 provides further information about how scaling up is addressed within the modelling process itself.

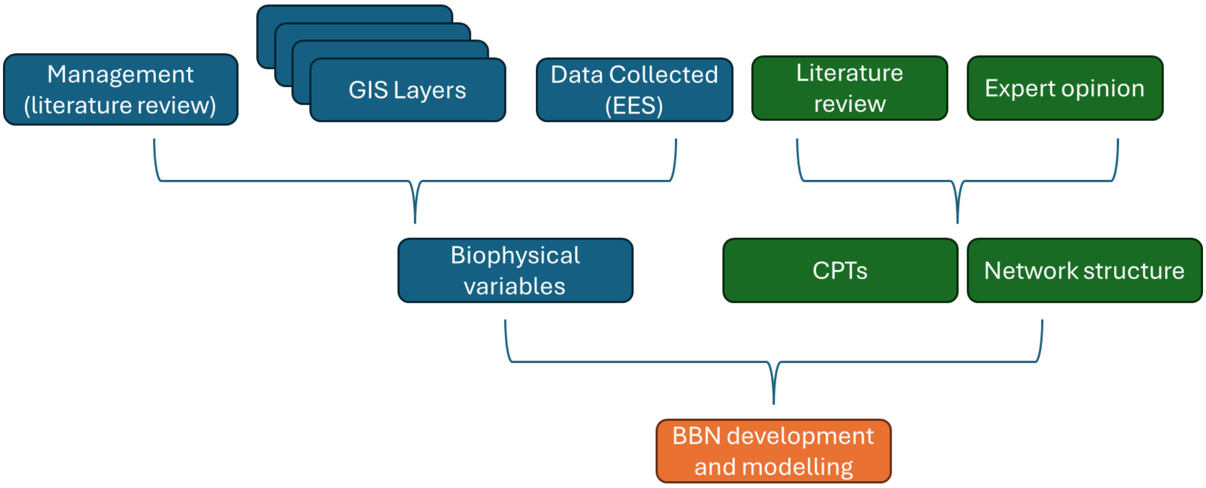

Figure 1. A visual representation of the data sources used, and how these are combined into the ultimate Bayesian Belief Network development and modelling (CPT = conditional probability tables, see Section 3 for further information).

2.4. Visualisation of results

2.4.1. Headline results

Each of the three ecosystem services (soils' long-term carbon storage, soils' contribution to water regulation through runoff reduction, and soils' contribution to food/fibre provision – see Sections 3.2 to 3.4 for further details) will have a headline result representing the probability that ES delivery is high. In addition, carbon will also have a second headline result, which simply reports on actual carbon stocks, as measured in the field by the EES. Having both measured and modelled versions for carbon is useful, as the measured values provide a snapshot in time of current levels of carbon being stored in our soils, whereas the modelled values predict the likely stability of this carbon, and ability of the soils to continue storing it longer term. Measured values for biodiversity will also be included within the suite of headline indicators presented, but are not discussed here as the approach to be taken remains at an earlier stage of development.

Each of the headline results will be presented as a gauge style visualisation, as illustrated in Figure 2.

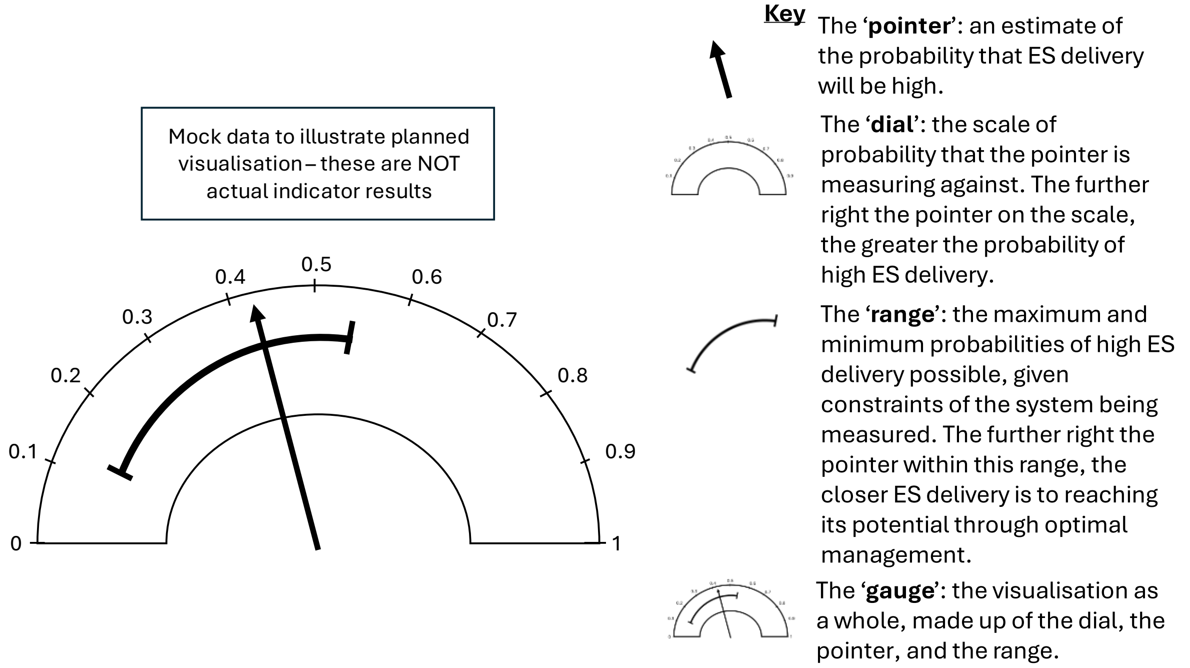

Figure 2. Mockup visualisation illustrating how results will be presented for each Ecosytem Service (ES) of interest. In this example, the pointer is to the left of middle, showing middle-low probability of high ES delivery. However, the pointer is fairly far to the right within the context of the range, suggesting that there is not great scope to increase the probability of high ES delivery. This would suggest that England's soils have significant inherent constraining factors on delivery of this ES (as the range is situated towards the left), but that factors that it is possible to influence (such as management) are being optimised relatively well within that context.

The pointer on the gauge shows the probability of high ES delivery, with this increasing as the pointer moves towards the right of the dial. The range shows how that estimate sits within the constraints of what is possible based on the inherent properties of England's soils. For example, it is difficult to influence soil texture or climatic factors, and so the variation possible based on these factors is not included within the range; whereas it is possible to influence other factors such as management, and so the variation possible related to these factors is included within the range.

It is important to understand both the absolute (pointer) and potential (range) values associated with the probability of ES delivery being high, because this can mean different things in different places. For example, if the country being analysed were to have a very high proportion of peaty soils, the range (what is possible) would sit towards the right of the gauge when estimating carbon storage. In contrast, if it had very sandy soils which inherently contain lower levels of carbon, it would sit towards the left of the gauge. The absolute value therefore allows for assessment of how great a contribution soils are making to the probability of ES delivery being high overall, presented on a comparable and consistent scale that can be used across measurements (e.g. if comparing the England value to a regional subset, to a subset of the data consisting of only a particular land use type, or to application of the same method in another UK country). In contrast, comparing the probability that ES delivery is high to the range of potential values allows for an understanding of how well England is doing at protecting ES delivery, as far as is in our control. For example, if the pointer is sitting towards the right of the range, then there is a high probability that ES delivery is high in comparison to what is possible, regardless of where on the gauge the range itself lies.

A greater probability of high ES delivery is therefore illustrated on the visualisation as the pointer being further to the right of the dial; whilst a greater probability of high ES delivery against its potential is illustrated on the visualisation as the pointer being further to the right of the range. Users of the data should consider both of these factors.

To show change through time, as will be required once data from a second time point are available, a second visualisation will be needed. Consultation is ongoing regarding the clearest way in which to present this.

2.4.2. Additional results within the indicator webpage

In addition to the national results presented as headline results, the indicator webpage will include a series of visualisations showing a more detailed breakdown of the data, within a later section. This will include the same styles of visualisation as described in Section 2.4.1, but with a separate gauge presented for each land cover and soil type combination. This will allow users to explore what is influencing the national-scale trends.

2.4.3. Additional results within the technical documentation

The results from the modelling will provide three probabilities, which sum to one. These represent the likelihood that ES delivery is low, medium and high, given the data that were input into the model. Feedback from the expert panel sessions and wider stakeholder engagement suggested that this concept, with its three separate pieces of information, was too complex to communicate and visualise simply. Therefore, the headline results, as described above, will focus only on the probability that ES delivery will be high. This does lose some information compared to what is available. However, that additional information will be available as an Appendix to the technical documentation for anyone who is interested. This will be presented as a series of histograms associated with each model node (Figure 3).

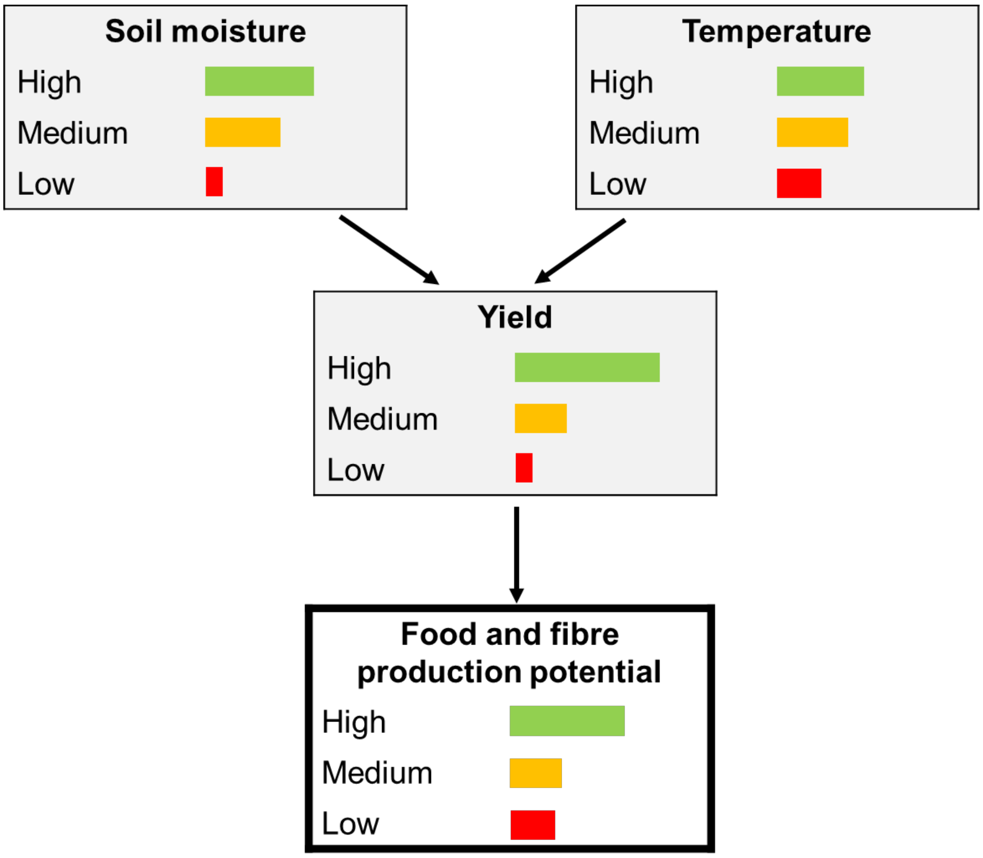

Figure 3. Mockup visualisations of the more detailed results that will be presented within an Appendix to the technical documentation when results are available (note that the above graphs are entirely illustrative and do not represent actual indicator results). At each input, intermediate, and final ES delivery node within the model, a histogram will be presented to represent the probability of that node being high, medium or low, based on the input data collated (for the input nodes), or the results of the BBN modelling (for intermediate and final nodes).

3. The underpinning models

This section provides an introduction to the type of modelling that will underpin the estimates for each of the three ecosystem services selected (water, carbon and food/fibre provision); and a summary of how this modelling will be employed and presented in each of these three cases. Further detail on the data sources that will be used, justification of the variables included, and the weightings and groupings that will be applied to these three models can be found in Appendices 1 to 3. The methods behind the proposed biodiversity part of the indicator suite are not presented here in full, but brief comment is made on the likely general approach to be taken.

3.1. An introduction to Bayesian Belief Networks

The type of modelling that will underpin the estimates of ecosystem service delivery is known as Bayesian Belief Network (BBN) modelling (Barbrook-Johnson & Penn 2022). Bayesian networks are a type of probabilistic model based on Bayes theorem, which mathematically describes what the probability of an event occurring is, based on prior knowledge of conditions that might be related to the event. BBNs can be represented visually (Figure 4), in a graphical 'flow chart' style known as a directed acyclic graph (DAG). This consists of 'nodes' (the variables) and 'edges' (the relationships between the variables). The relationships between two nodes ('conditional probabilities') can be defined based on training data, or manually based on values from the literature or expert knowledge. Specific relationships between variables can be modelled; for example, if one variable has a non-linear effect when interacting with another variable, conditional probabilities can be used to account for those specific interactions.

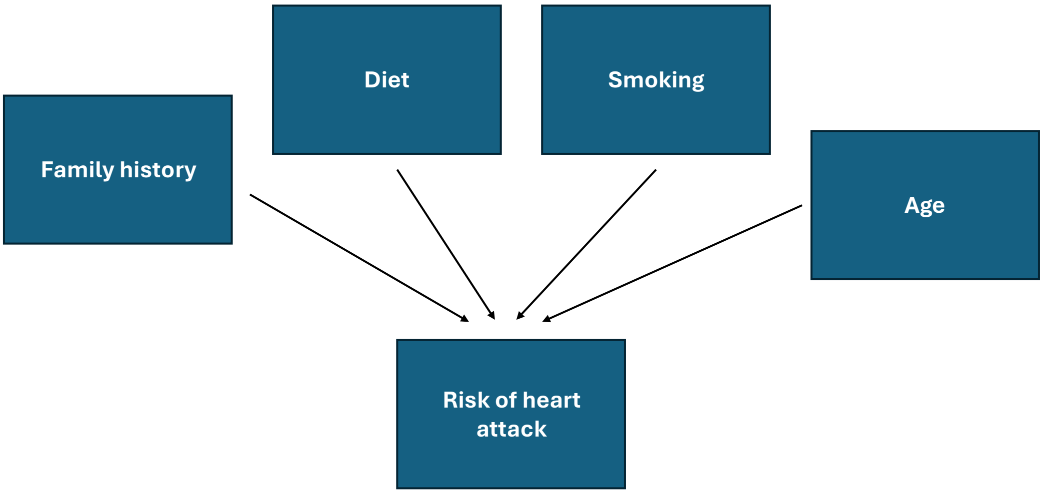

Figure 4. An illustrative example of a Bayesian Belief Network (BBN) in its graphical 'flow chart' style format, known as a directed acyclic graph (DAG). In this case the nodes consist of occupation, age, and medical history. The model will use conditional probabilities to predict the likelihood of admission to hospital based on these factors.

BBNs were selected as the modelling approach to use for a number of reasons. Their use makes it possible to integrate different types of knowledge, including spatial data and stakeholder expertise. Whilst data on the relationships between some soil variables are available, this is not true across the board. Being able to use expert input where required is therefore important. This flexibility will also allow for enhancement of the model in future as improved data sources are published.

The probabilistic nature of BBNs also allows them to inherently report on uncertainty. The most likely outcome of a particular combination of factors is often not the only possible outcome. Understanding the probability associated with this outcome is therefore important to gain a risk-based understanding of the issue.

3.1.1. Application of Bayesian Belief Networks within the indicator

At the time of writing, the methods for running the models are still in development. However, they will be based on the directed acyclic graphs (DAGs) illustrated within Sections 3.2 to 3.4, which were created based on literature review and expert panel consultation. Each initial node in the DAGs will have an associated input dataset. In preparation for input into the model, the data will be cleaned and classified according to the methods provided in Appendices 1, 2, and 3. Conditional Probability Tables (CPTs) for the model will also be created for the DAG based on input from experts on the effect of each node on the others, with the potential for some automation of this process in R.

The BBN will be created in R by combining the DAGs and CPTs, and results will likely be obtained through a query to the network that uses the prepared input data to update the probabilities of each input node and propagate this through the network. This may be through querying the model using data collected at known locations to “set” the nodes to a certain value, or by calculating averages across England for each input data node and using this to update the model. The output for the model will be the probability of the final node representing ecosystem service provision being high, medium, or low, all represented in decimal form, with particular emphasis for the purposes of the indicator being placed on the probability of the node being “high”.

3.2. Water: soils’ contribution to runoff reduction

3.2.1. What the results will show

As explained in Section 2.4., the headline results for the water model will capture two key pieces of information:

- **How much are soils contributing to reduction of runoff risk in England?** This will constitute the probability of high ecosystem service delivery, presenting the output of the water model, and represented by the pointer as shown in Figure 2 (Section 2.4.1). The specific interest chosen here is in understanding what role soil would play overall in mitigating flood risk in an intense weather event (not modelling the full hydrological system; for example, not for use in response to weather events to predict where flooding will take place). This will be calculated by running data from the NCEA programme and other sources through the BBN model outlined in Section 3.2.2.
- **How do these current levels of soils’ contribution to reduction of runoff risk compare to what is possible?** This information helps to put the previous bullet point into context. This is represented by comparing the pointer to the range shown in Figure 2 (Section 2.4.1). The ends of the range will be calculated by running the model described in Section 3.2.2 with real data for any variables that are inherent and not possible to change, but artificial data set to the highest and lowest possible values for any variables that are possible to influence with management.

In a separate part of the publication, a breakdown of results by land cover and (if possible based on data available at point of publication) soil type will also be presented. This breakdown will also incorporate the two types of result described above.

3.2.2. The model network

The structure of the water model is shown in Figure 5. The model predicts the probability that soils' contribution to reduction of runoff risk will be high. Two intermediate modelled nodes, surface runoff and subsurface runoff, feed into this final runoff risk node. The subsurface runoff node is based on data inputs relating to soil texture (grouped by runoff risk category based on the Defra soil classification framework) from samples taken deeper than 30 cm, soil depth, and bulk density to represent compaction. The surface runoff node takes into account soil texture (grouped by runoff risk category based on the Defra soil classification framework) from samples taken shallower than 30 cm, slope, and an intermediate modelled node representing infiltration rate. The infiltration rate node relies on input data on anecic earthworms (although the initial interim statistic may rely on total earthworms depending on data availability), soil moisture, land cover, and soil organic matter.

More detailed information, for example planned data sources, literature review references, and justification of variables included and excluded from the model network, can be found in Appendix 1.

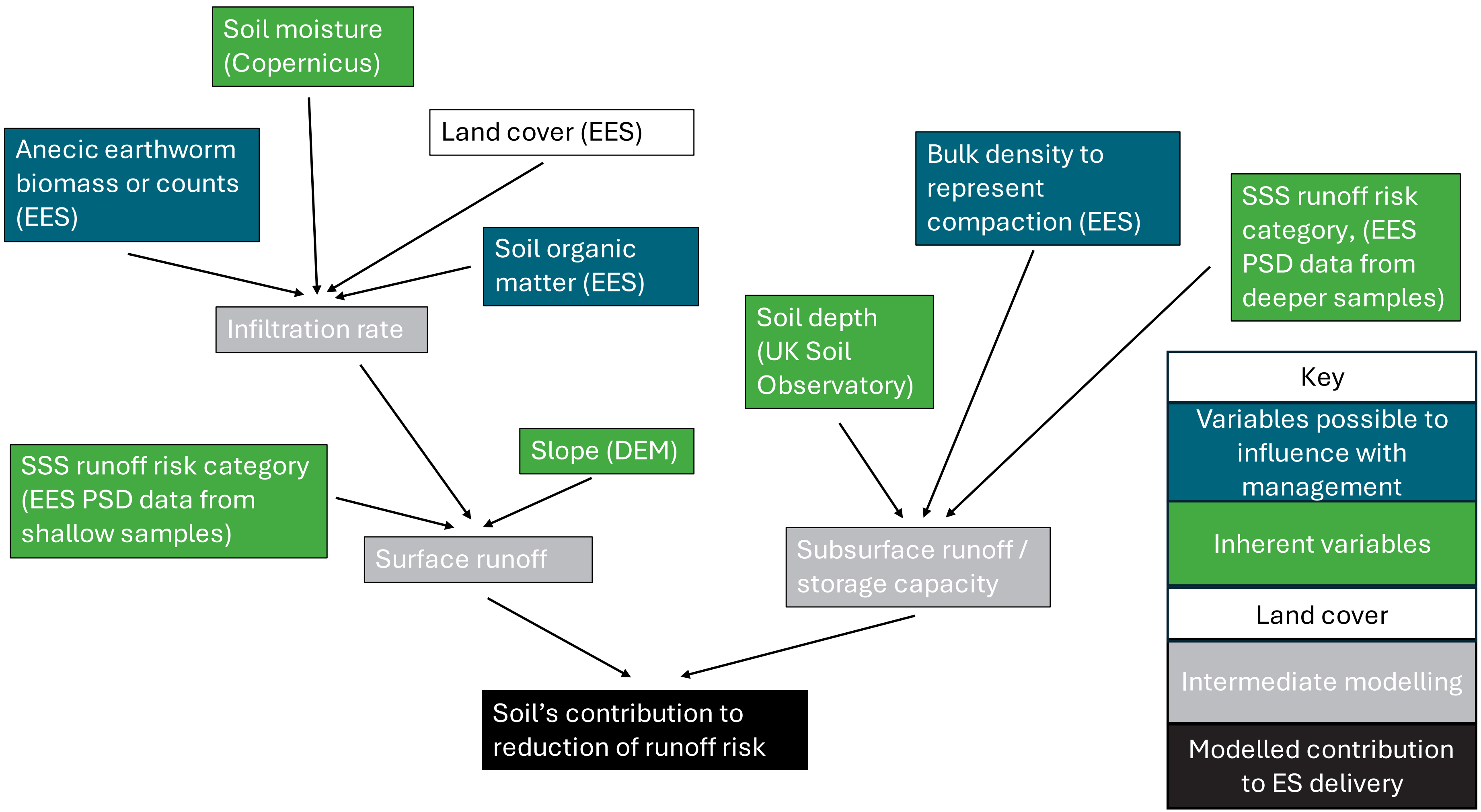

Figure 5. A visual representation of the nodes and edges in the water regulation model.

3.3. Carbon: soils' contribution to long-term carbon storage

3.3.1. What the results will show

As explained in section 2.4., the headline results for the carbon model will capture three key pieces of information:

- **How much carbon is the soil currently storing?** This will report on total estimated carbon stocks in tonnes per unit area. This will be calculated from the absolute values of carbon percentage per volume of soil across varying depths and the soil density measurements collected by the NCEA programme, alongside soil depth data from the UK Soil Observatory.
- **How much are our soils contributing to long-term carbon storage?** This will constitute the ecosystem service delivery estimate, presenting the output of the carbon model, and represented by the pointer as shown in Figure 2 (Section 2.4.1). The interest here is in understanding what role soil, in its current condition, would play in storing carbon long term. This is important because current levels of carbon in soil can bear little relation to its stability and ability to store that carbon long term, thereby contributing to ecosystem service delivery, with continued management required to permanently maintain them (Bellamy *et al*. 2005; BSSS LUNZ Hub 2023). Therefore, understanding both the current values and the probability of high predicted long-term storage values are important for gaining a balanced picture of soil health. This will be calculated by running data from the NCEA programme and other sources through the BBN model outlined in Section 3.3.2.
- **How much are our soils contributing to long term carbon storage, compared to what is possible?** This information helps to put the previous bullet point into context. This is represented by comparing the pointer to the range as shown in Figure 2 (Section 2.4.1). The ends of the range will be calculated by running the model described in Section 3.3.2 with real data for any variables that are inherent and not possible to change, but artificial data set to the highest and lowest possible values for any variables that are possible to influence with management.

In a separate part of the publication, a breakdown of results by land cover and soil type combination will also be presented. This breakdown will also incorporate the three types of result described above.

3.3.2. The model network

The structure of the carbon model is shown in Figure 6. The model predicts the probability that soils' contribution to long-term carbon storage will be high. Soil texture, and two intermediate modelled nodes (inputs and turnover) feed into this final carbon storage node. Data on the soil moisture, crop rotation, cover crops, manure and land cover feed into the input node. We hope to also include data on the ratio of respiration to microbial biomass, but this may not be possible in the initial interim statistic due to data availability. Data on erosion and tillage feed into the turnover node.

The model is currently optimised for results related to cropland. Work to integrate data and management options of relevance to forestry and other land cover types is ongoing.

More detailed information, for example planned data sources, literature review references, and justification of variables included and excluded from the model network, can be found in Appendix 2.

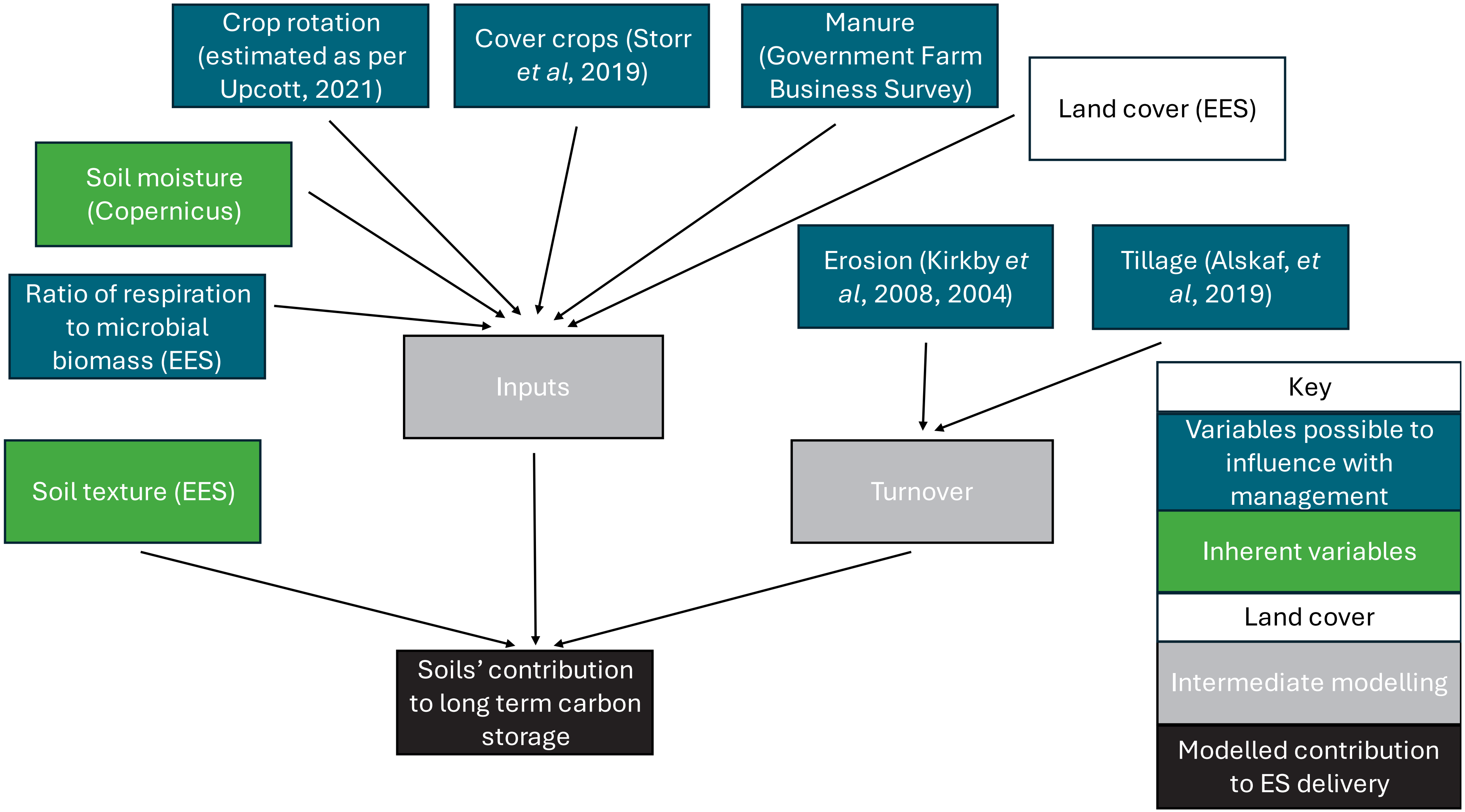

Figure 6. A visual representation of the nodes and edges in the long-term carbon storage model.

3.4. Food/fibre: soils' contribution to sustainable food/fibre provision

3.4.1. What the results will show

As explained in Section 2.4, the headline results for the food/fibre model will capture two key pieces of information:

- **How much are our soils contributing to sustainable food and fibre provision?** This will constitute the probability of high ecosystem service delivery, presenting the output of the food/fibre model, and represented by the pointer as shown in Figure 2 (Section 2.4.1). This will be calculated by running data from the NCEA programme and other sources through the BBN model outlined in Section 3.4.2.
- **How do these current levels of soils' contribution to food/fibre provision compare to what is possible?** This information helps to put the previous bullet point into context. This is represented by comparing the pointer to the range as shown in Figure 2 (Section 2.4.1). The ends of the range will be calculated by running the model described in Section 3.4.2 with real data for any variables that are inherent and not possible to change, but artificial data set to the highest and lowest possible values for any variables that are possible to influence with management.

In a separate part of the publication, a breakdown of results by land cover and soil type combination will also be presented. This breakdown will also incorporate both types of result described above.

3.4.2. The model network

The structure of the food/fibre model is shown in Figure 7. The model predicts the probability that soils' contribution to sustainable food and fibre provision will be high. Land cover, soil organic matter, risk of soil-borne pathogens and disease, earthworm counts, nutrient uptake and ALC (Agricultural Land Classification) for cropland or ESC (Ecological Site Classification) and Woodland Carbon Code biomass tables for forested areas, all feed into this final node food/fibre provision node. Nutrient uptake is a modelled intermediate node, requiring data inputs on percentage nitrogen, Olsen P measurements for available phosphorus, bulk density to represent compaction, erosion, and pH. Risk of soil-borne pathogens and disease is a modelled intermediate node, requiring data inputs on crop rotation, soil moisture and bulk density to represent compaction. It should be noted that different soil-borne pathogens and diseases will respond in different ways, and the factors modelled here are those commonly cited in the literature as widely associated with a range of pathogens and diseases.

The model is currently optimised for results related to agricultural cropland systems. Work to integrate data and management options of relevance to forestry and grazing land is ongoing.

The word 'sustainable' is included in the terminology to reflect the fact that the focus is on maximising long-term food/fibre provision, rather than short-term yields at the expense of future harvests.

More detailed information, for example planned data sources, literature review references, and justification of variables included and excluded from the model network, can be found in Appendix 3.

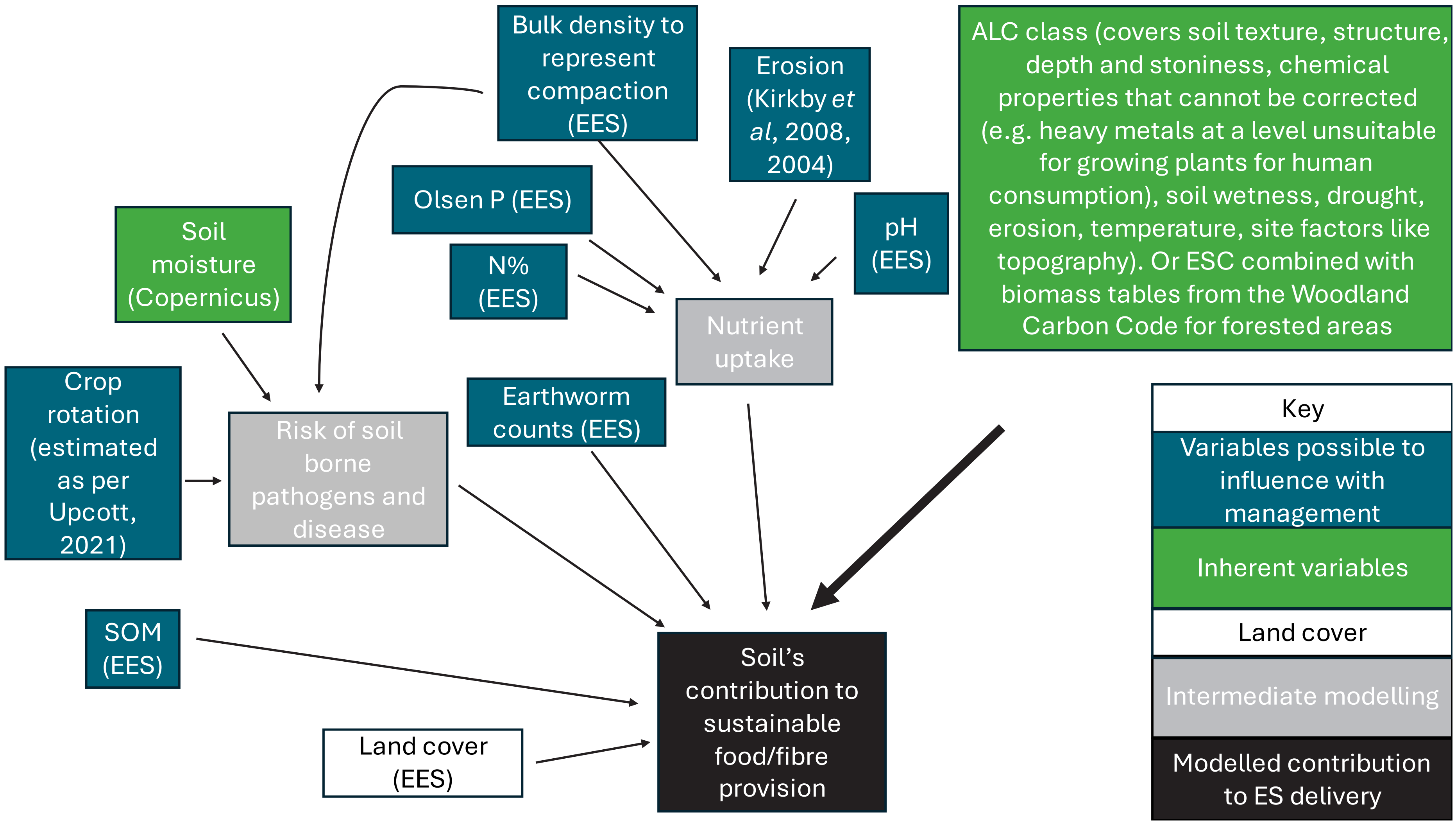

Figure 7. A visual representation of the nodes and edges in the food and fibre provision model.

3.5. Biodiversity

It is planned that data on biodiversity will ultimately be included within the indicator suite. These will be measured state data from the EES and NFI+, rather than modelled predictions. However, as the authors have not yet seen a sample of this part of the data due to the additional processing required (e.g. laboratory identifications), it has not been possible to propose a specific method for its inclusion at this stage.

4. Limitations, assumptions and uncertainty

For accurate interpretation of the results presented within this indicator, it is necessary to understand the following caveats:

- Limitations of the interim field datasets that will be used within the interim indicator in 2026:
    - The EES is producing a 5-year baseline. Monads are selected using random stratification based on Institute of Terrestrial Ecology Land Class, supplemented by an Inclusion Probability approach to increase chances of capturing rare classes of interest. This sampling design allows for statistical weightings to ensure results are representative of the sample population (England) or a subset, such as a specific geographical region. However, the sample is incomplete until the 5-year baseline is finished. Interim data may over- or under-represent some land classes, and this should be considered before drawing conclusions.
    - Certain land types, including dense urban areas, open water bodies over 2 hectares, and areas below Mean High Water, are excluded from the survey.
- Modelling assumptions:
    - The models are limited to considering only the variables shown in Figures 5, 6 and 7. Whilst other factors will undoubtedly affect soil health, the models assume that this is not the case. Variables were included where clear evidence of their effect could be found, and excluded where this was not the case (see Appendices 1 to 3 for detail on justifications for these decisions).
    - All variables within the models are grouped into categorical states. For example, land use in the water model is grouped into forest, grass/shrubland and cropland, or soil moisture into ‘high,’ ‘medium’ and ‘low’. The model is assuming that anything within the same category (e.g. something at the top end of ‘medium’ and something at the bottom end of ‘medium’) will respond in the same way. This limits the sensitivity of results. It is hoped that future development work will increase the number of categories available, thereby increasing the sensitivity of the models.
    - The relationship between the variables in the models is defined within the conditional probability tables based on information found within the literature or through the expert panel process. For example, if it is found that variable ‘a’ interacts with variable ‘b’ to give a non-linear response, then this can be defined. Similarly, if it is considered that variable ‘x’ has twice as large an effect size on ES delivery as variable ‘y’, this can be defined for the model to take into account. However, if no information is available to be able to define such interactions or weightings, it is assumed that there is no interaction and that effect sizes are equal to variables where effect size is considered ‘standard’ or ‘medium’.
    - Soils contribute to a wider range of ecosystem services than those presented here. For example, drought regulation, climate regulation through control of greenhouse gases beyond carbon, and soils’ contribution to human health will not be considered within the initial indicator.
    - The models combine spatial and non-spatial data, and assumes that these data can be treated in the same way. For example, sampled spatial data are used to derive the probability of a given parcel having high, medium, or low values for those data, while surveyed non-spatial data on farm management practices are used to determine the same thing. However, there may be patterns in the non-spatial data that are particular to nodes in the spatial data which were not picked up by the DAG, representing a limitation in the model.

5. Next steps

The planned next steps for the work are as follows:

- **Publication of an initial, interim statistic in 2026**. This will be based on the methods presented in this document, combined with any further improvements possible to integrate prior to publication. It will use data published from the first year (of a five-year baseline) of EES data collection, carried out in spring/autumn 2023 and winter 2023/24.
- **Further development work.** Work is planned to increase and test the sensitivity of the models, and to integrate more factors of relevance. The initial, interim models proposed here are of most relevance to cropland systems. For example, where management factors are considered within the models, these are currently actions that would only be appropriate to undertake on agricultural land. The effect of actions being undertaken in, for example, forest environments, is therefore not captured in the current proposal. The incorporation of more factors of relevance to other land-use types will therefore be an important development for the future to ensure that the model is appropriately sensitive. Data from Forest Research's National Forestry Inventory Plus programme are expected to be available in the near future to allow for this inclusion. Interim updates based on these improvements and integrating additional years of EES data may be released between publication of the initial statistic and final statistic.
- **Publication of a final baseline statistic in approximately 2029.** This will be based on data from the full five-years of EES data collection, and so will be nationally representative.
- **Publication of data for subsequent timepoints on the graph.** This will take place once further data collection has been completed. This would eventually enable trends to be assessed.

As improvements will be made iteratively, we encourage readers to get in contact (feedback@jncc.gov.uk) with any feedback they may have on the value and use of the indicator or any improvements that could be made in subsequent publications.

References

Abawi, G.S. & Widmer, T.L. 2000. Impact of soil health management practices on soilborne pathogens, nematodes and root diseases of vegetable crops, *Applied Soil Ecology*, **15**(1), 37–47. https://doi.org/10.1016/S0929-1393(00)00070-6.

Abu-Zreig, M.M., Tamimi, A. & Alazba, A.A. 2011. Soil Erosion Control and Moisture Conservation of Arid Lands with Stone Cover, *Arid Land Research and Management*, **25**(3), 294–307. https://doi.org/10.1080/15324982.2011.565859.

Ågren, G.I., Wetterstedt, J.Å.M. & Billberger, M.F.K. 2012. Nutrient limitation on terrestrial plant growth--modeling the interaction between nitrogen and phosphorus, *The New Phytologist*, **194**(4), 953–960. https://doi.org/10.1111/j.1469-8137.2012.04116.x.

Alam, M.Z., Braun, G., Norrie, J. & Hodges, D.M. 2014. Ascophyllum extract application can promote plant growth and root yield in carrot associated with increased root-zone soil microbial activity, *Canadian Journal of Plant Science*, **94**, 337-348. https://doi.org/10.4141/cjps2013-135.

Angst, G., Mueller, C.W., Prater, I., Angst, Š., Frouz, J., Jílková, V., Peterse, F & Nierop, K.G.J. 2019. Earthworms act as biochemical reactors to convert labile plant compounds into stabilized soil microbial necromass, *Communications Biology*, **2**(1), 1–7. https://doi.org/10.1038/s42003-019-0684-z.

Antony, D., Collins, C.D., Clark, J.M. & Sizmur, T. 2022. Soil organic matter storage in temperate lowland arable, grassland and woodland topsoil and subsoil, *Soil Use and Management*, **38**(4), 1532–1546. https://doi.org/10.1111/sum.12801.

Arvidsson, J. 1999. Nutrient uptake and growth of barley as affected by soil compaction, *Plant and Soil*, **208**(1), 9–19. https://doi.org/10.1023/A:1004484518652.

Assouline, S. 2004. Rainfall-Induced Soil Surface Sealing: A Critical Review of Observations, Conceptual Models, and Solutions, *Vadose Zone Journal*, **3**(2), 570–591. https://doi.org/10.2136/vzj2004.0570.

Assouline, S. & Mualem, Y. 1997. Modeling the dynamics of seal formation and its effect on infiltration as related to soil and rainfall characteristics, *Water Resources Research*, **33**(7), 1527–1536. https://doi.org/10.1029/96WR02674.

Athar, R. & Ahmad, M. 2002. Heavy Metal Toxicity: Effect on Plant Growth and Metal Uptake by Wheat, and on Free Living Azotobacter, *Water, Air, and Soil Pollution*, **138**(1), 165–180. https://doi.org/10.1023/A:1015594815016.

Audet, P. & Charest, C. 2007. Heavy metal phytoremediation from a meta-analytical perspective, *Environmental Pollution*, **147**(1), 231–237. https://doi.org/10.1016/j.envpol.2006.08.011.

Augustin, C. & Cihacek, L.J. 2016. Relationships Between Soil Carbon and Soil Texture in the Northern Great Plains, *Soil Science*, **181**(8), 386. http://dx.doi.org/10.1097/SS.0000000000000173.

Augusto, L. & Boča, A. 2022. Tree functional traits, forest biomass, and tree species diversity interact with site properties to drive forest soil carbon, *Nature Communications*, **13**(1), 1097. https://doi.org/10.1038/s41467-022-28748-0

Bakker, M.M., Govers, G., Jones, R.A. & Rounsevell, M.D.A. 2007. The Effect of Soil Erosion on Europe's Crop Yields, *Ecosystems*, **10**(7), 1209–1219. https://doi.org/10.1007/s10021-007-9090-3.

Barbrook-Johnson, P. & Penn, A.S. 2022. Bayesian Belief Networks. In: P. Barbrook-Johnson and A.S. Penn (eds) *Systems Mapping: How to build and use causal models of systems*. Cham: Springer International Publishing, pp. 97–112.

Batey, T. 2009. Soil compaction and soil management – a review, *Soil Use and Management*, **4**, 335–345. https://doi.org/10.1111/j.1475-2743.2009.00236.x.

Baumhardt, R.L., Römkens, M.J.M., Whisler, F.D. & Parlange, J.-Y. 1990. Modeling infiltration into a sealing soil, *Water Resources Research*, **26**(10), 2497–2505. https://doi.org/10.1029/WR026i010p02497.

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.

Biot, Y. & Lu, X.X. 1995. Loss of yield caused by soil erosion on sandy soils in the UK, *Soil Use and Management*, **11**(4), 157–162. https://doi.org/10.1111/j.1475-2743.1995.tb00949.x.

Boardman, J., Shepheard, M.L., Walker, E. & Foster, I.D.L. 2009. Soil erosion and risk-assessment for on- and off-farm impacts: A test case using the Midhurst area, West Sussex, UK, *Journal of Environmental Management*, **90**(8), 2578–2588. https://doi.org/10.1016/j.jenvman.2009.01.018.

Boardman, J. & Favis-Mortlock, D.T. (1993) Climate Change and Soil Erosion in Britain, *The Geographical Journal*, **159**(2), 179–183. https://doi.org/10.2307/3451408.

Bonanomi, G., Antignani, V., Capodilupo, M. & Scala, F. 2010. Identifying the characteristics of organic soil amendments that suppress soilborne plant diseases, *Soil Biology and Biochemistry*, **42**(2), 136–144. https://doi.org/10.1016/j.soilbio.2009.10.012.

Botta, G.F., Jorajuria, G., Balbuena, R., Ressia, M., Ferrero, C., Rosatto, H. & Tourn, M. 2006. Deep tillage and traffic effects on subsoil compaction and sunflower (*Helianthus annus* L.) yields', *Soil and Tillage Research*, **91**(1), 164–172. https://doi.org/10.1016/j.still.2005.12.011.

Bradford, M.A., Fierer, N. & Reynolds, J.F. 2008. Soil carbon stocks in experimental mesocosms are dependent on the rate of labile carbon, nitrogen and phosphorus inputs to soils, *Functional Ecology*, **22**(6), 964–974. https://doi.org/10.1111/j.1365-2435.2008.01404.x.

Brown, G., Pashanasi, B., Villenave, C., Patrón, J.C., S, Senapati, B.K., Giri, S., Barois, I., Lavelle, P., Blancharf, E., Blakemore, R.J., Spain, A.V. & Boyer, J. 1999. Effect of Earthworms on Plant Production in the Tropics', in *Earthworm Management in Tropical Agroecosystems*. CABI.

Brown, J.L., Stobart, R., Hallett, P.D., Morris, N.L., George, T.S., Newton, A.C., Valentine, T.A. & McKenzie, B.M. 2021. Variable impacts of reduced and zero tillage on soil carbon storage across 4–10 years of UK field experiments, *Journal of Soils and Sediments*, **21**(2), 890–904. https://doi.org/10.1007/s11368-020-02799-6.

BSSS. 2021. *Science Note: Soil Carbon*. British Society for Soil Science. Available at: https://soils.org.uk/wp-content/uploads/2022/05/BSSS_Science-Note_Soil-Carbon_Final_May22_75YRS_DIGITAL.pdf [Accessed 17 March 2025].

BSSS LUNZ Hub. 2023. *Guidance Note for Land Managers Soil Carbon: What are carbon stocks and how can they be measured?* Available from: https://soils.org.uk/wp-content/uploads/2023/06/BSSS_Science-Note_June-23_Soil-Carbon-Stocks_FINAL-DIGITAL_300623.pdf [Accessed 17 March 2025].

Chaplot, V. & Smith, P. 2023. Cover crops do not increase soil organic carbon stocks as much as has been claimed: What is the way forward?, *Global Change Biology*, **29**(22), 6163–6169. https://doi.org/10.1111/gcb.16917.

Clark, R.B. 1983. Plant genotype differences in the uptake, translocation, accumulation, and use of mineral elements required for plant growth, *Plant and Soil*, **72**(2/3), 175–196.

Cong, W.-F., Hoffland, E., Li, L, Siz, J., Sun, J.-H., Bao, X.-G., Zhang, F.-S. & Van Der Werf, W. 2015. Intercropping enhances soil carbon and nitrogen, *Global Change Biology*, **21**(4), 1715–1726. https://doi.org/10.1111/gcb.12738.

Cooper, R.J., Hama-Aziz, Z.Q., Hiscock, K.M., Lovett, A.A., Vrain, E., Dugdale, S.J., Sünnenberg, G., Dockerty, T., Hovesen, P. & Noble, L. 2020. Conservation tillage and soil health: Lessons from a 5-year UK farm trial (2013–2018), *Soil and Tillage Research*, **202**, 104648. https://doi.org/10.1016/j.still.2020.104648.

Crowther, T.W., Riggs, C., Lind, E.M., Borer, E.T., Seabloom, E.W., Hobbie, S.E., Wubs, J., Adler, P.B., Firn, J., Gherardi, L., Hagenah, N., Hofmockel, K.S., Knops, J.M.H, McCulley, R.L., MacDougall, A.S., Peri, P.L., Prober, S.M., Stevens, C.J. & Routh, D. 2019. Sensitivity of global soil carbon stocks to combined nutrient enrichment, *Ecology Letters*, **22**(6), 936–945. https://doi.org/10.1111/ele.13258.

Cui, Y., Moorhead, D.L., Wang, X., Xu, M., Wang, X., Wei, X., Zhu, Z., Ge, T., Peng, S., Zhu, B., Zhang, X. & Fang, L. 2022. Decreasing microbial phosphorus limitation increases soil carbon release, *Geoderma*, **419**, 115868. https://doi.org/10.1016/j.geoderma.2022.115868.

Curtin, D., Campbell, C.A. & Jalil, A. 1998. Effects of acidity on mineralization: pH-dependence of organic matter mineralization in weakly acidic soils, *Soil Biology and Biochemistry*, **30**(1), 57–64. https://doi.org/10.1016/S0038-0717(97)00094-1.

Dalias, P., Anderson, J.M., Bottner, P. & Coûteaux, M.-M. 2001. Long-term effects of temperature on carbon mineralisation processes', *Soil Biology and Biochemistry*, **33**(7), 1049–1057. https://doi.org/10.1016/S0038-0717(01)00009-8.

Davidson, E.A. & Janssens, I.A. 2006. Temperature sensitivity of soil carbon decomposition and feedbacks to climate change, *Nature*, **440**(7081), 165–173. https://doi.org/10.1038/nature04514.

Debska, B., Kotwica, K., Banach-Szott, M., Spychaj-Fabisiak, E., Tobiašová, E. 2022. Soil Fertility Improvement and Carbon Sequestration through Exogenous Organic Matter and Biostimulant Application, *Agriculture*, **12**(9), 1478. https://doi.org/10.3390/agriculture12091478.

Defra. 2018. *A Green Future: Our 25 Year Plan to Improve the Environment*. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/693158/25-year-environment-plan.pdf [Accessed 17 March 2025].

Defra. 2021. *Outcome Indicator Framework for the 25 Year Environment Plan*. Available from: https://oifdata.defra.gov.uk/ [Accessed 17 March 2025].

Defra. 2022. *Sustainable Farming Incentive: guidance for applicants and agreement holders*. Available from: https://www.gov.uk/government/collections/sustainable-farming-incentive-guidance [Accessed 17 March 2025].

Defra (2023) *Environmental Improvement Plan*. Available from: https://www.gov.uk/government/publications/environmental-improvement-plan [Accessed 17 March 2025].

Derouard, L., Tondoh, J., Vilcosqui, L. & Lavelle, P. 1997. Effects of earthworm introduction on soil processes and plant growth, *Soil Biology and Biochemistry*, **29**(3), 541–545. https://doi.org/10.1016/S0038-0717(96)00035-1.

Di Prima, S., Concialdi, P., Lassabatere, L., Angulo-Jaramillo, R., Pirastru, M., Cerdà, A. & Keesstra, S. 2018. Laboratory testing of Beerkan infiltration experiments for assessing the role of soil sealing on water infiltration, *CATENA*, **167**, 373–384. https://doi.org/10.1016/j.catena.2018.05.013.

Dudka, S., Piotrowska, M. & Chlopecka, A. 1994. Effect of elevated concentrations of Cd and Zn in soil on spring wheat yield and the metal contents of the plants, *Water, Air, and Soil Pollution*, **76**(3), 333–341. https://doi.org/10.1007/BF00482710.

Eagleman, J.R. & Decker, W.L. 1965. The Role of Soil Moisture in Evapotranspiration, *Agronomy Journal*, **57**(6), 626–629. https://doi.org/10.2134/agronj1965.00021962005700060033x.

Eglin, T., Ciais, P., Piao, S.L., Barré, P., Belassen, V., Cadule, P., Chenu, C., Gasser, T., Reichstein, M. & Smith, P. 2011. Overview on Response of Global Soil Carbon Pools to Climate and Land-Use Changes. In: *Sustaining Soil Productivity in Response to Global Climate Change*. John Wiley & Sons, Ltd, pp. 183–199. https://doi.org/10.1002/9780470960257.ch13.

Environment Agency. 2021. *The state of the environment: soil*. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/805926/State_of_the_environment_soil_report.pdf [Accessed 17 March 2025].

Enya, O., Heaney, N., Iniama, G. & Lin, C. 2020. Effects of heavy metals on organic matter decomposition in inundated soils: Microcosm experiment and field examination, *Science of The Total Environment*, **724**, 138223. https://doi.org/10.1016/j.scitotenv.2020.138223.

Epstein, E., Grant, W.J. & Struchtemeyer, R.A. 1966. Effects of Stones on Runoff, Erosion, and Soil Moisture, *Soil Science Society of America Journal*, **30**(5), 638–640. https://doi.org/10.2136/sssaj1966.03615995003000050029x.

FAO. 2015. *Healthy soils are the basis for healthy food production*. Available from: https://www.fao.org/soils-2015/news/news-detail/en/c/277682/ [Accessed 17 March 2025].

Feeney, C.J., Robinson, D.A., Keith, A.M., Vigier, A., Bentley, L., Smith, R.P., Garbutt, A, Maskell, L.C., Norton, L., Wood, C.M., Cosby, B.J. & Emmett, B.A. 2023. Development of soil health benchmarks for managed and semi-natural landscapes, *Science of The Total Environment*, **886**, 163973. https://doi.org/10.1016/j.scitotenv.2023.163973.

Filser, J., Faber, J.H., Tiunov, A.V., Brussaard, L., Frouz, J., De Deyn, G., Uvarov, A.V., Berg, M.P., Lavelle, P., Loreau, M., Wall, D.H., Querner, P., Eijsackers, H. & Jiménez, J.J. 2016. Soil fauna: key to new carbon models, *SOIL*, **2**(4), 565–582. https://doi.org/10.5194/soil-2-565-2016.

Fornara, D. & Higgins, A. 2022. Tillage and reseeding effects on soil carbon stocks: evidence from 500 agricultural grasslands in the UK, *Agronomy for Sustainable Development*, **42**(4), 71. https://doi.org/10.1007/s13593-022-00804-5.

Gales, K. 1983. Yield variation of wheat and barley in Britain in relation to crop growth and soil conditions—A review, *Journal of the Science of Food and Agriculture*, **34**(10), 1085–1104. https://doi.org/10.1002/jsfa.2740341008.

Gallagher, J.N. 1979. Field Studies of Cereal Leaf Growth: I. Initiation and expansion in relation to temperature and ontogeny, *Journal of Experimental Botany*, **30**(117), 625–636.

de Graaff, M.-A., Kardol, A.P. & Throop, H.L. 2015. A meta-analysis of soil biodiversity impacts on the carbon cycle, *SOIL*, **1**(1), 257–271. https://doi.org/10.5194/soil-1-257-2015.

van Groenigen, J.W., Lubbers, I.M., Vos, H.M.J., Brown, G.G., De Deyn, G.B. & van Groenigen, K.J. 2014. Earthworms increase plant production: a meta-analysis, *Scientific Reports*, **4**, 6365. https://doi.org/10.1038/srep06365.

van Groenigen, K.J., Hastings, A., Forristal, D., Roth, B., Jones, M. & Smith, P. 2011. Soil C storage as affected by tillage and straw management: An assessment using field measurements and model predictions, *Agriculture, Ecosystems & Environment*, **140**(1), 218–225. https://doi.org/10.1016/j.agee.2010.12.008.

Gross, A. & Glaser, B. 2021. Meta-analysis on how manure application changes soil organic carbon storage, *Scientific Reports*, **11**(1), 5516. https://doi.org/10.1038/s41598-021-82739-7.

Guerra, A.J.T., Fullen, M.A., Jorge, M.D.C.O., Bezerra, J.F.R. & Shokr, M.S. 2017. Slope Processes, Mass Movement and Soil Erosion: A Review, *Pedosphere*, **27**(1), 27–41. https://doi.org/10.1016/S1002-0160(17)60294-7.

Hamarashid, N.H., Othman, M.A. & Hussain, M.-A.H. 2010. Effects of soil texture on chemical compositions, microbial populations and carbon mineralization in soil, *Egypt. J. Exp. Biol. (Bot.)*, 6(1), 59–64.

Hargreaves, P.R., Baker, K.L., Graceson, A., Bonnett, S., Ball, B.C. & Cloy, J.M. 2019. Soil compaction effects on grassland silage yields and soil structure under different levels of compaction over three years, *European Journal of Agronomy*, **109**, 25916. https://doi.org/10.1016/j.eja.2019.125916.

Harper, J.R. & Balke, N.E. 1981. Characterization of the Inhibition of K+ Absorption in Oat Roots by Salicylic Acid 1, *Plant Physiology*, **68**(6), 1349–1353.

Harris, M., Hoskins, H., Robinson, A., Hutchinson, J., Withers, A., Deeks, L., Hannam, J., Harris, J., Way, L., & Rickson, J. 2023. *Towards Indicators of Soil Health*. 737. JNCC, Peterborough, ISSN 0963-8091. Available from: https://hub.jncc.gov.uk/assets/71cece04-eef3-4d34-b118-33ddad50912c [Accessed 17 March 2025].

Hartemink, A.E. & Barrow, N.J. 2023. Soil pH-nutrient relationships: the diagram, *Plant and Soil*, **486**(1–2), 209–215. https://doi.org/10.1007/s11104-022-05861-z.

Hartley, I.P., Hill, T.C., Chadburn, S.E. & Hugelius, G. 2021. Temperature effects on carbon storage are controlled by soil stabilisation capacities, *Nature Communications*, **12**(1), 6713. https://doi.org/10.1038/s41467-021-27101-1.

Holland, J.E., Bennett, A.E., Newton, A.C., White, P.J., McKenzie, B.M., George, T.S., Pakeman, R.J., Bailey, J.S., Fornara, D.A. & Hayes, R.C. 2018. Liming impacts on soils, crops and biodiversity in the UK: A review, *Science of The Total Environment*, **610–611**, 316–332. https://doi.org/10.1016/j.scitotenv.2017.08.020.

Hugar, D.G.M., Sorganvi, V. & Hiremath, G.M. 2012. Effect of Organic Carbon on Soil Moisture, *Indian Journal Of Natural Sciences*, **3**(15), 1191-1235.

Hunde, K.K. 2015. Evaluation of Soil Carbon Pool potential under different Land use system and Its Correlation with different Soil Properties in North Wales, UK, *Climate Change*, **1**(2), 54–61.

Hyvönen, R., Ågren, G., Linder, S., Persson, T., Cotrufo, M.F., Ekblad, A., Freeman, M., Grelle, A., Janssens, I.A., Jarvis, P.G., Kellomäki, S., Lindroth, A., Loustau, D., Lundmark, T., Norby, R.J., Oren, R., Pilegaard, K., Ryan, M.G., Sigurdsson, B.D., Strömgren, M., van Oijen, M. & Wallin, G. 2007. The likely impact of elevated [CO2], nitrogen deposition, increased temperature and management on carbon sequestration in temperate and boreal forest ecosystems: a literature review, *New Phytologist,* **173**, 463–480. https://doi.org/10.1111/j.1469-8137.2007.01967.x.

Insam, H., Mitchell, C.C. & Dormaar, J.F. 1991. Relationship of soil microbial biomass and activity with fertilization practice and crop yield of three ultisols, *Soil Biology and Biochemistry*, **23**(5), 459–464. https://doi.org/10.1016/0038-0717(91)90010-H.

Ishak, L. 2017. *Soil microbial communities and disease suppression as affected by soil compaction resulting from different management strategies*. Thesis. CQUniversity.

Jalli, M., Huusela, E., Jallie, H., Kauppi, K., Niemi, M., Himanen, S. & Jauhiainen, L. 2021. Effects of Crop Rotation on Spring Wheat Yield and Pest Occurrence in Different Tillage Systems: A Multi-Year Experiment in Finnish Growing Conditions, *Frontiers in Sustainable Food Systems*, **5**. https://doi.org/10.3389/fsufs.2021.647335.

Janssens, I.A., Dieleman, W., Luyssaert, S., Subke, J.-A., Reichstein, M., Ceulemans, R., Ciais, P., Dolman, A.J., Grace, J., Matteucci, G., Papale, D., Piao, S.L., Schulze, E.-D., Tang, J. & Law, B.E. 2010. Reduction of forest soil respiration in response to nitrogen deposition, *Nature Geoscience*, **3**, 315–322. https://doi.org/10.1038/ngeo844

Jordon, M.W., Smith, P., Long, P.R., Bürkner, P.-C., Petrokofsky, G. & Willis, K.J. 2022. Can Regenerative Agriculture increase national soil carbon stocks? Simulated country-scale adoption of reduced tillage, cover cropping, and ley-arable integration using RothC, *Science of The Total Environment*, **825**, 153955. https://doi.org/10.1016/j.scitotenv.2022.153955.

Keatinge, J.D.H., Stewart, R.H. & Garrett, M.K. 1979. The influence of temperature and soil water potential on the leaf extension rate of perennial ryegrass in Northern Ireland, *The Journal of Agricultural Science*, **92**(1), 175–183. https://doi.org/10.1017/S0021859600060627.

Keesstra, S., Sannigrahi, S., López-Vicente, M., Pulido, M., Novara, A., Visser, S. & Kalantari, Z. 2021. The role of soils in regulation and provision of blue and green water, *Philosophical Transactions of the Royal Society B: Biological Sciences*, **376**(1834), 20200175. https://doi.org/10.1098/rstb.2020.0175.

Kemmitt, S.J., Wright, D., Goulding, K.W.T. & Jones, D.L. 2006. pH regulation of carbon and nitrogen dynamics in two agricultural soils, *Soil Biology and Biochemistry*, **38**(5), 898–911. https://doi.org/10.1016/j.soilbio.2005.08.006.

Kerr, D.D. & Ochsner, T.E. 2020. Soil organic carbon more strongly related to soil moisture than soil temperature in temperate grasslands, *Soil Science Society of America Journal*, **84**(2), 587–596. https://doi.org/10.1002/saj2.20018.

Khaerudin, D.N., Suharyanto, A. & Harisuseno, D. 2017. Infiltration Rate for Rainfall and Runoff Process with Bulk Density Soil and Slope Variation in Laboratory Experiment, *Nature Environment and Pollution Technology*, **16**(1).

Kirkegaard, J.A., Lilley, J.M., Howe, G.N. & Graham, J.M. 2007. Impact of subsoil water use on wheat yield, *Crop & Pasture Science*, **58**(4), 303–315. https://doi.org/10.1071/AR06285.

Koch, H.-J., Heuer, H., Tomanová, O. & Märländer, B. 2008. Cumulative effect of annually repeated passes of heavy agricultural machinery on soil structural properties and sugar beet yield under two tillage systems, *Soil and Tillage Research*, **101**(1), 69–77. https://doi.org/10.1016/j.still.2008.07.008.

Kumar, S., Nakajima, T., Mbonimpa, E.G., Gautam, S., Somireddy, U.R. Kadono, A., Lal, R., Chintala, R., Rafique, R. & Fausey, N. 2014. Long-term tillage and drainage influences on soil organic carbon dynamics, aggregate stability and corn yield, *Soil Science and Plant Nutrition*, **60**(1), 108–118. https://doi.org/10.1080/00380768.2013.878643.

Lal, R. & Moldenhauer, W. 1987. Effects of soil erosion on crop productivity, *Critical Reviews in Plant Sciences*, **5**(4).

Langdale, G.W.& Shrader, W.D. 1982. Soil Erosion Effects on Soil Productivity of Cultivated Cropland. In: *Determinants of Soil Loss Tolerance*. John Wiley & Sons, Ltd, pp. 41–51. https://doi.org/10.2134/asaspecpub45.c4.

Lange, M., Eisenhauer, N., Sierra, C.A., Bessler, H., Engels, C., Griffiths, R.I., Mellado-Vázquez, P.G., Malik, A.A., Roy, J., Scheu, S., Steinbeiss, S., Thomson, B.C., Trumbore, S.E. & Gleixner, G. 2015. Plant diversity increases soil microbial activity and soil carbon storage, *Nature Communications*, **6**(1), 6707. https://doi.org/10.1038/ncomms7707.

Li, S., Ye, S., Liu, Z., Umair Hassan, M., Huang, G. & Zhou, Q. 2024. How does intercropping contribute to soil organic carbon accumulation? A global synthesis, *Agriculture, Ecosystems & Environment*, **374**, 109173. https://doi.org/10.1016/j.agee.2024.109173.

Li, Z., Wu, P., Feng, H, Zhao, X., Huang, J. & Zhuang, W. 2009. Simulated experiment on effect of soil bulk density on soil infiltration capacity, *Transactions of the Chinese Society of Agricultural Engineering*, **25**(6), 40–45.

Liu, F., Ying, G.-G., Tao, R., Zhao, J.-L., Yang, J.-F. & Zhao, L.-F. 2009. Effects of six selected antibiotics on plant growth and soil microbial and enzymatic activities, *Environmental Pollution*, **157**(5), 636–1642. https://doi.org/10.1016/j.envpol.2008.12.021.

López-Marcos, D., Martínez-Ruiz, C., Turrión, M.-B., Jonard, M., Titeux, H., Ponette, Q. & Bravo, F. 2018. Soil carbon stocks and exchangeable cations in monospecific and mixed pine forests, *European Journal of Forest Research*, **137**(6), 831–847. https://doi.org/10.1007/s10342-018-1143-y.

Loveland, P. & Webb, J. 2003. Is there a critical level of organic matter in the agricultural soils of temperate regions: a review, *Soil and Tillage Research*, **70**(1), 1–18. https://doi.org/10.1016/S0167-1987(02)00139-3.

Lubbers, I.M., van Groenigan, K., Fonte, S.J., Six, J., Brussaard, L. & van Groenigan, J.W. 2013. Greenhouse-gas emissions from soils increased by earthworms, *Nature Climate Change*, **3**(3), 187–194. https://doi.org/10.1038/nclimate1692.

Luo, M., Moorhead, D.L., Ochoa-Hueso, R., Mueller, C.W., Ying, S.C. & Ji Chen, Y. 2022. Nitrogen loading enhances phosphorus limitation in terrestrial ecosystems with implications for soil carbon cycling, *Functional Ecology*, **36**(11), 2845–2858. https://doi.org/10.1111/1365-2435.14178.

Lusardi, J., Rice, P., Craven, J., Hinson, C., Bell, F., Morgan, A., Martin, K., Dobson, M., Sunderland, T. & Waters, R. 2024. *State of Natural Capital Report for England 2024: Risks to nature and why it matters*. Natural England Research Report Number NERR137.

Lyons, S.M. & Gifford, G.F. 1980. Impact of Incremental Surface Soil Depths on Plant Production, Transpiration Ratios, and Nitrogen Mineralization Rates, *Journal of Range Management*, **33**(3), 189. https://doi.org/10.2307/3898282.

Maas, E.V. & Ogata, G. 1971. Absorption of magnesium and chloride by excised corn root, *Plant Physiology*, **47**(3), 357–360. https://doi.org/10.1104/pp.47.3.357.

Maillard, É. & Angers, D.A. 2014. Animal manure application and soil organic carbon stocks: a meta-analysis, *Global Change Biology*, **20**(2), 666–679. https://doi.org/10.1111/gcb.12438.

McClelland, S.C., Paustian, K. & Schipanski, M.E. 2021. Management of cover crops in temperate climates influences soil organic carbon stocks: a meta-analysis, *Ecological Applications*, **31**(3), e02278. https://doi.org/10.1002/eap.2278.

McGinty, W.A., Smeins, F.E. & Merrill, L.B. 1979. Influence of Soil, Vegetation, and Grazing Management on Infiltration Rate and Sediment Production of Edwards Plateau Rangeland, *Journal of Range Management*, **32**(1), 33. https://doi.org/10.2307/3897380.

Nassal, D., Spohn, M., Eltlbany, N., Jacquiod, S., Smalla, K., Marhan, S. & Kandeler, E. 2018. Effects of phosphorus-mobilizing bacteria on tomato growth and soil microbial activity, *Plant and Soil*, **427**(1), 17–37. https://doi.org/10.1007/s11104-017-3528-y.

Nciizah, A.D. & Wakindiki, I.I.C. 2015. Soil sealing and crusting effects on infiltration rate: a critical review of shortfalls in prediction models and solutions, *Archives of Agronomy and Soil Science*, **61**(9), 1211-1230. https://doi.org/10.1080/03650340.2014.998203

Neina, D. 2019. The Role of Soil pH in Plant Nutrition and Soil Remediation, *Applied and Environmental Soil Science*, **2019**(1), p. 5794869. Available at: https://doi.org/10.1155/2019/5794869.

Nevens, F. & Reheul, D. 2003. The consequences of wheel-induced soil compaction and subsoiling for silage maize on a sandy loam soil in Belgium, *Soil & Tillage Research*, **70**(2), 175–184.

Nielsen, K.F., Halstead, R.L., MacLean, A.J., Bourget, S.J. & Holmes, R.M. 1961. The Influence of Soil Temperature on the Growth and Mineral Composition of Corn, Bromegrass and Potatoes, *Soil Science Society of America Journal*, **25**(5), 369–372. https://doi.org/10.2136/sssaj1961.03615995002500050019x.

OEP. 2025 *Progress in improving the natural environment in England 2023/2024*. Available from: https://www.theoep.org.uk/report/government-has-chance-get-track-meet-legal-environmental-commitments-window-opportunity [Accessed 17 March 2025].

Ontl, T.A. & Schulte, L.A. 2012. Soil Carbon Storage, *Nature Education Knowledge*, **3**(10), 35.

Orgiazzi, A. & Panagos, P. 2018. Soil biodiversity and soil erosion: It is time to get married, *Global Ecology and Biogeography*, **27**(10), 1155–1167. https://doi.org/10.1111/geb.12782.

Ostle, N.J., Levy, P.E., Evans, C.D. & Smith, P. 2009. UK land use and soil carbon sequestration, *Land Use Policy*, **26**, S274–S283. https://doi.org/10.1016/j.landusepol.2009.08.006.

Poeplau, C. & Don, A. 2015. Carbon sequestration in agricultural soils via cultivation of cover crops – A meta-analysis, *Agriculture, Ecosystems & Environment*, **200**, 33–41. https://doi.org/10.1016/j.agee.2014.10.024.

Poll, C., Marham, S., Back, F., Niklaus, P.A. & Kandeler, E. 2013. Field-scale manipulation of soil temperature and precipitation change soil CO2 flux in a temperate agricultural ecosystem, *Agriculture, Ecosystems & Environment*, **165**, 88–97. https://doi.org/10.1016/j.agee.2012.12.012.

Poulton, P., Johnston, J., MacDonald, A., White, R. & Powlson, D. 2018. Major limitations to achieving “4 per 1000” increases in soil organic carbon stock in temperate regions: Evidence from long-term experiments at Rothamsted Research, United Kingdom, *Global Change Biology*, **24**(6), 2563–2584. https://doi.org/10.1111/gcb.14066.

Powlson, D.S., Bhogal, A., Chambers, B.J., Coleman, K. Macdonald, A.J., Goulding, K.W.T. & Whitmore, A.P. 2012. The potential to increase soil carbon stocks through reduced tillage or organic material additions in England and Wales: A case study, *Agriculture, Ecosystems & Environment*, **146**(1), 23–33. https://doi.org/10.1016/j.agee.2011.10.004.

Pugh, C. 2020. Soil bulk density effects on runoff estimation. *Biosystems and Agricultural Engineering,* **69**. https://doi.org/10.13023/etd.2020.172.

Qi, R., Li, J., Lin, Z., Li, Z., Li, Y., Yang, X., Zhang, J. & Zhao, B. 2016. Temperature effects on soil organic carbon, soil labile organic carbon fractions, and soil enzyme activities under long-term fertilization regimes, *Applied Soil Ecology*, **102**, 36–45. https://doi.org/10.1016/j.apsoil.2016.02.004.

Qu, T., Du, X., Peng, Y., Guo, W., Zhao, C. & Losapio, G. 2021. Invasive species allelopathy decreases plant growth and soil microbial activity, *PLOS ONE*, **16**(2), e0246685. https://doi.org/10.1371/journal.pone.0246685.

Qu, W., Han, G., Li, J., Zhao, M., He, W., Li, X. & Wei, S. 2021. Short-term effects of soil moisture on soil organic carbon decomposition in a coastal wetland of the Yellow River Delta, *Hydrobiologia*, **848**(14), 3259–3271. https://doi.org/10.1007/s10750-020-04422-8.

Quine, T.A. & Van Oost, K. 2007. Quantifying carbon sequestration as a result of soil erosion and deposition: retrospective assessment using caesium-137 and carbon inventories, *Global Change Biology*, **13**(12), 2610–2625. https://doi.org/10.1111/j.1365-2486.2007.01457.x.

Quinton, J.N., Catt, J.A., Wood, G.A. & Steer, J. 2006. Soil carbon losses by water erosion: Experimentation and modeling at field and national scales in the UK, *Agriculture, Ecosystems & Environment*, **112**(1), 87–102. https://doi.org/10.1016/j.agee.2005.07.005.

Radford, B.J., Yule, D.F., McGarry, D. and Playford, C. 2001. Crop responses to applied soil compaction and to compaction repair treatments', *Soil and Tillage Research*, 61(3), pp. 157–166. Available at: https://doi.org/10.1016/S0167-1987(01)00194-5.

Rothrock, C.S. 1992. Tillage systems and plant disease, *Soil Science*, **154**(4), 308.

Rubio, G., Zhu, J. & Lynch, J.P. 2003. A critical test of the two prevailing theories of plant response to nutrient availability, *American Journal of Botany*, **90**(1), 143–152. https://doi.org/10.3732/ajb.90.1.143.

Samaddar, S., Karp, D.S., Schmidt, R., Devarajan, N., McGarvey, J.A., Pires, A.F.A. & Scow, K. 2021. Role of soil in the regulation of human and plant pathogens: soils' contributions to people, *Philosophical Transactions of the Royal Society B: Biological Sciences*, **376**(1834), 20200179. https://doi.org/10.1098/rstb.2020.0179.

Scheu, S. 2003. Effects of earthworms on plant growth: patterns and perspectives, *Pedobiologia*, **47**(5), 846–856. https://doi.org/10.1078/0031-4056-00270.

Schjønning, P., Munkholm, L.J., Elmholt, S. & Olesen, J.E. 2007. Organic matter and soil tilth in arable farming: Management makes a difference within 5–6 years, *Agriculture, Ecosystems & Environment*, **122**(2), 157–172. https://doi.org/10.1016/j.agee.2006.12.029.

Seaton, F.M., Barrett, G., Burden, A., Creer, S., Fitos, E., Garbutt, A., Griffiths, R.I., Henrys, P., Jones, D.L., Keenan, P., Keith, A., Lebron, I., Maskell, L., Pereira, M.G., Reinsch, S., Smart, S.M., Williams, B., Emmett, B.A. & Robinson, D.A. 2021. Soil health cluster analysis based on national monitoring of soil indicators, *European Journal of Soil Science*, **72**(6), 2414–2429. https://doi.org/10.1111/ejss.12958.

Sharda, A.K. 1977. Influence of soil bulk density on horizontal water infiltration, *Soil Research*, **15**(1), 83–86. https://doi.org/10.1071/sr9770083.

Sible, C.N., Seebauer, J.R. & Below, F.E. 2021. Plant Biostimulants: A Categorical Review, Their Implications for Row Crop Production, and Relation to Soil Health Indicators, *Agronomy*, **11**(7), 1297. https://doi.org/10.3390/agronomy11071297.

da Silva, A.P. & Kay, B.D. 1996. The sensitivity of shoot growth of corn to the least limiting water range of soils, *Plant and Soil*, **184**(2), 323–329. https://doi.org/10.1007/BF00010461.

Singh, B.K., Delgado-Baquerizo, M., Egidi, E., Guirado, E., Leach, J.E., Liu, H. & Trivedi, P. 2023. Climate change impacts on plant pathogens, food security and paths forward, *Nature Reviews Microbiology*, **21**(10), 640–656. https://doi.org/10.1038/s41579-023-00900-7.

Solly, E.F., Weber, V., Zimmermann, S., Walthert, L., Hagedorn, F. & Schmidt, M.W.I. 2020. A Critical Evaluation of the Relationship Between the Effective Cation Exchange Capacity and Soil Organic Carbon Content in Swiss Forest Soils, *Frontiers in Forests and Global Change*, **3**. https://doi.org/10.3389/ffgc.2020.00098.

Sowerby, A., Emmett, B.A., Tietema, A. & Beier, C. 2008. Contrasting effects of repeated summer drought on soil carbon efflux in hydric and mesic heathland soils, *Global Change Biology*, **14**(10), 2388–2404. https://doi.org/10.1111/j.1365-2486.2008.01643.x.

Tao, F., Huang, Y., Hungate, B.A., Manzoni, S., Frey, S.D., Schmidt, M.W.I., Reichstein, M., Carvalhais, N., Ciais, P., Jiang, L., Lehmann, J., Wang, Y.-P., Houlton, B.Z., Ahrens, B., Mishra, U., Hugelius, G., Hocking, T.D., Lu, X., Shi, Z., Viatkin, K., Vargas, R., Yigini, Y., Omuto, C., Malik, A.A., Peralta, G, Cuevas-Corona, R., Di Paolo, L.E., Luotto, I., Liao, C., Liang, Y.-S., Saynes, V.S., Huang X. & Luo, Y. 2023. Microbial carbon use efficiency promotes global soil carbon storage, *Nature*, **618**(7967), 981–985. https://doi.org/10.1038/s41586-023-06042-3.

Thomas, E., Prabha, V.S., Kurien, V.T. & Thomas, A.P. 2020. The potential of earthworms in soil carbon storage: a review, *Environmental and Experimental Biology*, **18**(2). https://doi.org/10.22364/eeb.18.06.

Thorup-Kristensen, K., Halberg, N., Nicolaisen, M., Olesen, J.E., Crews, T.E., Hinsinger, P., Kirkegaard, J., Pierret, A. & Dresbøll, D.B. 2020. Digging Deeper for Agricultural Resources, the Value of Deep Rooting, *Trends in Plant Science*, **25**(4), 406–417. https://doi.org/10.1016/j.tplants.2019.12.007.

Tracy, S.R., Black, C.R., Roberts, J.A. & Mooney, S.J. 2011. Soil compaction: a review of past and present techniques for investigating effects on root growth, *Journal of the Science of Food and Agriculture*, **91**(9), 1528–1537. https://doi.org/10.1002/jsfa.4424.

UK Government. 2021. *Net Zero Strategy: Build Back Greener*.

Verheijen, F.G.A., Bellamy, P.H., Kibblewhite, M.G. & Gaunt, J.L. 2005. Organic carbon ranges in arable soils of England and Wales, *Soil Use and Management*, **21**(1), 2–9. https://doi.org/10.1111/j.1475-2743.2005.tb00099.x.

Verstraeten, W.W., Veroustraete, F. & Feyen, J. 2008. Assessment of Evapotranspiration and Soil Moisture Content Across Different Scales of Observation, *Sensors*, **8**(1), 70–117. https://doi.org/10.3390/s8010070.

Wadduwage, J., Liu, H., Egidi, E., Singh, B.K. & Macdonald, C.A. 2023. Effects of biostimulant application on soil biological and physicochemical properties: A field study, *Journal of Sustainable Agriculture and Environment*, **2**(3), 285–300. https://doi.org/10.1002/sae2.12057.

Wan, X., Xiao, L., Vadeboncoeur, M.A., Johnson, C.E. & Huang, Z. 2018. Response of mineral soil carbon storage to harvest residue retention depends on soil texture: A meta-analysis, *Forest Ecology and Management*, **408**, 9–15. https://doi.org/10.1016/j.foreco.2017.10.028.

Wang, Q., Zeng, Z. & Zhong, M. 2016. Soil Moisture Alters the Response of Soil Organic Carbon Mineralization to Litter Addition, *Ecosystems*, **19**(3), 450–460. https://doi.org/10.1007/s10021-015-9941-2.

Wang, Y., Zhang, Y., Yu, X., Jia, G., Liu, Z., Sun, L., Zheng, P. & Zhu, X. 2021. Grassland soil moisture fluctuation and its relationship with evapotranspiration, *Ecological Indicators*, **131**, 108196. https://doi.org/10.1016/j.ecolind.2021.108196.

Whitmore, A.P., Watts, C.W., Stroud, J.L., Sizmur, T., Ebrahim, S.M., Pawlett, M., Harris, J., Ritz, K., Wallace, P., White, E., Stobart, R., McKenzie, B. and Thallon, G. 2017. *Improvement of soil structure and crop yield by adding organic matter to soil (AHDB Project Report No.576)*. Stoneleigh: Agriculture and Horticulture Development Board. Available from: https://repository.rothamsted.ac.uk/item/96x63/improvement-of-soil-structure-and-crop-yield-by-adding-organic-matter-to-soil-ahdb-project-report-no-576 [Accessed 24 January 2025].

Wilson, W.S. 1991. *Advances in Soil Organic Matter Research: The Impact on Agriculture and the Environment*. Woodhead Publishing.

Xu, M., Cui, Y., Beiyuan, J., Wang, X., Duan, C. & Fang, L. 2021. Heavy metal pollution increases soil microbial carbon limitation: Evidence from ecological enzyme stoichiometry, *Soil Ecology Letters*, **3**(3), 230–241. https://doi.org/10.1007/s42832-021-0094-2.

Yang, K., Wang, H., Luo, L., Zhu, S., Huang, H., Wei, Z., Zhu, Y., Guo, L. & He, X. 2023. Effects of different soil moisture on the growth, quality, and root rot disease of organic *Panax notoginseng* cultivated under pine forests, *Journal of Environmental Management*, **329**, 117069. https://doi.org/10.1016/j.jenvman.2022.117069.

Yang, Y., Tilman, D., Furey, G. & Lehman, C. 2019. Soil carbon sequestration accelerated by restoration of grassland biodiversity, *Nature Communications*, **10**(1), 718. https://doi.org/10.1038/s41467-019-08636-w.

Zani, C.F., Manning, D.A.C., Abbott, G.D., Taylor, J.A., Cooper, J. & Lopez-Capel, E. 2023. Diversified crop rotations and organic amendments as strategies for increasing soil carbon storage and stabilisation in UK arable systems, *Frontiers in Environmental Science*, **11**. https://doi.org/10.3389/fenvs.2023.1113026.

Zhang, L., Huang, Y., Rong, L., Duan, X., Zhang, R., Li, Y. & Guan, J. 2021. Effect of soil erosion depth on crop yield based on topsoil removal method: a meta-analysis, *Agronomy for Sustainable Development*, **41**(5), 63. https://doi.org/10.1007/s13593-021-00718-8.

Zhou, Y., Yang, Z., Liu, J., Li, X., Wang, X., Dai., C., Zhang, T., Carrión, J., Wei, Z., Cao, F., Delgado-Baquerizo, M. & Li, X. 2023. Crop rotation and native microbiome inoculation restore soil capacity to suppress a root disease, *Nature Communications*, **14**(1), 8126. https://doi.org/10.1038/s41467-023-43926-4.

Weblinks

Table 1. Full URLs for weblinks used in the text.

Weblink text	Full URL
ALERT Tool	https://www.farmingadviceservice.org.uk/csf/tools
AgZero Soil Moisture Map	https://agzeroplus.org.uk/soil-moisture-app
Defra Soil Classification Framework	https://www.farmingadviceservice.org.uk/csf/tools
NCEA's England Ecosystem Survey	https://naturalengland.blog.gov.uk/2024/04/03/england-ecosystem-survey-introducing-englands-largest-ever-field-survey/
Natural Capital and Ecosystem Assessment	https://www.gov.uk/government/publications/natural-capital-and-ecosystem-assessment-programme
Official Statistic in Development	https://www.ons.gov.uk/methodology/methodologytopicsandstatisticalconcepts/guidetoofficialstatisticsindevelopment
Scimap	https://scimap.org.uk/
UK GHG Inventory	https://naei.energysecurity.gov.uk/reports?title=&field_categories_target_id=13

Glossary

Table 2. Glossary of terms.

Term	Definition
Agricultural Land Classification (ALC)	A system used within the UK to assess the quality of agricultural land based on unchangeable factors, such as soil type and slope.
Anecic earthworms	Deep-burrowing earthworms, that make deep, permanent and vertical burrows in the soil, surfacing to feed on leaves.
Assumption	Something that is accepted as true without question or proof. All models are based on assumptions in order to function.
Baseline statistic	A measurement or calculation acting as a starting point for comparison. For example, an indicator can only be considered an indicator once it shows change through time, so the first time point collected would be termed a baseline statistic until further time points are added.
Bayesian Belief Network (BBN)	A type of probabilistic model based on Bayes theorem, which mathematically describes what the probability of an event occurring is, based on prior knowledge of conditions that might be related to the event.
Biodiversity	The variability of life on Earth. It can encompass diversity from a genetic, species, ecosystem or functional perspective.
Bulk density	Mass divided by volume.
Compaction	Occurs when pore space between soil particles is reduced due to mechanistic pressure.
Conceptual model	A high-level representation of a system. For example, in this study, conceptual models of soils' contributions to ecosystem services are constructed. These consist of the factors deemed likely to be most significantly contributing to ES delivery. Conceptual models can be visualised graphically, for example as a flow chart linking factors that influence each other.
Conditional probability	The relationships between two nodes. Can be defined based on training data, or manually based on values from the literature or expert knowledge. Specific relationships between variables can be modelled; for example, if one variable has a non-linear effect when interacting with another variable, conditional probabilities can be used to account for those specific interactions.
Dashboard	A tool displaying data in an easy-to-understand manner.

Term	Definition
Data cycle	The period of time over which one time point of data is collected.
Directed acyclic graph (DAG)	A visual representation of a BBN, in a graphical 'flow chart' style. This consists of 'nodes' (the variables) and 'edges' (the relationships between the variables).
Dumas combustion	Burning a sample at a high temperature in pure oxygen, in order to determine the relative amounts of various constituents of the sample (e.g. nitrogen, carbon).
Ecological Site Classification (ESC)	A decision support system to help forest managers and planners select tree species that are ecologically suited to particular sites.
Ecosystem Service (ES)	The direct and indirect contributions that ecosystems provide which benefit humans (e.g. flood prevention, food/fibre provision).
Edge	In the context of a BBN, edges are the relationships between the variables.
England Ecosystem Survey (EES)	An England-wide survey of soils, vegetation and landscape change being undertaken by Natural England, using a stratified random sampling approach combined with use of inclusion probability weightings. Part of the Natural Capital and Ecosystem Assessment (NCEA) programme funded by Defra.
Inclusion probability	A statistical setup in which each data point collected is given a weighting for use in final analysis according to its probability of being selected as part of the original sampling process. For example, if points from rare land classes and soil types were included in the original sample to ensure adequate coverage to understand trends relating to that soil or land type, these would be given a lower weighting in national analyses, to ensure that they do not bias results.
Indicator	A statistic that describes change through time.
Infiltration	Permeation of a liquid into something by filtration.
Inherent	A permanent and unchangeable characteristic. For example, soil type is an inherent characteristic of soil; we cannot fundamentally change or influence it with human interventions or management.
Land cover	The physical characteristics of the Earth's surface, such as grassland, forest, or bare soil.
Land use	The human activities taking place on the Earth's surface, such as agriculture, urban, or forestry.

Term	Definition
Long-term carbon storage	The ability of a system to hold carbon in a stable form for decades to come.
Management	Actions undertaken by humans with the intention of achieving a particular aim. For example, agricultural management covers actions typically aiming to increase yields, such as tillage and fertiliser application.
Microbial biomass	A measure of the mass of the living component of soil organic matter.
National Forest Inventory Plus survey	The National Forest Inventory survey is a rolling programme designed to provide accurate information about our forests and woodlands, and the changes taking place in them through time. National Forest Inventory Plus is aiming to collect additional information within forests, such as data on soils, as part of the Natural Capital and Ecosystem Assessment programme.
Node	In the context of BBNs, a node refers to any one of the variables included within the DAG.
Olsen P	A measure of the amount of soil phosphorus available to plants. The Olsen P test uses sodium bicarbonate to extract P chemically from a soil solution.
Soil respiration	The production of carbon dioxide when soil organisms respire.
Runoff reduction	A decrease in the amount of water (and substances carried within it) that drains away from an area of land. Reducing runoff helps to prevent flooding downstream.
Soil health	Soils' contributions to ecosystem service delivery
Soil type	A group of soils with similar properties; a taxonomic group of soil.
Spatially explicit	Mapped.
Stratified	A type of statistical sampling that involves dividing a population into groups based on known characteristics, and selecting samples independently from each of these groups, to ensure representation from all groups of interest.
Subsurface	Based on data inputs from samples taken deeper than 30 cm.

Term	Definition
Sustainable food/fibre provision	The ability to produce high yields of food and fibre in a way that can continue long-term into the future (i.e. that is optimising yields against ecosystem services, rather than optimising yields at the expense of ecosystem services and thereby degrading the system for future use).
Trend	Measurable change through time.
Woodland Carbon Code biomass tables	Data tables developed to carry out a prediction of carbon sequestration for a woodland project.

Appendix 1: Supplementary detail on the water model

This appendix provides information about the variables that were included in, and considered but excluded from, the water regulation model illustrated in the main report (Figure 5), including justification and references for doing so. It also provides additional information about data sources planned to be used, how variables will be categorised, and a proposal for how they will be weighted (although weightings will be further tested in a sense-check exercise, in which the expert panel will identify whether a given combination of inputs produce an expected output result). These decisions were taken as the result of a literature review and expert panel process (see 'Acknowledgements' section on the inside cover of the report for information on panel representation).

Variables included in the model

Anecic earthworm biomass if available, or counts if not

- **Justification for inclusion:** The expert panel suggested that this should be added, provided that it was restricted to anecic (deep burrowing) earthworms, rather than all earthworms. Targeted reading following this suggestion found evidence to support this inclusion, especially relating to biomass rather than counts (Bouché & Al-Addan 1997; Clements *et al.* 1991; Ehlers 1975; Fischer *et al.* 2014), although noted that the effect may vary throughout the year (Blouin *et al.* 2013).
- **Data source:** NCEA data (EES and NFI+ data). The data will be divided evenly into categories of 'high', 'medium' and 'low', based on the top, middle and bottom thirds of the values within the dataset overall.
- **Relationship, interactions and weightings:** More anecic earthworm biomass/counts will be considered to increase infiltration rate (and through this reduce surface runoff, which increases soils' contribution to reduction of runoff risk). A standard weighting will be applied.

Soil depth

- **Justification for inclusion:** The panel initially suggested that depth to groundwater should be added. Targeted reading following this suggestion found evidence to support it (Bouwer & Rice 1989; Locatelli *et al.* 2015; Mangangka 2008). However, openly available data on depth to groundwater were not found. Soil depth has therefore been included in its absence, as a variable that was excluded by the panel only because it was considered to affect water regulation through the same mechanism as depth to groundwater. The literature review largely supported the importance of soil depth on water regulation, although conclusions were somewhat mixed, with some sources suggesting it as a main explanatory variable of infiltration rate but others suggesting little effect (Lyons & Gifford 1980; McGinty *et al.* 1979).
- **Data source:** UK Soil Observatory.
- **Relationship, interactions and weightings:** A higher depth to groundwater will be considered to reduce subsurface runoff / increase storage capacity, thereby increasing soils' contribution to reduction of runoff risk. A standard weighting will be applied.

Land cover

- **Justification for inclusion:** Both the literature review and the expert panel process provided clear evidence that different land covers will have different infiltration rates, with forests leading to the highest infiltration rates, shrubland/grassland leading to intermediate infiltration rates, and cropland leading to the lowest infiltration rates (Archer *et al.* 2012; Marshall *et al.* 2014; Milazzo *et al.* 2023; Sun *et al.* 2018; Yimer *et al.* 2008).

- **Data source:** NCEA data (EES and NFI+ data), with land cover categories aggregated into 'tree cover', 'shrub/grassland', 'cropland' and (if possible based on final data) 'wetland'. We note that EES data do not cover urban areas.
- **Relationship, interactions and weightings:** Infiltration will be considered to be higher in forests > shrubland/grassland > cropland. A double weighting will be applied to this variable based on expert panel input.

Soil organic matter

- **Justification for inclusion:** The literature review concluded that increased organic matter improves infiltration (Ankenbauer & Loheide II 2017; Boyle *et al.* 1989; Haghnazari *et al.* 2015; Lal 2020; Liu *et al.* 2019b). The expert panel agreed and added that higher organic matter levels also increase the soil's resilience to perturbation such as compaction and sealing.
- **Data source:** NCEA data (EES and NFI+ data). The data will be divided evenly into categories of 'high', 'medium' and 'low', based on the top, middle and bottom thirds of the values within the dataset overall.
- **Relationship, interactions and weightings:** Higher levels of organic matter will be considered to increase infiltration rate (and through this reduce surface runoff, which increases soils' contribution to reduction of runoff risk). A standard weighting will be applied.

Soil moisture

- **Justification for inclusion:** In the proof-of-concept study, soil moisture was modelled based on a number of other factors. Given direct data on soil moisture are available, the decision was taken to replace this modelled node with observed data. Literature review reading and expert panel consultation confirmed a relationship between soil moisture and infiltration rate (Gray & Norum 1967; Hino *et al.* 1988; Liu *et al.* 2011, 2019a; Philip 1957; Ruggenthaler *et al.* 2016; Wei *et al.* 2022).
- **Data source:** Copernicus soil water index (Copernicus 2024). We also considered the COSMOS dataset, but found the Copernicus data to have greater spatial resolution and to provide deeper data. The data will be divided evenly into categories of 'high', 'medium' and 'low', based on the top, middle and bottom thirds of the values within the dataset overall.
- **Relationship, interactions and weightings:** Increased soil moisture is considered to reduce infiltration rate (and through this increase surface runoff, which reduces soils' contribution to reduction of runoff risk). A standard weighting will be applied.

Slope

- **Justification for inclusion:** The expert panel considered slope an essential variable to add. Whilst the initial literature review had suggested a very mixed picture, this had focused on how slope affects infiltration rates (based on where this variable was included in the proof-of-concept study. Subsequent targeted research on how slope affects runoff rates returned more significant evidence for its inclusion as an input to the surface runoff node instead (Chen *et al.* 2022; Duley & Hays 1933; Fang *et al.* 2015; Haggard & Moore 2005; Jourgholami *et al.* 2021; Rehman *et al.* 2015). Slope was included over more complicated/complete topography information, as the model is relating to runoff risk, rather than to detailed mapping of where is likely to flood.

- **Data source:** A satellite derived digital elevation model will be used. The data will be divided into categories of 'high,' 'medium' and 'low,' aligning with those used in the ALERT tool (less than 3 degrees = low, 3–7 degrees = medium, and over 7 degrees = high).
- **Relationship, interactions and weightings:** Increased slope will be considered to increase surface runoff (and through this, reduce soils' contribution to reduction of runoff risk). The expert panel highlighted an interaction between this factor and soil texture. The weightings in the conditional probability table will therefore be applied in such a way that slope will have little effect when the soil texture class is peaty, but will have a greater effect in cases where soil texture is not classed as peaty.

SSS runoff risk category based on soil texture data for shallow samples

- **Justification for inclusion:** Soil Structure Survey groupings were suggested by the expert panel to group the soil texture classes, as they are designed to group texture classes by runoff risk already. Based on this, heavy and light soils are considered to be high risk, with medium texture soils considered moderate risk, and peat soils high risk but unaffected by slope. Both the panel and the literature provided evidence for the inclusion of soil texture, but highlighted the importance of breaking this down into surface texture and subsurface texture (Jourgholami & Labelle 2020; Kemper & Noonan 1970; Li *et al.* 2016; Mamedov *et al.* 2001; Mazaheri & Mahmoodabadi 2012).
- **Data source:** NCEA data from samples taken at depths of between 0 cm and 30 cm (EES and NFI+ data), grouped into high/medium/low risk for runoff based on SSS guidance. Possibility in future to consider use of the SSS map instead once available, depending on resolution.
- **Relationship, interactions and weightings: Increased** risk level will be considered to increase surface runoff (and through this, reduce soils' contribution to reduction of runoff risk). Weightings for this factor will interact with slope, as described in the slope section.

SSS runoff risk category based on soil texture data for deeper samples

- **Justification for inclusion:** Soil Structure Survey groupings were suggested by the expert panel to group the soil texture classes, as it is designed to group texture classes by runoff risk already. Based on this, heavy and light soils are considered to be high risk, with medium texture soils considered moderate risk, and peat soils high risk but unaffected by slope. Both the panel and the literature provided evidence for the inclusion of soil texture, but highlighted the importance of breaking this down into surface texture and subsurface texture (Jourgholami & Labelle 2020; Kemper & Noonan 1970; Li *et al.* 2016; Mamedov *et al.* 2001; Mazaheri & Mahmoodabadi 2012).
- **Data source:** NCEA data from samples taken at depths greater than 30 cm (EES and NFI+ data), grouped into high/medium/low risk for runoff based on SSS guidance. Possibility in future to consider use of the SSS map instead once available, depending on resolution.
- **Relationship, interactions and weightings:** Increased slope will be considered to increase subsurface runoff (and through this, reduce soils' contribution to reduction of runoff risk). A standard weighting will be applied.

Bulk density to represent compaction

- **Justification for inclusion:** The expert panel considered compaction an essential variable to include, but suggested representing this with bulk density as this will be available as part of the NCEA data. Whilst VESS was also considered, the panel concluded that bulk density would provide a more consistent and quantifiable measure to use. The literature review found evidence that infiltration rates are negatively correlated with bulk density (Khaerudin *et al.* 2017; Li *et al.* 2009; Pugh 2020; Sharda 1977).
- **Data source:** NCEA data (EES and NFI+ data). The data will be divided evenly into categories of 'high', 'medium' and 'low', based on the top, middle and bottom thirds of the values within the dataset overall.
- **Relationship, interactions and weightings:** Higher bulk density will be considered to lead to lower infiltration rates. A standard weighting will be applied.

Variables that were considered, but excluded from the model

- **AgZero soil moisture map:** This was suggested as a possible data source in follow-up discussions after the expert panel workshops. However, it was found to provide data for the current day only, and is based on a hydrological model that is aiming to show water storage capacities and river flows at any one point in time. As such, it is mainly focused on detailed rainfall inputs, so was not considered appropriate for our more general use case.
- **Capping / sealing extent:** The expert panel considered this important to include, and the literature review found clear evidence that more sealing leads to slower infiltration (Assouline 2004; Assouline & Mualem 1997; Baumhardt *et al.* 1990; Di Prima *et al.* 2018; Nciizah & Wakindiki 2015). However, direct data on this are not available. The closest proxy for capping is urban vs. not urban land use, but as the EES excludes urban areas, we will not have data available to link this to each data point within the model.
- **Compaction:** Bulk density is being used as a proxy for compaction, in the absence of data measuring compaction directly.
- **Depth to groundwater:** Openly available data were not found.
- **Drainage:** The expert panel suggested that this would be reflected by the soil texture, and so we did not need to include both.
- **The Environment Agency's Scimap:** This was suggested by the expert panel as a possible replacement to the model overall. However, it is designed to assess risk when a particular flood event is occurring (e.g. you input rainfall pattern maps from specific dates and it runs this through a full hydrological model for a particular catchment) and so does not meet the more generalised use case of a national indicator of soils' contribution to runoff reduction.
- **Evapotranspiration:** There was consensus among the expert panel that evapotranspiration has a large or medium effect. Strong evidence was also found in the literature review ((Eagleman & Decker 1965; Verstraeten *et al.* 2008; Wang *et al.* 2021). However, given this was a variable being used to model soil moisture, and data on soil moisture are available directly, it was considered simpler and more accurate to replace that section of the model with measured soil moisture data.
- **Excess rainfall:** Given this was a variable being used to model soil moisture, and data on soil moisture are available directly, it was considered simpler and more accurate to replace that section of the model with measured soil moisture data.

- **Humidity:** The panel suggested that this would be a useful variable to add to better understand evapotranspiration. However, given that the evapotranspiration node was cut as part of the simplification of the soil moisture section of the model, it is no longer relevant to include.
- **Plant / crop type:** The panel suggested that this could be interesting to include because of the different types of rooting system that influence water catchment. However, they agreed that this will add too much complexity to the model, especially in the context of a national scale indicator.
- **Porosity:** The panel suggested porosity should be included, but then conceded that if already including bulk density or VESS then this would be superfluous.
- **Soil profile:** This represents the soils' physical properties overall. Given that each of the relevant individual properties (e.g. texture) have been considered separately, this was not included.
- **Soil water content:** Concerns were raised over the use of the NCEA soil water content data, as this will be captured at one point in time and so will not be representative of the site over the year. The Copernicus soil moisture dataset is therefore being used instead (see soil moisture, above).
- **Rainfall:** Given this was a variable being used to model soil moisture, and data on soil moisture are available directly, it was considered simpler and more accurate to replace that section of the model with soil moisture data (estimated from Copernicus satellite data).
- **Temperature:** Given this was a variable being used to model soil moisture, and data on soil moisture are available directly, it was considered simpler and more accurate to replace that section of the model with measured soil moisture data.
- **Tillage direction:** Data on this variable were not available at a national scale.
- Vegetation: Whilst vegetation would increase interception, it was considered out of scope, as it is not part of *soils'* contribution to the ES – it is a separate part of the system.
- **VESS:** VESS was considered by the expert panel as a potential proxy for compaction. However, bulk density was selected in its place, as a more consistent and quantifiable metric.

Appendix 2: Supplementary detail on the carbon model

This appendix provides information about the variables that were included in, and considered but excluded from, the carbon storage model illustrated in the main report (Figure 6), including justification and references for doing so. It also provides additional information about data sources planned to be used, how variables will be categorised, and how they will be weighted.

Variables included in the model

Cover crops

- **Justification for inclusion:** Evidence from both the literature review and the expert panel process was in agreement that cover crops increase soils' contribution to long term carbon storage (Jordon *et al.* 2022; McClelland *et al.* 2021; Poeplau & Don 2015; Schjønning *et al.* 2007), although some literature review evidence suggested that this was only the case over long timescales and that claims about the magnitude of impact may be inflated by factors such as the fact that many studies only measure carbon in the top 30 cm of soil (Chaplot & Smith 2023).
- **Data source:** Storr *et al.* 2019. This provides data for a single point in time so will be used for the initial baseline statistic. A new data search will take place to identify whether more recent data are available to use for the second time point when this is required (approximately five years after the first time point). This will include searching for data that consider whether it is the first time growing cover crops, or whether they have been included for many iterations in a rotation. For the initial release, cover crops will be assessed categorically as either present or absent for samples from cropland.
- **Relationship, interactions and weightings:** Presence of cover crops will be considered to increase carbon inputs. As spatial data are not available, this will need to be treated in the model separately. This node is only relevant to arable land use types, not plots with other land use types, so it will only be applied to a subset of the overall dataset. Whilst the proof-of-concept project weighted this node in a way that considered the interactions between this and other management factors, for the indicator it will just be given a standard weighting, as the lack of spatial data means it is not possible to tell whether each management practice is taking place at the same location or not.

Crop rotation

- **Justification for inclusion:** Evidence from both the literature review and the expert panel process was in agreement that in general, crop rotation increases soils' contribution to long term carbon storage (Jordon *et al.* 2022; Schjønning *et al.* 2007; Zani *et al.* 2023).
- **Data source:** We plan to estimate crop rotation based on the UKCEH Land Cover plus Crops dataset, using the concept described in Upcott (2019). For the initial interim release, crop rotation will be assessed categorically as either present or absent for samples from cropland. Ongoing work will continue to search for improved datasets.
- **Relationship, interactions and weightings:** Presence of crop rotation will be considered to increase carbon inputs. As spatial data are not available, this will need to be treated in the model separately. This node is only relevant to arable land use types, not plots with other land use types, so it will only be applied to a subset

of the overall dataset. Whilst the proof-of-concept project weighted this node in a way that considered the interactions between this and other management factors, for the indicator it will just be given a standard weighting, as the lack of spatial data means it is not possible to tell whether each management practice is taking place at the same location or not. Whilst some literature review evidence flagged that the optimum crop-rotation system will vary between contexts, we will be unable to include this level of nuance in the initial indicator due to data constraints.

Erosion

- **Justification for inclusion:** Evidence from both the literature review and the expert panel process was in agreement that erosion reduces soils' contribution to long term carbon storage at site level (Quinton *et al.* 2006). However, we note some debate in the literature about the overall impacts of erosion/soil redistribution dynamics and whether this results in a net sink or net source of carbon (Quine & Van Oost 2007).
- **Data source:** Pan European Soil Erosion Risk Assessment – PESERA (described in Kirkby *et al.* 2004; 2008). The data will be divided evenly into categories of 'high', 'medium' and 'low', based on the top, middle and bottom thirds of the values within the dataset overall.
- **Relationship, interactions and weightings:** Erosion risk will be considered to increase carbon turnover (thereby decreasing soils' contribution to long term carbon storage). As the dataset used is a modelled dataset itself, taking into account a variety of factors to estimate erosion risk, all factors raised as potential interactions by the expert panel (e.g. texture, land use) are already accounted for within the dataset being used. As such, the conditional probability tables (which define interacting relationships between the model variables) will give this a standard weighting and do so evenly, rather than changing its weight based on the state of other variables within the model.

Land use

- **Justification for inclusion:** Evidence from the literature review was conclusive (and found that the difference between each land use type was larger than that for other variables assessed) and so the expert panel were not consulted (Antony *et al.* 2022; Feeney *et al.* 2023; Ostle *et al.* 2009).
- **Data source:** NCEA data (EES and NFI+ data), aggregated into cropland, woodland grassland/shrubland, and (if possible based on final data) wetland.
- **Relationship, interactions and weightings:** This variable will be weighted more strongly than others within the model. Data from figure 2a of Ostle *et al.* (2009) will be used to define the difference between each land-use type, with cropland leading to significantly lower carbon inputs than the other two categories, and woodland leading to slightly higher carbon inputs than grassland/shrubland. The conditional probability tables will ensure that cropland always has a lower predicted carbon value than the other two land use types, whatever the combination of other factors are.

Manure application

- **Justification for inclusion:** Evidence from both the literature review and the expert panel process was in agreement that manure application increases soils' contribution to long term carbon storage (Gross & Glaser, 2021; Maillard & Angers, 2014; Poulton *et al.* 2018; Powlson *et al.* 2012). However, the literature review recognised that this is only relevant over a timeframe of several decades; after that point a new equilibrium is reached (Poulton *et al.* 2018).

- **Data source:** Defra estimates of fertiliser use on farms in England sourced from the Farm Business Survey (Defra 2024). Manure application will be assessed categorically as either present or absent, as further categorisation (e.g. to high, medium and low) is not possible based on the data available.
- **Relationship, interactions and weightings:** Presence of manure application will be considered to increase carbon inputs. As spatial data are not available, this will need to be treated in the model separately. This node is only relevant to arable land use types, as the Farm Business Survey only covers arable land, so it will only be applied to a subset of the overall dataset (excluding plots with grassland/shrubland and forest land cover). Whilst the proof-of-concept project weighted this node in a way that considered the interactions between this and other management factors, for the indicator it will just be given a standard weighting, as the lack of spatial data means it is not possible to tell whether each management practice is taking place at the same location or not.

Ratio of respiration and microbial biomass

- **Justification for inclusion:** This is included as a proxy for carbon use efficiency. Whilst this was not included in the proof-of-concept, original literature review or expert panel process, it was subsequently highlighted as a key gap to include in targeted follow-up discussions. Targeted reading to validate this suggestion found significant evidence in the literature to back this up (e.g. Anthony *et al.* 2020; Tao *et al.* 2023).
- **Data source:** Data sources for this variable, such as whether it may be possible to calculate from NCEA data, are still being explored. It may be necessary to exclude this from analysis depending on the final data that NCEA provide. The data will be divided evenly into categories of 'high', 'medium' and 'low', based on the top, middle and bottom thirds of the values within the dataset overall.
- **Relationship, interactions and weightings:** A higher ratio of respiration to microbial biomass (i.e. high levels of respiration for each unit of biomass present) will be considered to reduce carbon inputs. One study found that "CUE is at least four times as important as other evaluated factors, such as carbon input, decomposition or vertical transport, in determining SOC storage and its spatial variation across the globe" (Tao *et al.* 2023). This factor will therefore be weighted strongly in the model; to be conservative (as it did not come up at all in initial discussions and the factors listed in the study do not match perfectly with the other factors we are considering), we will weight it in the conditional probability tables as twice as important as the variables given a 'standard' weighting.

Soil moisture

- **Justification for inclusion:** In the initial literature review, expert panel session and subsequent email exchanges, the temperature, rainfall and drainage nodes caused some disagreement. Further targeted reading concluded that the mechanism by which these factors principally influence soil carbon is through soil moisture content, and so this node was included in their place (Hunde 2015; Kerr & Ochsner 2020; W. Qu *et al.* 2021; Wang *et al.* 2016). It is noted that some sources suggest that the causation is in the opposite direction, with high SOC leading to higher water retention and therefore soil moisture rather than high soil moisture causing high SOC (Hugar *et al.* 2012). However, either way a clear correlation between the measured variable and the predicted variable exists and so for the purposes of this work, higher soil moisture can be considered to be likely associated with higher carbon storage.

- **Data source:** Copernicus soil water index (Copernicus 2024). We also considered the COSMOS dataset, but found the Copernicus data to have greater spatial resolution and to provide deeper data.
- **Relationship, interactions and weightings:** Increased soil moisture will be considered to increase carbon inputs. A standard weighting will be applied.

Soil organic carbon (not included within the model, but presented as separate results, alongside results from the model)

- **Justification for inclusion:** The literature review considered this to be a factor that varies and is context dependent in terms of its contribution to long term carbon storage (Bellamy *et al.* 2005); higher carbon can lead to higher release of carbon depending on the other conditions, so a higher stock at one point in time does not necessarily mean higher long-term storage or contribution to ES delivery. In the proof-of-concept model, it was included as a node feeding into the final node alongside the intermediate nodes of input and turnover (i.e. long-term carbon storage depends on current levels of soil organic carbon, and on the carbon cycling relating to both processes adding to the carbon stock and removing carbon from the stock). However, this presentation caused considerable confusion at an April 2024 meeting of the Defra Family Soil Science Network (attended by those working on soil across organisations within the Defra group). All consulted considered this an essential variable to include, as it is so close in concept to the model outcome, but there was some confusion around why a model was required at all. Subsequent targeted discussions landed on a solution of presenting the soil organic carbon values separately from the model outputs, and framing these as current carbon stocks, with the model estimating how likely is it that the current levels of carbon will be maintained into the future assuming current conditions continue, and how this compares to what is possible given constraining factors such as soil texture. Data on soil organic carbon will therefore be presented alongside outputs from the model, but not included within the model network itself.
- **Data source:** NCEA data (EES and NFI+ data), reporting the averaged absolute values of carbon per volume of soil.
- **Relationship, interactions and weightings:** Not applicable – not part of the main model.

Soil texture

- **Justification for inclusion:** Evidence from both the literature review and the expert panel process was in agreement that soil texture affects soils' contribution to long term carbon storage (Augustin & Cihacek 2016; Hamarashid *et al.* 2010; Kerr & Ochsner 2020; Wan *et al.* 2018). In particular, clay soils have higher capacity to retain carbon. Organic/peat soils behave differently to inorganic soils, and so should be treated differently in the model.
- **Data source:** NCEA data (EES and NFI+ data), grouped into 'heavy', 'medium', 'light' and 'peaty' soils.
- **Relationship, interactions and weightings:** Heavier soil classes will be considered to increase soils' contribution to long term carbon storage. As this factor was considered particularly important and following a similar approach in the original proof-of-concept study, a weighting of double the standard will be applied. Peaty soils will be excluded from the initial interim output, as our current literature review focused on mineral soils. However, the conditional probability tables will

eventually allow us to define different relationships for peat soils with the other factors in the network compared to the other three classes.

Tillage

- **Justification for inclusion:** The expert panel gave strong evidence to include tillage. The literature review found that typically, minimum and no tillage increases SOC compared to conventional tillage, but that the magnitude of the effect is small (Brown *et al.* 2021; Cooper *et al.* 2020; Fornara & Higgins 2022; Powlson *et al.* 2012; van Groenigen *et al.* 2011). However, we note that the UK GHG Inventory does not differentiate between tillage practices in their calculations as they found minimal effects in UK environments in relation to emissions (rather than long-term storage potential). It should also be noted that different cultivation methods can result in different distributions of SOC in the soil profile.
- **Data source:** Alskaf *et al.* 2019. This provides data for a single point in time so will be used for the initial baseline statistic. A new data search will take place to identify whether more recent data are available to use for the second time point when this is required (approximately five years after the first time point). Tillage will be assessed categorically as conventional, minimum or no tillage.
- **Relationship, interactions and weightings:** Higher levels of tillage will be considered to increase carbon turnover (thereby decreasing soils' contribution to long term carbon storage). As spatial data are not available, this will need to be treated in the model separately. This node is only relevant to arable land use types, not plots with other land use types, so it will only be applied to a subset of the overall dataset. Whilst the proof-of-concept project weighted this node in a way that considered the interactions between this and other management factors, for the indicator it will just be given a standard weighting, as the lack of spatial data means it is not possible to tell whether each management practice is taking place at the same location or not.

Variables that were considered, but excluded from the model

- **Application of mulch/residues:** This was considered important to include in the expert panel process and a clear link (although small in magnitude) was identified in the literature review (Powlson *et al.* 2012; van Groenigen *et al.* 2011). However, no data were found that would enable its inclusion in the model.
- **Atmospheric emissions:** This was considered in the literature review, with the hypothesis that increased atmospheric concentrations of carbon may affect carbon cycling within the soil, and so may be an important factor to consider from a climate change resilience perspective. However, any effects identified in the literature were found to be variable, context dependent, and/or impacting soil carbon through other factors, such as microbial activity or plant primary productivity ((Hyvönen *et al.* 2007).
- **Biological activity (e.g. earthworm counts, eDNA):** The literature review gave some conflicting evidence on the relevance of this, but overall concluded that any effects vary and are context dependent, so identifying a generalisable effect to include in the model was not possible (Angst *et al.* 2019; de Graaff *et al.* 2015; Lubbers *et al.* 2013; Thomas *et al.* 2020).
- **Bulk density:** The literature review found soil bulk density to be negatively correlated with soil carbon concentration (Fornara & Higgins 2022; Hunde 2015; Kerr & Ochsner 2020), but was unable to establish a clear link with SOC stocks per hectare, as more compact soils, by definition, are higher density per unit area. The

review also found it to be highly correlated with soil moisture. As moisture is already included in the model, bulk density was not added as well. It was not raised as a priority to add within the expert panel discussion.

- **Drainage:** The literature review did not find evidence for drainage effecting soil carbon storage within the UK. Some minimal evidence was found from elsewhere in the world, but typically with minimal effects (Kumar *et al.* 2014). In contrast, the expert panel did consider this an important factor to retain. However, discussions suggested that the mechanism by which this would affect carbon storage was through soil moisture. Given that soil moisture has now been added to the model itself, drainage is not included as well.
- **Exchangeable cations:** Evidence from the literature review was unclear, but suggested a possible effect in forest environments ((López-Marcos *et al.* 2018; Solly *et al.* 2020). The expert panel considered it a low priority to include.
- **Heavy metal content:** Limited and variable evidence was found related to heavy metal content impacts on soil carbon storage within the literature review ((Enya *et al.* 2020; Xu *et al.* 2021). The expert panel considered it a low priority to include.
- **Inorganic fertilisers / biostimulants:** Some evidence was found linking biostimulants to soil carbon storage ((Debska *et al.* 2022; Sible *et al.* 2021; Wadduwage *et al.* 2023). However, data on this were not available. Inconclusive evidence was found linking inorganic fertilisers to long term soil carbon storage (although many papers did link them to increased biomass production, and so this will be kept under review for future iterations).
- **Intercropping:** The literature review found evidence that intercropping increases soil carbon (Cong *et al.* 2015; Li *et al.* 2024). The expert panel process supported its inclusion, but support was weaker than for the other management related variables (e.g. cover crops, crop rotation). However, no data were found that would enable its inclusion in the model.
- **Micro- and macro-nutrients:** The literature review suggested that there may be some effect, but that this varies depending on the nutrients in question (Crowther *et al.* 2019). Not enough evidence was found to be able to confidently identify which combinations of nutrients would have which effects. This was considered a low priority to include in the expert panel process.
- **N (total):** The literature review did not find conclusive evidence that N affects carbon storage ((Hyvönen *et al.* 2007; Janssens *et al.* 2010; Luo *et al.* 2022). The expert panel suggested that N is often correlated with carbon content, but that this is a correlation rather than a driver.
- **P (available and total):** The literature review identified some laboratory studies and studies outside the UK with a very small effect on carbon storage, but nothing conclusive ((Bradford *et al.* 2008; Cui *et al.* 2022). The expert panel were divided on whether this should be included or not, with many unsure. It was therefore concluded that there is not enough evidence to be confident in its inclusion.
- **pH and electric conductivity:** One expert suggested that pH could affect carbon through affecting primary productivity. However, the panel overall considered it a low priority to include. The literature review found it to have variable and inconclusive effects on soil carbon storage (Holland *et al.* 2018; Hunde 2015; Kemmitt *et al.* 2006; Seaton *et al.* 2021).
- **Rainfall:** The literature review found rainfall to have a complex and non-linear relationship with soil carbon storage, with conflicting evidence sources (Bellamy *et al.* 2005; Eglin *et al.* 2011; Poll *et al.* 2013; Sowerby *et al.* 2008; Verheijen *et al.* 2005). This variable also caused much debate within the expert panel process and subsequent email exchanges. The panel agreed that the direct effect on carbon was via soil moisture, rather than based on rainfall levels directly. The node was

therefore replaced with a soil moisture node instead, in order to measure the factor of most relevance directly, rather than attempting to model it based on climatic data.

- **Slope:** It was concluded that this affects soil carbon storage through erosion (Boardman *et al.* 2009; Guerra *et al.* 2017). Erosion is already included within the model.
- **Soil profile:** This represents the soils' physical properties overall. Given that each of the relevant individual properties (e.g. texture) have been considered separately, this was not included.
- **Soil water content:** Concerns were raised over the use of the NCEA soil water content data, as these will be captured at one point in time and so will not be representative of the site over the year. The Copernicus soil moisture dataset is therefore being used instead (see soil moisture, above).
- **Temperature:** The literature review found temperature to have a complex and context dependent relationship with soil carbon storage, with a lack of consensus in the literature about the nature of the relationship (Davidson & Janssens 2006). Some evidence was found that suggests an increase due to increased plant productivity and increased C mineralisation through microbial activity (Dalias *et al.* 2001), whilst other evidence was found that suggests increased temperature tends to result in carbon losses (Hartley *et al.* 2021; Qi *et al.* 2016). This variable also caused much debate within the expert panel process and subsequent email exchanges. Whilst in the discussion itself, the consensus was to remove the node form the model, subsequent email exchanges highlighted the influence of temperature on soil moisture, which does have a significant impact on soil carbon storage. The node was therefore replaced with a soil moisture node instead, in order to measure the factor of most relevance directly, rather than attempting to model it based on climatic data.
- **Threats to biodiversity:** The literature review found that there is evidence about the role of soil biodiversity in carbon cycling (e.g. higher diversity tends to be associated with higher soil respiration rates) but little evidence demonstrating impacts on SOC stocks (de Graaff *et al.* 2015; Filser *et al.* 2016). It also found that different species and functional groups can affect soil carbon via different mechanisms, for instance impacts on soil erosion, so identifying a generalised effect would be very difficult and likely associated with a high degree of error (Orgiazzi & Panagos 2018). There was high uncertainty and conflicting comments in the expert panel process about whether this node should be included or not. It seems likely that biodiversity does have an impact on soil carbon, but not one that we are currently able to simplify to the extent that it could be confidently included within the model.
- **Vegetation:** The literature review process found that higher plant biodiversity has sometimes been linked to higher SOC, but this may only be the case when higher diversity results in increased root and aboveground biomass, and therefore greater litter inputs to soil (Augusto & Boča 2022; Lange *et al.* 2015; Yang *et al.* 2019). The expert panel process concluded that vegetation in the sense of plant biodiversity is unlikely to affect soil carbon storage, but that vegetation in the sense of percentage cover would be important to include. Whilst it may be possible to include this variable ultimately based on a vegetation survey taking place in parallel to the soil survey as part of the EES, the authors have not yet seen those data and so could not take a decision on whether or not it could be included. Additionally, the inclusion of land cover is already considering vegetation to a certain extent.
- **VESS:** This was suggested by the expert panel as a variable that may be useful to add to the model. However, this is likely to correlate with texture, tillage, land use and many of the other variables also included within the model, so has been excluded.

Appendix 3: Supplementary detail on the food/fibre model

This appendix provides information about the variables that were included in, and considered but excluded from, the food/fibre model illustrated in the main report (Figure 7), including justification and references for doing so. It also provides additional information about data sources planned to be used, how variables will be categorised, and how they will be weighted.

Variables included in the model

ALC class for agricultural land, or ESC combined with biomass tables from the Woodland Carbon Code for forested areas

- **Justification for inclusion:** ALC class was suggested during the expert panel process to be used instead of a wide range of the other variables that were being considered, as it is an established, accepted and clearly documented method for achieving largely what we were proposing. Whilst it was not assessed in the initial literature review, many of the factors considered within ALC methods were assessed (see 'Variables that were considered, but excluded from the model' section, below). Follow up discussions also supported this new approach, although highlighted that it would only be appropriate for the agricultural and not the forestry aspects of food and fibre provision. Additional follow-up discussions with Forest Research and subsequent reading landed on use of ALC class for agricultural land, and Ecological Site Classification combined with biomass tables from the Woodland Carbon Code as an equivalent approach that could be used in forested areas.
- **Data source:** The initial interim statistic will make use of existing ALC maps. Future work will explore whether it would be possible to use the NCEA data to perform an ALC style assessment (or an assessment of specific ALC modules) at each monad in subsequent iterations. Data will be grouped into 'high' (a score of 1 or 2), 'medium' (a score of 3) and 'low' (a score of 4 or 5).
- **Relationship, interactions and weightings:** Higher quality (lower ALC score) will be considered to increase soils' contribution to food and fibre provision. Given that this node is incorporating many other factors that were initially of interest, it will be given a quadruple weighting compared to the other nodes within this network.

Bulk density to represent compaction

- **Justification for inclusion:** The literature review found evidence of compaction as a key factor affecting nutrient uptake (Arvidsson 1999; Batey 2009; Botta *et al.* 2006; da Silva & Kay 1996; Hargreaves *et al.* 2019; Koch *et al.* 2008; Nevens & Reheul 2003; Radford *et al.* 2001; Tracy *et al.* 2011). Evidence was also found of compaction as a key factor affecting risk of soil borne pathogens and disease (Abawi & Widmer 2000; Ishak 2017; Rothrock 1992).
- **Data source:** NCEA data (EES and NFI+ data). The data will be divided evenly into categories of 'high', 'medium' and 'low', based on the top, middle and bottom thirds of the values within the dataset overall.
- **Relationship, interactions and weightings:** Lower compaction will be considered to increase nutrient uptake and decrease risk of soil borne pathogens and disease (both thereby soils' contribution to sustainable food/fibre provision). A standard weighting will be applied in both cases.

Crop rotation

- **Justification for inclusion:** Targeted reading following expert panel discussions identified this as an additional key variable of relevance to risk of soil borne pathogens and disease ((Abawi & Widmer 2000; Jalli *et al.* 2021; Samaddar *et al.* 2021; Zhou *et al.* 2023). We note that whilst there is plenty of evidence supporting its inclusion, it does vary per pathogen/disease and per plant, so highlight that the risk of soil borne pathogens and disease node is aiming to act as a generic risk factor, rather than say anything specific about any individual case.
- **Data source:** We plan to estimate crop rotation based on the UKCEH Land Cover plus Crops dataset, using the concept described in Upcott (2019). For the initial interim release, crop rotation will be assessed categorically as either present or absent for samples from cropland. Ongoing work will continue to search for improved datasets.
- **Relationship, interactions and weightings:** Presence of crop rotation will be considered to reduce risk of soil borne pathogens and disease. As spatial data are not available, this will need to be treated in the model separately (e.g. a model run out spatially for each plot, and then aggregated, then a separate model run out adding non-spatial data). This node is only relevant to arable land use types, not plots with other land use types, so it will only be applied to a subset of the overall dataset. A standard weighting will be applied. Whilst some literature review evidence flagged that the optimum crop-rotation system will vary between contexts, we will be unable to include this level of nuance in the initial indicator due to data constraints.

Earthworm counts

- **Justification for inclusion:** The expert panel suggested the addition of this variable as one with an established relationship to crop yields. Evidence to support this was found as part of the literature review process (Brown *et al.* 1999; Derouard *et al.* 1997; Scheu 2003; van Groenigen *et al.* 2014; Whitmore *et al.* 2017).
- **Data source:** NCEA data (EES and NFI+ data). The data will be divided evenly into categories of ‘high’, ‘medium’ and ‘low’, based on the top, middle and bottom thirds of the values within the dataset overall.
- **Relationship, interactions and weightings:** Higher presence of earthworms will be considered to increase soils’ contribution to food and fibre provision. Based on evidence that this is a factor of relevance to agricultural crops but not forest production, the conditional probabilities tables will be constructed in a way that interacts with the landcover variable, giving it a standard weighting when landcover is cropland or grassland, and a zero weighting for forest.

Erosion

- **Justification for inclusion:** The literature review found evidence that erosion reduces yield, via nutrient availability, water availability, etc. (Bakker *et al.* 2007; Biot & Lu 1995; Boardman & Favis-Mortlock 1993; Lal & Moldenhauer 1987; Langdale & Shrader 1982; Zhang *et al.* 2021). Erosion of less than (<) 5 cm, or leaving more than (>) 25 cm of topsoil does not significantly impact yield. Erosion of 5–30 cm proportionally decreases yield. Erosion of more than (>) 30 cm does not cause a significant decrease in yield beyond that which has already occurred up to that point. The expert panel agreed that large amounts of erosion will have a huge impact on yield, whereas small amounts of erosion will have minimal impact.

- **Data source:** Pan European Soil Erosion Risk Assessment – PESERA (described in Kirkby *et al.* 2004; 2008). Rather than using a high, medium, low breakdown that is evenly split based on the range of the data, we will calculate a rough estimate of the weight of 5 cm soil per hectare (ha) and 20 cm soil per ha to translate the literature review findings into threshold units that will allow the data to be grouped into three more meaningful categories of high, medium and low.
- **Relationship, interactions and weightings:** Erosion risk will be considered to decrease nutrient uptake (thereby decreasing soils' contribution to food and fibre provision). As the dataset used is a modelled dataset itself, taking into account a variety of factors to estimate erosion risk, all factors raised as potential interactions by the expert panel (e.g. texture, land use) are already accounted for within the dataset being used. As such, the conditional probability tables (which define interacting relationships between the model variables) will give even weightings compared to other factors in the model, rather than changing its weight based on the state of other variables within the model. However, weighting within this category will be such that sites with less than 5 cm erosion are weighted as having no effect in the CPTs, those with 5–20 cm will lead to a small reduction in nutrient uptake, and those above 20 cm will lead to a medium reduction in yield.

Land cover

- **Justification for inclusion:** Other factors in the model (e.g. earthworms, ALC versus ESC) are dependent on / interact with land cover, and so this must be included in order to be able to have varying effects for these nodes.
- **Data source:** NCEA data (EES and NFI+ data), with land cover categories aggregated into 'tree cover', 'shrub/grassland' and 'cropland'. We note the limitation that EES data do not cover urban areas.
- **Relationship, interactions and weightings:** This node is included to allow for differentiated responses in forest versus cropland. See earthworm section for description of interaction between this node and earthworms. Further discussions with Forest Research are planned which will allow us to design the conditional probability tables in a way that will similarly differentiate for other variables.

N%

- **Justification for inclusion:** The literature review provided clear evidence that soil nutrients, including N, had a significant effect on crop yield, although this interacts with availability of other nutrients (Ågren *et al.* 2012; Rubio *et al.* 2003; Zhang *et al.* 2021). The expert panel agreed unanimously, although noting that it could be controlled by management and fertiliser application.
- **Data source:** NCEA data (EES and NFI+ data). The data will be divided evenly into categories of 'high', 'medium' and 'low', based on the top, middle and bottom thirds of the values within the dataset overall.
- **Relationship, interactions and weightings:** Higher N% will be considered to increase nitrogen uptake (thereby increasing soils' contribution to food and fibre provision); unless P is low, in which case P will be considered as the limiting factor and increasing N will not have an effect. A standard weighting will be applied.

Olsen P

- **Justification for inclusion:** The literature review provided clear evidence that soil nutrients, including P, had a significant effect on crop yield, although this interacts with availability of other nutrients (Ågren *et al.* 2012; Rubio *et al.* 2003; Zhang *et al.*

2021). The expert panel agreed unanimously, although noting that it could be controlled by management and fertiliser application. Use of Olsen P as more representative of P that is available to plants for uptake was suggested as more appropriate to use than simply P%. It is noted that Olsen P results cannot be compared against other methods for quantifying P in a soil sample. However, as Olsen P is the only method for which data are available, this should not be an issue.

- **Data source:** NCEA data (EES and NFI+ data). The data will be divided into categories of 'high', 'medium' and 'low', based on the AHDB soil health score card values, with below 9 mg/l or above 71 mg/l considered to be low, 10–15 mg/l and 46–70 mg/l as considered as medium, and 16–45 mg/l as high. The high category will lead to highest nutrient uptake, whilst the low category will lead to lowest uptake. Any increases above the threshold of 45 mg/l will not increase uptake further, but will have unsustainable effects on the system; hence the decreasing categories as P values reach levels above this point, rather than only increasing up to that point.
- **Relationship, interactions and weightings:** Higher Olsen P will be considered to increase nutrient uptake (thereby increasing soils' contribution to food and fibre provision); unless N is low, in which case N will be considered as the limiting factor and increasing P will not have an effect. A standard weighting will be applied.

pH

- **Justification for inclusion:** The literature review concluded that whilst context dependent to some degree, the optimum pH for micro-and macro-nutrient availability is slightly acidic, and that this is likely to hold true for most plant species (Clark 1983; Curtin *et al.* 1998; Harper & Balke 1981; Hartemink & Barrow 2023; Maas & Ogata 1971; Neina 2019). The expert panel were in agreement that pH 6.5–7.5 results in higher production potential (for arable land). This matches the AHDB soil health scorecard and RB209 Nutrient Manual. The mechanism by which this affects yield / food and fibre provision is through nutrient availability.
- **Data** source: NCEA data (EES and NFI+ data). Data will be grouped into sites with a pH of 6.5–7.5 (optimum), and a pH above or below this (sub-optimum).
- **Relationship, interactions and weightings:** pH 6.5–7.5 has a positive effect on nutrient availability, above or below this has a negative effect. A standard weighting will be applied.

Soil organic matter

- **Justification for inclusion:** The literature review found a clear correlation between SOM and crop yield, but the mechanism behind this was unclear (Loveland & Webb 2003; Wilson 1991; Zhang *et al.* 2021). The expert panel agreed that yield increases with SOM, but only up to a point (approximately 4%). The expert panel suggested that SOM should also feed into the soil-borne pests and disease node. However, targeted literature review reading did not find enough evidence to support its inclusion (Bonanomi *et al.* 2010).
- **Data source:** NCEA data (EES and NFI+ data). Data above 4% will be considered 'high'. Data below 4% will be split into two equal 'medium' and 'low' categories based on the dataset overall.
- **Relationship, interactions and weightings: Increasing** SOM will directly lead to increasing ES delivery. A standard weighting compared to other nodes within the model will be applied.

Soil moisture

- **Justification for inclusion:** The expert panel considered waterlogged soils to be a key risk factor for soil borne pests and diseases. Subsequent targeted reading supported its inclusion (Samaddar *et al.* 2021; Singh *et al.* 2023; Yang *et al.* 2023). Other effects of moisture are captured through the ALC node.
- **Data source:** Copernicus soil water index (Copernicus 2024). We also considered the COSMOS dataset, but found the Copernicus data to have greater spatial resolution and to provide deeper data.
- **Relationship, interactions and weightings:** High soil moisture will be considered to increase risk of soil borne pests and disease. A standard weighting will be applied going into the modelling of the soil borne pests and disease node. However, the soil borne pests and disease node will be weighted half that of the other intermediate nodes when bringing the intermediate modelling together, as it was considered possible to control for the most part with management.

Variables that were considered, but excluded from the model

- **Aggregate stability:** This variable was considered to be closely related to compaction, which is already included in the model, represented by bulk density.
- **Compaction:** Bulk density is being used as a proxy for compaction, in the absence of data measuring compaction directly.
- **Contamination (heavy metals):** This variable was considered important (Athar & Ahmad 2002; Audet & Charest 2007; Dudka *et al.* 1994), but is now covered by inclusion of the ALC node.
- **Growth:** Growth and yield were removed for simplicity, with all factors feeding into the overall ES instead of trying to break out which factors would affect growth versus yield.
- **Hot water extractable carbon:** No clear link with yield was established through the panel process or the literature review.
- **Radiation use efficiency:** The expert panel did not consider this to be a variable related to the soil system.
- **Slope:** This variable was considered important by the expert panel, but is now covered by inclusion of the ALC node.
- **Soil depth:** This variable was considered important by both the expert panel and the literature review (Kirkegaard *et al.* 2007; Thorup-Kristensen *et al.* 2020), but is now covered by inclusion of the ALC node.
- **Soil microbial activity:** This was considered important by both the expert panel and the literature review, but linked to the specific functional traits of particular microbes, and so a greater understanding of these would be needed before being able to include it within the model (Alam *et al.* 2014; Insam *et al.* 1991; Liu *et al.* 2009; Nassal *et al.* 2018; T. Qu *et al.* 2021).
- **Soil strength:** This variable was removed due to confusion within the expert panel about definitions, and a lack of data on how this would be measured.
- **Stone content:** This variable was considered important by both the expert panel and the literature review (Abu-Zreig *et al.* 2011; Epstein *et al.* 1966), but is now covered by inclusion of the ALC node.
- **Temperature:** This variable was considered important by both the expert panel and the literature review (Gales 1983; Gallagher 1979; Keatinge *et al.* 1979; Nielsen *et al.* 1961), but is now covered by inclusion of the ALC node.

- **Texture:** This variable was considered important by the expert panel, but is now covered by inclusion of the ALC node.
- **Tillage:** Whilst some studies suggested that tillage may be a factor influencing risk of soil borne pathogens and disease, the evidence was found to conflict and be inconclusive (Samaddar *et al.* 2021).
- **Topography:** This variable was considered important by the expert panel, but is now covered by inclusion of the ALC node.
- **VESS:** This variable was considered to be closely related to compaction, which is already included in the model, represented by bulk density.
- **Yield:** Growth and yield were removed for simplicity, with all factors feeding into the overall ES instead of trying to break out which factors would affect growth versus yield.