JNCC Report 818

Environmental Indicator E7: Healthy soils – technical documentation for a soil health indicator for England's Environmental Improvement Plan

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[1] Joint Nature Conservation Committee

[2] Defra

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Summary

This report acts as the technical documentation for an initial, interim soil health statistic for England, explaining the detail of the methods behind the results. It is planned that these methods will be updated, and this documentation overwritten, as development work continues and a final baseline statistic is produced.

The statistic has been designed for use against the Environmental Improvement Plan's Environmental Indicator Framework, and has been published by JNCC as an Official Statistic Under Development. Results can be found in the associated indicator fiche.

Many ecosystem services 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 aimed to develop a method and undertake the analysis to produce 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.

For the purposes of this project, soil health is defined as "soils' contributions to ecosystem service delivery." Models have been developed to describe soils' contributions to three ecosystem services: climate regulation, water regulation, and sustainable production of arable crops. For each of these, a literature review and expert elicitation process has identified the soil-relevant variables that affect them most significantly, described the relationships between these variables and ecosystem service delivery, and identified data to represent them. A type of probabilistic modelling known as Bayesian Belief Networks has then been used to input these data and produce results estimating the likelihood of ecosystem service delivery based on current conditions. Results are presented in a way that allows for both an absolute estimate (which is consistent and comparable across different analyses, contexts and time points) and places this result within system constraints (which represents how well England is doing at protecting ecosystem service delivery, as far as is in our control).

The interim results presented are based on data from several sources, including NCEA's England Ecosystem Survey (EES). The data collection process for the EES is designed to be representative (across English ecosystems and habitats, excluding freshwater, marine, woodlands and urban areas) after five years of data collection (i.e. five years = one data point). However, only the first year of data from the EES are currently available.

Alongside integrating subsequent years of EES data, development work will continue to improve the indicator's sensitivity and applicability across different environments (e.g. forests) beyond this publication, leading to publication of a final baseline statistic in ~2030. It is hoped that additional time points will be added each ~5 years after this point, ultimately creating an indicator (showing change through time) rather than a baseline statistic. 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.

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 concepts used, including the definition of soil health that is being adopted in the context of this work, descriptions of what an indicator is, how a national scale indicator differs from a local scale tool, 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 being used 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 arable crop provision) that are being reported on, 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 models underlying the results.

The report acts as the technical documentation to accompany the initial interim results. The interim results presented are based on data from several sources, including NCEA's England Ecosystem Survey (EES). EES is designed to produce a five-year baseline (i.e. five years = one data point) that is representative for land use types within scope. However, only the first year of data from the EES are currently available. Results should therefore be treated as demonstrative rather than in any way conclusive at this stage. In addition, development work to improve the indicator's sensitivity and applicability across different environments (e.g. forests) is ongoing. It is planned that the method will be updated, and this documentation overwritten, as this work continues and a final baseline statistic is produced. We invite user input and feedback as part of this process (feedback@jncc.gov.uk). It is planned that additional data points will be added following future data collection cycles using the same method, to eventually turn the baseline statistic into an indicator.

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). Globally, 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 later revisions, the Environmental Improvement Plan (Defra 2023, 2025), which commit to including an indicator on "healthy soils" as one of 66 indicators of environmental change in their associated Environmental Indicator Framework (Defra 2019);
- 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 soil's 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 National Adaptation Programme (UK Government 2023), which acknowledges the essential nature of healthy soil as an asset and our need to ensure adequate adaptations against climate change;
- The EFRA Inquiry on Soil Health (2023), which analysed the Government's role in preventing further soil degradation and restoring soils across England;
- The Office for Environmental Protection has highlighted in their reporting that "there is uncertainty around delivering sustainable soils due to the lack of an available soil health indicator" (OEP 2025) and that "a robust monitoring system is crucial to ensure that soil health is maximised" (OEP 2026).

The importance of monitoring soil health is also gaining recognition internationally, for example with the European Commission's Soil Monitoring Law (2025) and the EU's planned Soil Observatory Indicator Dashboard.

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 for England has been lacking prior to this current publication.

This report therefore aims to outline an initial 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, which can be improved on iteratively as more data become available and as model development work continues. The commitment to publishing an indicator as part of the Environmental Indicator Framework is the work's primary policy driver.

1.2. Aims and scope

The aim of the current work is to produce an initial, interim national-scale statistic for use in Defra's Environmental Indicator Framework. It seeks a way to provide a nationally representative baseline statistic estimating soil health for rural 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. Scoping work to consider the potential to adapt this to produce a mapped output in future is planned.

The current report acts as the technical documentation to describe the methods for the initial, interim statistic. It is planned that a final baseline statistic will be published in ~2030, once the full underlying EES dataset is available.

It should be noted that this scope differs significantly from previous JNCC 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," aligning with the definition of soil health referenced in the Environmental Improvement Plan (2025). 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;
- arable crop provision through soils' contribution to sustainable production of crops (noting that scope in the current work focuses on arable crops, but that expansion to cover all food/fibre provision remains a development goal for future work).

Metrics relating to soil biodiversity are also under development, but are at an earlier stage due to data availability, and so are only briefly presented within this document as a proposal for future work. 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, arable crop provision and one of the two carbon metrics that are presented are based on modelled impact indicators. In the case of the other carbon metric, and eventually the biodiversity metrics, state indicators will be used.

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.

A 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 would be difficult 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 it is 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 (e.g. higher current levels of carbon could lead to higher future carbon emissions if conditions are poor).

In the case of this project, the initial aim is to produce a baseline statistic (an interim version in the current publication, and a final, representative baseline statistic planned for ~2030). It will not be possible to describe change through time until the analyses have been re-run with additional data cycles, planned to be available each five years after that point. The baseline statistic will be national in scope aiming to be representative for rural England as a whole, based on bringing together field data from the NCEA's England Ecosystem Survey (EES) and the National Forest Inventory Plus survey (NFI+; the equivalent for forested locations), alongside other national data sources (e.g. farmer surveys and spatial data, such as GIS layers).

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 cannot rely on local knowledge and management decisions to input into the model, as was done in the proof-of-concept study. It requires 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).

Many of these data are being 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 (used within the current publication) and the NFI+ surveys (planned to be incorporated following further development work). 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 summary of data sources used, and Appendices 1 to 3 for a detailed list of data sources against each variable). 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.

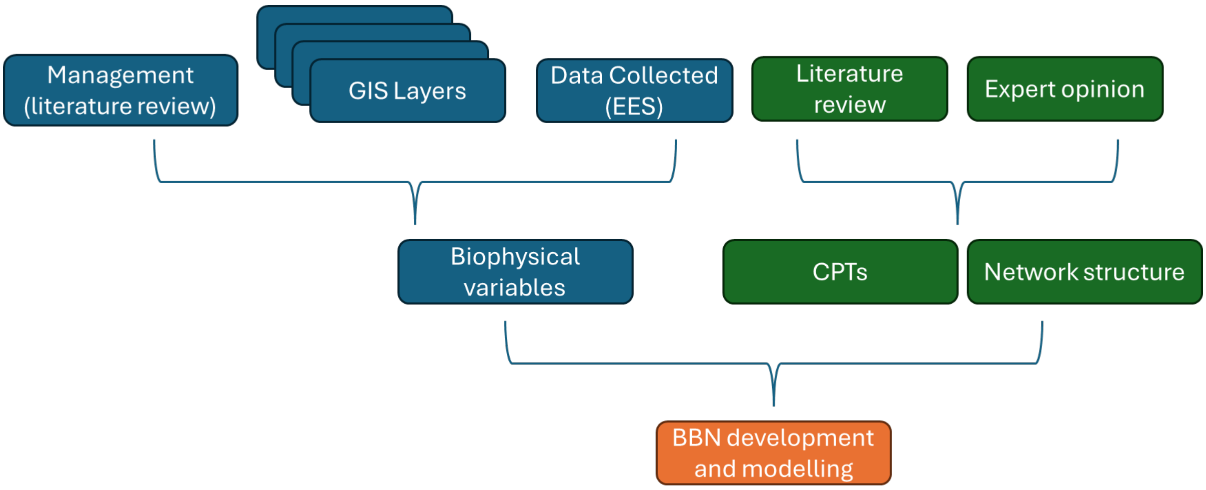


Figure 1. A visual summary of the data sources used, and how these are combined into the ultimate Bayesian Belief Network development and modelling. (CPT = conditional probability tables, see Section 3 for further information; GIS = Geographic Information System; EES = England Ecosystem Survey).

2.4. Visualisation of results

Each of the three ecosystem services (soils' long-term carbon storage, soils' contribution to water regulation through runoff reduction, and soils' contribution to sustainable arable crop provision – see Sections 3.2 to 3.4 for further details) has a headline result representing estimated ecosystem service delivery. In addition, carbon also has a second headline result, which 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 only briefly discussed here as the approach to be taken remains at an earlier stage of development.

Each of the headline results are presented in the fiche as a gauge style visualisation, as illustrated in Figure 2 using soils' contribution to runoff reduction as an example. Additional results, such as results from intermediate nodes of the model, are planned in future data releases.

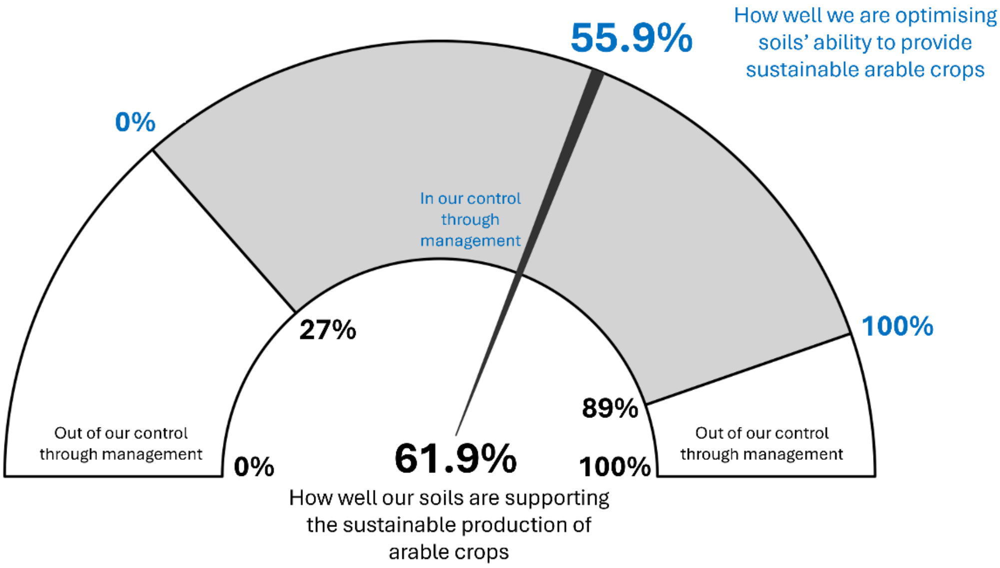


Figure 2. Visualisation illustrating that the likelihood that current soil conditions will lead to sustainable crop production, in England is 61.9%. The range of possible probabilities that soil conditions will lead to mitigated surface water flood risk in this example is 27% to 89%, given inherent constraints of rural soils in England (i.e. the maximum probability is 89%, if variables that can be influenced by management are optimised). The further right the pointer within this inner range, the closer ES delivery is to reaching its potential through optimal management. 0% represents a theoretical minimum whereby there is zero probability that soils will contribute to mitigated surface water flood risk (including variables not possible to manage); 100% represents a theoretical maximum whereby it is certain that soils will contribute to mitigated surface water flood risk (including variables not possible to manage). Note that soil conditions are not the only factor affecting flood risk, but only soil-related variables are included in the model as the scope is to show soil health in relation to flood risk, not overall flood risk.

The 'pointer' on the gauge represents the likelihood that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff. A result of 100% indicates the highest chance that soils are in optimum condition to mitigate surface water flood risk (e.g. a highly absorbent soil texture, high earthworm counts that support infiltration), whilst a result of 0% indicates the lowest chance of this (e.g. a poorly absorbent texture, highly compacted soils meaning low infiltration rates: soils are unlikely to mitigate surface water flood risk in this condition).

The underlying model includes both 'inherent variables' (such as soil texture and climatic variables) which are difficult to influence with management, and variables that are possible to influence with management (such as earthworm counts and soil organic matter). The gauge represents the full range of possible results (0–100%) from worst to best possible conditions for ecosystem service delivery, *including* for inherent variables (e.g. a score of 100% could only be achieved if soil texture and climate are also optimised to mitigate surface water flood risk). Within the gauge, results are provided about two different pieces of information:

- The shaded part of the gauge represents the range of possible scores (in Figure 2, 27–89%) as constrained by inherent properties of the soils in rural England (i.e. the soils' capability, averaged across sampled sites). The position of the 'pointer' within this inner range therefore shows the likelihood that soils are contributing to surface water flood risk mitigation compared to what is possible based on optimum management. **This allows for an understanding of how well England is doing at protecting ES delivery, as far as is in our reasonable control.**
- The position of the 'pointer' within the full range of the gauge (0–100%) shows how well soils are contributing to surface water flood risk mitigation compared to a theoretical optimum (100%). **This allows for assessment of how great a contribution soils are making to the likelihood of surface water flood risk mitigation overall, presented on a comparable and consistent scale that can be used across contexts** (e.g. if comparing the England value to a regional subset, or 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).

The shaded part of the gauge is nested within the full range of the gauge to estimate how much of the variation within the overall results is possible to control with management, versus what is outside the capability of rural English soils to deliver because of inherent constraints such as soil texture. Each ES is affected by different variables in different ways, meaning that the shaded range and capability vary in each gauge presented.

The other two models follow the same logic in terms of how results are presented, and only differ in what those results focus on. Namely, the carbon model estimates the likelihood that current soil conditions will lead to long-term carbon storage, through changes in both carbon entering and leaving the soil system (inputs and turnover), whilst the arable crop model represents the likelihood that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields.

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 on the clearest way in which to present this is ongoing.

3. The underpinning models

This section provides an introduction to the type of modelling that underpins the estimates for each of the three ecosystem services selected (water, carbon and food provision); and a summary of how this modelling is employed and presented in each of these three cases. Further detail on the data sources that have been used, justification of the variables included, and the relationships and groupings that have been applied to these 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 underpins 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 3), 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.

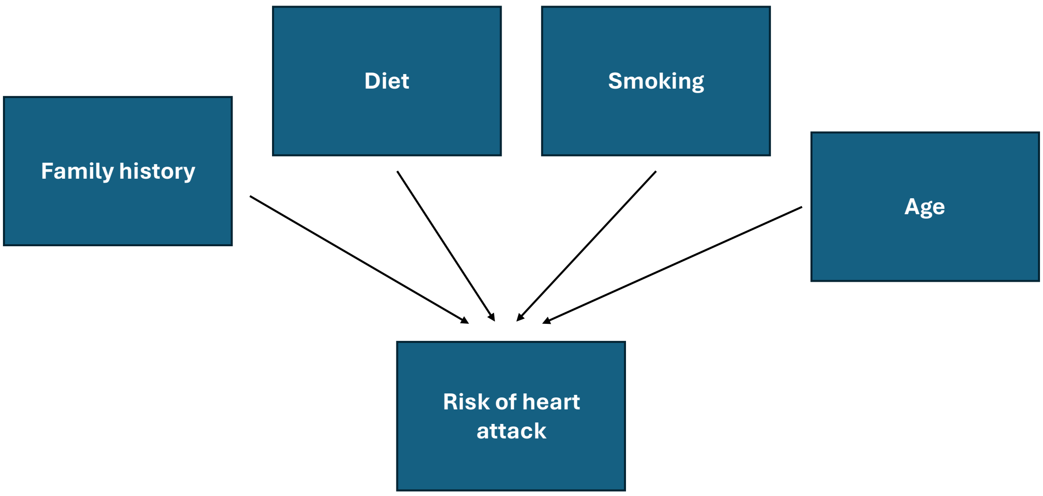


Figure 3. An illustrative example of a BBN in its graphical 'flow chart' style format, known as a Directed Acyclic Graph (DAG). In this case the nodes consist of family history, diet, smoking and age. The model will use conditional probabilities to predict the likelihood of heart attack based on these 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.

3.1.1. Application of Bayesian Belief Networks within the indicator

The structure of the Bayesian Belief Network models used for the indicators have been built using the Directed Acyclic Graphs illustrated within Sections 3.2 to 3.4, which were created based on literature review and expert panel consultation.

In preparation for input into the model, the data have been cleaned and classified into categories relevant to the final probability of Ecosystem Service delivery (e.g. “low”, “medium”, and “high” probability of delivery). Each root node (outermost nodes with no parents, e.g. ‘soil moisture’ in the water model) relates to a column in the input dataset, and the possible states of the node are equivalent to the classes in the input data (e.g. the soil moisture node has potential node states of “low”, “medium”, and “high”). These nodes / classified input data columns are either directly related to a variable from the input data or calculated through a combination of variables in the datasets. The England Ecosystem Survey (EES) formed the basis of the input data generation, as this survey was designed to cover a representative sample of the land uses across rural England at the plot level (excluding land use types detailed in Section 4). Where spatial datasets were used to find variables not measured through the EES, a vector dataset of the EES plot locations was used to extract the value of each spatial dataset at that point. This was done so that the representativeness of the spatial data could be directly comparable to that of the EES, and so that combinations of variables such as land use on soil type could be included in the model. All measured variables were then classified following the methods outlined in Appendices 1 to 3. The final cleaned input datasets consisted of the monad and plot number for each plot in the England Ecosystem Survey, and the classified node state of each model input variable according to the measured values for that plot.

To update the Bayesian network models with the data, each root node with a data input was re-fitted from the default settings of equal probabilities of all root node states using the custom.fit() function for bnlearn, with the probabilities of each root node state redefined as the proportion of that state’s occurrence in the cleaned input datasets. For the root nodes “crop rotation”, “cover crops”, “manure”, and “tillage”, estimates of rates of these practices from literature were used to update their conditional probability tables (CPTs, which define the relationships between each parent node and its child node in the model – see more on these in the subsequent paragraph). This was done by creating a new CPT in the model arguments composed of the literature estimates for rates of adoption of these practices.

CPTs for the models were created in R based on literature review and expert panel input. The CPTs define the relationship between each parent node and its child node (‘edges’ in the model), and ultimately the final ecosystem service, as described in Appendices 1 to 3. All nodes were treated as categorical variables, including those for which there is continuous data. For example, soil moisture data were, during the data classification stage, allocated to ‘high’, ‘medium’ or ‘low’ categories. The categories for each node were determined based on literature review and expert panel input. The aim was to balance model simplicity and accuracy, recognising that any model inputs within the same category (e.g. ‘high’ soil moisture being anything above 62% for all of the models) will cause the model to respond in the same way (Chen & Pollino 2012).

One CPT was created for each child node in each model (i.e. all the intermediate modelling steps and the final ecosystem service). Each row of a given CPT describes a different combination of states of the parent nodes feeding into the child node. Conditional probabilities were assigned for every possible combination of states (see example in Table 1).

Table 1. Conditional Probability Table (CPT) for the final ecosystem service in the water (runoff reduction) model. Each row of the CPT shows a different combination of states of the parent nodes (subsurface runoff and surface runoff). Each possible combination of parent node states ('high' or 'low'), was assigned an associated probability that current soil conditions will lead to mitigated surface water flood risk through changes in runoff.

	Subsurface runoff	Surface runoff	Probability that runoff reduction will lead to mitigated surface water flood risk, through changes in runoff
1	high	high	**0%**
2	low	high	**50%**
3	high	low	**50%**
4	low	low	**100%**

The conditional probabilities for each row in the CPT represent the sum effect of the parent node states on their child node and the final ecosystem service (i.e. in each row of Table 1, the effect of subsurface runoff is added to the effect of surface runoff to generate the resulting probabilities). When the combination of states of parent nodes is 'optimised' (as per row 4 of Table 1) then there is maximum probability that the child node will lead to ES delivery (100%), and the inverse is also true when the combination of states is at its 'worst' (as per row 1). A 'linear' relationship was assumed between most parent and child nodes, and between most parent nodes and the final ecosystem service. For example, if changing soil moisture from 'high' to 'medium' in the water model increased the probability of runoff reduction by X%, then changing soil moisture from 'medium' to 'low' also increased the probability of runoff reduction by X%. Note that because these are categorical variables this does not represent a linear relationship between numeric data underlying several of the input categories (e.g. actual soil moisture) and final results. Some exceptions did not follow these assumptions (e.g. relationships that are not 'linear' or interactions between variables which mean that their effects on model results should not be additive), as informed by evidence from literature review and expert panel; details on relationships between variables and the final ecosystem service are given in Appendices 1 to 3.

Further, it should be noted that some variables that are treated independently in the model are likely to be not entirely independent from one another in reality. This means that there is a risk of 'double counting' some variables in the model as the effects of one variable may be impossible to fully disentangle from another. For example, expected earthworm counts or soil moisture may typically be higher in some land covers than others, but we could not isolate a 'pure' land cover effect independent from variables that correlate with it. However, we accounted for this non-independence as far as possible when calibrating the % effect size of each change in variable in the model as informed by literature review and expert panel input. For example, if it was identified that the effect of variable X was largely driven by its correlation with variable Y (and if variable Y was included separately in the model), then we reduced the % effect size driven by variable X accordingly to avoid such double counting. The % effect sizes were calibrated by experts as described in the subsequent paragraph.

The % effect size that each variable state has on the final ecosystem service (effectively, the weighting for this variable state) is determined by two things: a numeric score assigned to the variable state during creation of the CPTs, and model asymmetry. The numeric score determines the effect that a given variable state has relative to other variable states within that CPT (i.e. all nodes feeding into the same child node). Model asymmetry determines the effect that a given variable state has relative to other variable states in other parts of the model. The ‘dummy model’ shown in Figure 4 below illustrates this model asymmetry effect. In this example, assuming that the same numeric score is assigned to each variable (e.g. variables 1–6 all score 1), variable 6 will have the strongest effect on the final probability because it feeds directly into this (final) node of the model. Variables 1 and 2 will each have half the effect that variable 6 has on the final probability because they both feed into intermediate modelling node 1 (which then itself feeds into the final node). Variables 3–5 will have one-third of the effect of variable 6, because these three variables feed into intermediate modelling node 2. Put simply, the more variables feeding into a given intermediate node, the more their effect on the final probability is ‘diluted’. This effect has therefore been accounted for in the CPT scores in order to produce % effect sizes that agree with the literature and expert panel inputs.

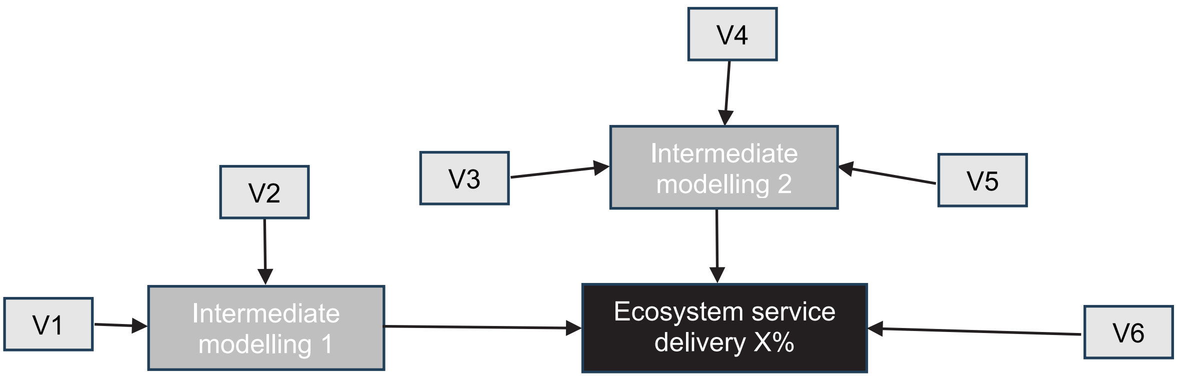


Figure 4. An illustrative example of a Directed Acyclic Graph to demonstrate how model asymmetry impacts the % effect size each variable has on ecosystem service delivery. All else being equal, variable 6 (V6) will have the strongest effect on the final probability because it feeds directly into this (final) node of the model. Variables 1 and 2 will each have half the effect that variable 6 has on the final probability because they both feed into intermediate modelling node 1 (which then itself feeds into the final node). Variables 3–5 will have one-third of the effect of variable 6, because these three variables feed into intermediate modelling node 2.

The BBNs were created in R by combining the DAGs and CPTs. Early versions of the models were calibrated with experts, whereby they were shown a series of different ‘dummy’ model inputs and associated results and asked whether the results were plausible and defensible based on their knowledge and how they would expect the model to behave. In this exercise, the experts were shown a sequence of model inputs and corresponding results, with the node values changing one at a time when moving through the sequence. For example, one result might show that, all else being equal, changing variable X from 'high' to 'low' reduces the likelihood of ES delivery by 5%. They could then calibrate the (absolute and relative) magnitudes and direction of effect of each individual node in the model, as well as any interactions with other variables. For example, the experts might suggest that variable X should have twice this effect on likelihood of ecosystem service delivery. The CPTs were updated to reflect these suggested changes, for example in this case, the scores in the CPTs were amended so that changing variable X from 'high' to 'low' would reduce the likelihood of ES delivery by around 10%.

Results for this initial interim indicator are obtained through a query to the model networks. Querying a Bayesian network is the method for extracting the probability of a specified "event" (for example, the likelihood of ecosystem service delivery through reduced runoff) given the "evidence" provided in the query (for example, the land cover being "cropland" and moisture being "high"). Each model developed has a final output node representing ecosystem service delivery with two possible states, "result" and "inverse result". The "inverse result" is equal to one minus the "result", and so only the "result" is presented in the indicator. For the model outputs, two queries were performed on the models that had been fitted using the input data to find the probability of the final ecosystem service node "result" and "inverse result". For these queries, no specific evidence was specified as the queries are looking for the probability of the events given the fitted model probability distributions.

There are two methods of querying a Bayesian network. "Exact inference" transforms the network into a "tree" and propagates the evidence input through it to extract the distributions of the nodes of interest. "Approximate inference" uses Monte Carlo simulations to run repeated simulations of the model with the independent variables generated randomly from the conditional probability tables provided – this then provides a set of representative model runs that can be used to calculate the probability of a given result from the model. Approximate inference was chosen as the method for querying of the soil health indicator models due to it being supported in the bnlearn package and being designed to scale better to Bayesian networks with a large number of nodes (Scutari & Denis 2021) to allow for flexibility to add more nodes in future development of the models.

The queries were carried out using the cpquery() function from the bnlearn package (Scutari 2010). This function offers two different methods for approximate inference querying. "Logic sampling" generates independent observations of the Bayesian network and calculates the ratio between the number of observations that match the evidence the query is conditioned on and the number of observations that match the event whose probability is being computed. Because many generated observations are discarded, this method can be very inefficient, especially when dealing with small probabilities. In the alternative "likelihood weighting" method, random observations are generated so that they all match the evidence. These observations are assigned weights based on the likelihood components of the nodes in the Bayesian network, and these values are combined into the final node state probability distributions. This method is intended to provide results that are closer to the exact inference value while less computationally expensive to run than the "logic sampling" method (Scutari & Denis 2021), so was chosen as the querying method for generating the indicator. In this method there is natural variation in each run due to the variation in random samples generated per query. In order to get results that were consistent to one decimal place, the query function was set to generate 10^7 random samples from the data per run.

To find national value model estimates of ecosystem service delivery, each root node of the models was fitted using the input data. In order to avoid issues arising from the query method generating “impossible” combinations of data as covered in the limitations section, the input data were subset depending on the model, as detailed in the following sections, then combined into one indicator. To generate the maximum and minimum probabilities of ecosystem service delivery given constraints on the system being measured (the "range" of the gauge visualisation), separate models were fitted to scenarios where the nodes that were determined to be improvable through management have a 100% probability of contributing to ecosystem service delivery (for example, in the water model the high scenario fitted model has a 100% probability of earthworm counts being "high" and the low scenario has a 100% probability of earthworm counts being "low"). These “high” and “low” scenario fitted models are then queried using the same method to obtain the probability of ecosystem service provision in those scenarios.

3.2. Water: soils’ contribution to runoff reduction

3.2.1. What the results show

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

- **How much are soils contributing to reduction of runoff risk in England?** This constitutes the likelihood that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff. A result of 100% indicates the highest chance that soils are in optimum condition to mitigate surface water flood risk (e.g. a highly absorbent soil texture, high earthworm counts that support infiltration), whilst a result of 0% indicates the lowest chance of this (e.g. poorly absorbent soil texture, highly compacted soils meaning low infiltration rates: soils are unlikely to mitigate surface water flood risk in this condition). The specific interest here is in understanding what role soil would play overall in mitigating surface water 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 is calculated by running data from NCEA 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 shaded part of the gauge shown in Figure 2 (Section 2.4.1). The edges of the shaded part of the gauge are calculated by running the model described in Section 3.2.2 using real data for any variables that are inherent and not possible to change, but artificial data set to the (a) highest and (b) lowest possible values for any variables that are possible to influence with management.

The scope of this model is rural environments; therefore cases where precipitation cannot reach the soil (e.g. concrete sealing) are excluded from consideration. Results do not provide information on the extent or magnitude of potential surface water flooding, nor predict when or where flooding might take place; they provide information on the likelihood that soils will contribute to mitigating surface water flood risk given their current condition. It should also be noted that some runoff is natural. The theoretical maximum (100%) is therefore not a state of no runoff (or of no flooding), but rather of mitigating surface water flood risk as far as is possible.

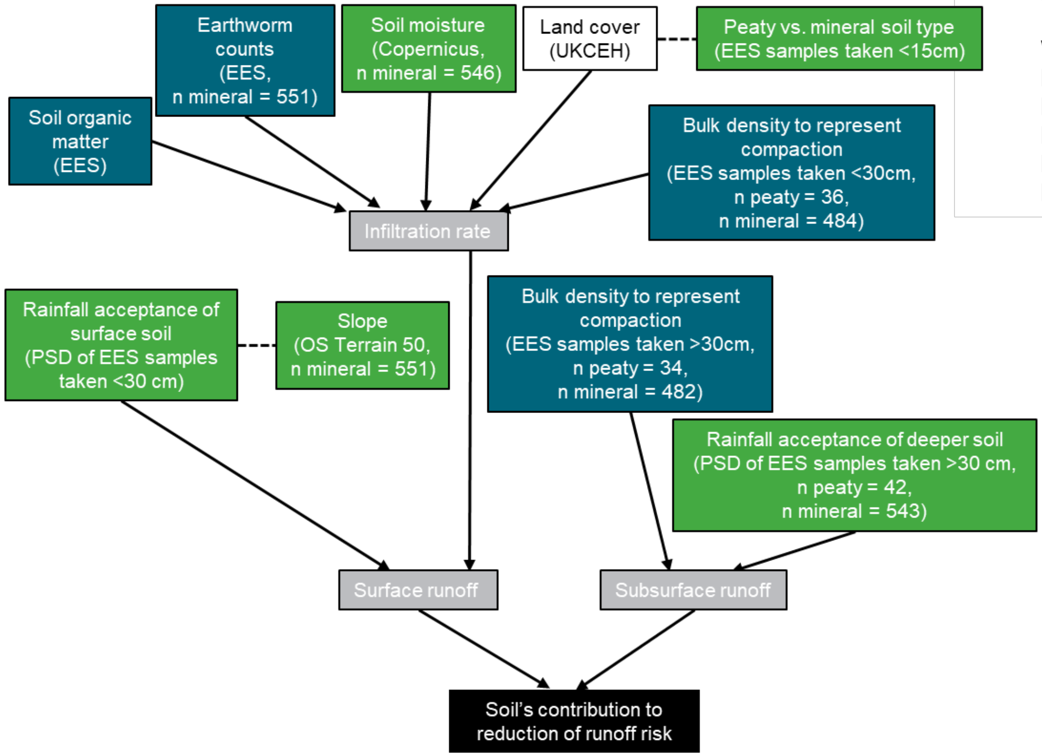
3.2.2. The model network

The structure of the water model is shown in Figure 5. Two intermediate modelled nodes, surface runoff and subsurface runoff, feed into this final runoff risk node. The subsurface runoff node is based on rainfall acceptance data (based on soil texture) and bulk density to represent compaction, both using data only from samples taken deeper than 30 cm. The surface runoff node takes into account rainfall acceptance (based on soil texture) from samples taken shallower than 30 cm, slope, and an intermediate modelled node representing infiltration rate. Note that there is a conditional relationship between slope and rainfall acceptance (< 30 cm samples) whereby slope has no effect on peaty soil types, as defined in the CPTs. The infiltration rate node relies on input data on earthworms counts, soil moisture (mean value across the year), land cover (which is in particular being used to represent vegetation cover), soil type (peaty versus not peaty), bulk density (from samples taken shallower than 30 cm), and soil organic matter. There is a conditional relationship between land cover and soil type whereby the impact of land cover on infiltration rate (as defined in the CPTs) depends on whether soil type is peaty or mineral.

The input data for the water model was subsetted into peaty soil sites (n = 47) and mineral soil sites (n = 553), and the model was fitted to each of these two datasets separately, before combining results based on the proportions of peaty and mineral samples in the overall dataset, as outlined in Figure 5. This approach was taken to mitigate against potential limitations arising from fitting the models to the input data, which is based on the proportions of node states occurring in the data. One of these potential limitations is that this method can result in ‘impossible’ data combinations, such as locations with land cover type ‘bog’ on ‘mineral’ soils. Subsetting the data and running peaty and mineral site data through the model separately avoids this and other issues. More details are given in Section 4.

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

Step 1. Model fit to input data – separate runs for peaty (n=47) and mineral (n=553) soil types.



Step 2. Model results for separate runs combined into a single value using the equation:

R = (P result * P proportion) + (M result * M proportion)

Where:
R = Soil's overall contribution to reduction of runoff risk
P result = Model result for peaty soils
P proportion = Proportion of peaty samples in overall dataset
M result = Model result for mineral soils
M proportion = Proportion of mineral samples in overall dataset.

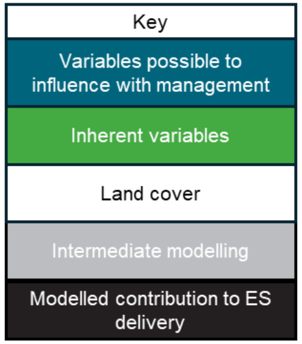


Figure 5. Process for generating model results and an estimate of soils' contribution to reduction of runoff risk. Step 1 involves fitting the water model to subsets of the data split into peaty and mineral soil types. The diagram on the left is a visual representation of the nodes (variables, described in each box, data sources and n samples shown in brackets) and edges (the relationship between parent and child nodes, represented by arrows) in the model. The number of samples for each variable is the maximum possible for peaty (n = 47) and mineral (n = 553) soil types unless otherwise stated. Dashed lines indicate where a conditional relationship between variables has been defined in the CPTs (e.g. the relationship between 'land cover' and 'infiltration rate' depends on whether 'soil type' is peaty or mineral). While these are separate nodes in the model network, they can be considered as working as a single node due to this conditional relationship (hence a single edge shown for each pair of variables with a conditional relationship). Step 2 involves combining the results for the peaty and mineral runs based on the proportion of samples in the overall dataset, to give a combined model result.

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

3.3.1. What the results show

As explained in Section 2.4, the headline results for the carbon model captures three key pieces of information:

- **How much carbon is the soil currently storing?** This reports on total estimated carbon stocks in tonnes per hectare ($T\ C\ ha^{-1}$). This is calculated from the absolute values of soil organic carbon (SOC) and fine bulk density (BD) for the top 30 cm of soil depth, following IPCC guidelines for calculating carbon stock change (IPCC 2003). These measurements were collected by the NCEA programme.

$$C = BD_{soil} * Depth_{soil} * SOC * 100$$

Where:
C = Carbon stock ($T\ C\ ha^{-1}$)
BD_{soil} = Bulk density ($g\ cm^{-3}$)
$Depth_{soil}$ = Soil depth (cm)
SOC = organic carbon (%)

  As the data are not normally distributed (Shapiro-Wilk, $p < 0.05$), results are presented as the median average carbon stock from 509 applicable sites (excluding urban, fen, and littoral sites), separated by mineral and peaty soil classification. We align with the NE Peat Map definition of peaty soils (Kratz *et al.* 2025), i.e. soils with at least 20% organic matter, or 25% where there is more than 50% clay, which is averaged across the full 0–30 cm sample depth. Averaging across the full 30 cm sample depth was selected over splitting by shallow or deep samples to ensure there was no mismatch between soil classification at different depths. Mineral classification includes three textures: 'heavy', 'medium' and 'light'. Given the properties of EES survey data, there are 56 occurrences where there is a mismatch of textural classification between depths for mineral soil types, in these cases the texture for the top 15 cm is used as this is most likely to reflect current soil texture. We further separate results to show the median average carbon stock across land cover type and texture class, in cases where there are at least 30 data points in each type/class combination.

- **How much are our soils contributing to long term carbon storage?** This constitutes the likelihood that current soil conditions will lead to long-term carbon storage, through changes in both carbon entering and leaving the soil system (inputs and turnover). Results can be considered an indicator of the stability of carbon present in the soil. 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 is important for gaining a balanced picture of soil health. This is calculated by running data from NCEA and other sources through the BBN model outlined in Section 3.3.2. A score of 100% indicates the chance that soils are in optimum condition to store carbon long term (e.g. management practices favourable to carbon storage, such as crop rotation and cover crops, are being utilised), whilst a score of 0% indicates the lowest chance of this (e.g. soils that are highly disturbed and have a light texture class, which is not favourable to carbon storage).

- **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 shaded part of the gauge as shown in Figure 2 (Section 2.4.1). The ends of the shaded part of the gauge are calculated by running the models described in Section 3.3.2, using real data for any variables that are inherent and not possible to change, but artificial data set to the (a) highest and (b) lowest possible values for any variables that are possible to influence with management.

"Long-term" carbon storage is considered to be on a > 20 year timescale. Results do not provide information on the extent or magnitude of carbon stored or released; they only provide information on the likelihood that soils will contribute to long-term storage given their current condition. Variables that are likely to have a short-term impact on carbon stock before reaching a new equilibrium (e.g. crop rotation, cover crops, reduced tillage) are considered within scope, but the assumption behind this is that any current activity would continue into the long term (i.e. a system regularly undertaking these activities would have higher long-term carbon storage than a system not undertaking them). Currently, the measured values include data from peaty soils, whilst the modelled values exclude them. Future development work will seek to include data from both peaty and mineral soils in both, for example through adding a module to the models that describe the mechanisms that are relevant for carbon stability in peaty soils.

3.3.2. The model network

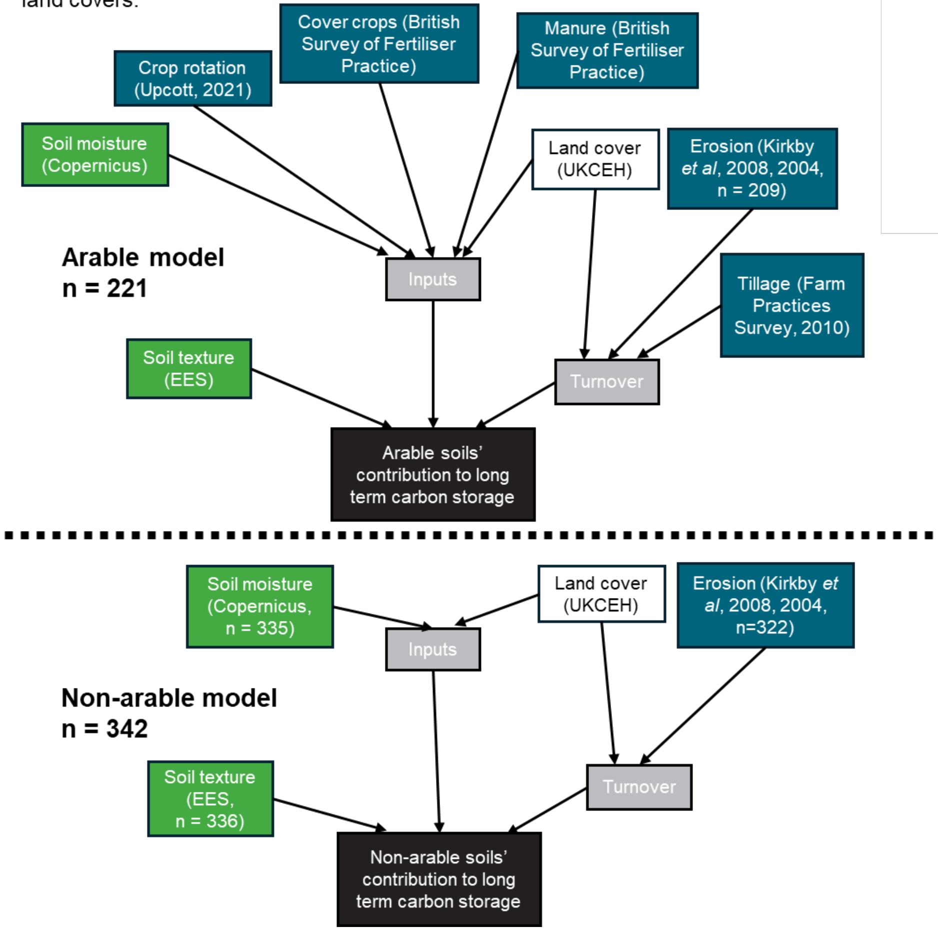
The structure of the carbon models (in this case there are two models – one for arable sites and one for non-arable sites, with results later combined) are shown in Figure 6. The models predict soils' contribution to long-term carbon storage in both arable and non-arable land covers. Soil texture, and two intermediate modelled nodes (inputs and turnover) feed into this final carbon storage node in both models. Data on soil moisture (mean across the year) feed into the inputs node while data on erosion feed into the turnover node in both models. Land cover feeds into both the inputs and turnover nodes in both models. In the arable model (fit to data for arable land covers only), crop rotation, cover crops and manure also feed into the inputs node while tillage feeds into the turnover node.

The input data were subsetted into arable soil sites (n = 221) and non-arable sites (n = 342), with the relevant model fit to each of these two datasets separately, before combining results based on the proportions of arable and non-arable samples in the overall dataset, as outlined in Figure 6. This approach was taken to mitigate against potential limitations arising from fitting the models to the input data, which is based on the proportions of node states occurring in the data. One of these potential limitations is that this method can arise in 'impossible' data combinations, such as crop rotation being 'present' on non-arable land. Subsetting the data and running arable and non-arable site data (and removing irrelevant nodes from the non-arable model) through the models separately avoids this and other issues. More details are given in Section 4.

The management variables in the model are currently most relevant to cropland and thus are included in the arable model only. Work to integrate data and management options of relevance to forestry and other land cover types is ongoing.

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

Step 1. Model fit to input data – separate models and runs for arable and non-arable land covers.



Step 2. Model results for separate runs combined into a single value using the equation:

R = (Ar result * Ar proportion) + (NAr result * NAr proportion)

Where:
R = Soil's overall contribution to long term carbon storage
Ar result = Model result for arable soils
Ar proportion = Proportion of arable samples in overall dataset
NAr result = Model result for non-arable soils
NAr proportion = Proportion of non-arable samples in overall dataset.

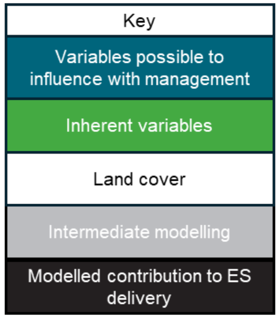


Figure 6. Process for generating model results and an estimate of soils' contribution to long-term carbon storage. Step 1 involves fitting different versions of the model to subsets of the data split into arable and non-arable land covers. The diagram on the left is a visual representation of the nodes (variables, described in each box, data sources and n samples shown in brackets) and edges (the relationship between parent and child nodes, represented by arrows) in the model. The number of samples for each variable is the maximum possible for arable (n = 221) and non-arable (n = 342) land covers unless otherwise stated. Step 2 involves combining the results for the arable and non-arable models based on the proportion of samples in the overall dataset, to give a combined model result.

3.4. Arable crops: soils' contribution to sustainable crop provision

3.4.1. What the results show

As explained in Section 2.4, the headline results for the arable crop provision model capture two key pieces of information:

- **How much are our soils contributing to sustainable arable crop provision?** This constitutes the likelihood that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields, if the land in question were used for this purpose. A score of 100% indicates the highest chance that soils are in optimum condition to sustainably support crop provision (e.g. optimum nutrient availability for growth, a low risk of soil-borne pests and pathogens), whilst a score of 0 indicates the lowest chance of this (e.g. soils are too acidic, soils have a low organic matter content). This is calculated by running data from NCEA and other sources through the BBN model outlined in Section 3.4.2.
- **How does the current potential for soils' contribution to arable crop 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 shaded part of the gauge as shown in Figure 2 (Section 2.4.1). The ends of the shaded part of the gauge are calculated by running the model described in Section 3.4.2 using real data for any variables that are inherent and not possible to change, but artificial data set to the (a) highest and (b) lowest possible values for any variables that are possible to influence with management.

In this context, 'sustainable' demonstrates that the focus is on sustaining long-term arable crop provision into the future (a balance between yields and ability to sustain those yields), rather than maximising short-term yields (in the current or next few years) at the expense of future harvests. Variables that are likely to have a short-term impact on yields (e.g. crop rotation, nitrogen levels) are considered within scope, but the assumption behind this is that the state of these variables would continue into the long term.

3.4.2. The model network

The structure of the arable crop provision model is shown in Figure 7. The model predicts soils' contribution to sustainable arable crop provision (n = 218). Soil organic matter, risk of soil borne pathogens and disease, earthworm counts, nutrient uptake and the Likelihood of Best and Most Versatile Agricultural Land dataset, all feed into this final arable crop provision node. Nutrient uptake is a modelled intermediate node, requiring data inputs on 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 (mean across the year), land cover 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.

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 arable crop provision, rather than short-term yields in cases where this is at the expense of future harvests.

The current scope of the model is restricted to arable crops. However, development work in future years will aim to expand this to describe all food/fibre provision, including integrating data and variables of relevance to perennial crops, timber from forestry and meat from grazing land. Results do not provide information on yields directly; they provide information on the likelihood that soils could contribute to sustainable provision given their current condition. Areas not currently used as arable cropland are considered excluded from scope; for example the potential of current grassland to provide crops if land were used for this purpose is not considered. The model does not consider trade-offs between crop provision and other ecosystem services. It is also restricted to illustrating broad principles and is not able to say anything about any one particular crop type; for example, high SOM is considered to lead to high yields in general across many crops such as spring cereals, root crops and maize, but does not do so for every crop.

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

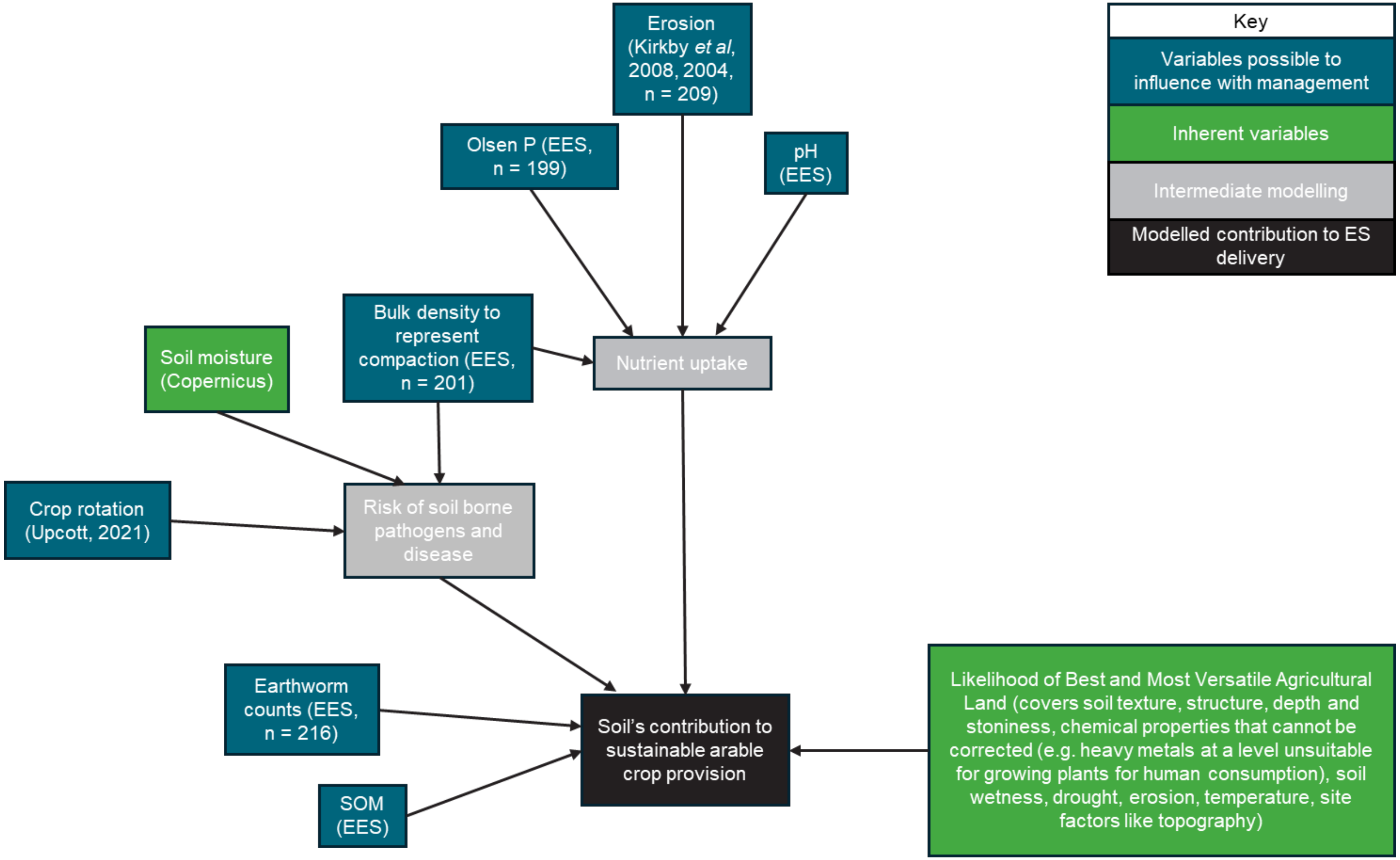


Figure 7. A visual representation of the nodes (variables, described in each box, data sources and n samples shown in brackets) and edges (the relationship between parent and child nodes, represented by arrows) in the arable crop provision model. The number of samples for each variable is the maximum possible (n = 218) in the dataset unless otherwise stated. This model is run for data from arable land covers only. Unlike for the water and carbon models, the model is run only once (with the model fit to the full dataset for arable land covers) rather than separately on subsets of the data with these results later combined to give the headline result. Therefore there is no 'step 2' in this case, the modelled contribution to ES delivery is the headline result for this ecosystem service.

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. As the authors have only had access to a sample of this part of the data, and this was received much later than the physical and chemical soil data (due to the additional processing required, for example laboratory identifications), the methods remain less well developed, but an initial proposal is outlined below.

It is planned that the biodiversity results will include data on bacteria, nematodes, fungi, and metazoans, as Amplicon Sequence Variant (ASV) counts from metabarcoding data. It is expected that earthworms will be included as a separate group as these data are likely to be presented as counts per functional group, instead of within metabarcoding data. The methods presented here are proposed as an initial investigation and preliminary plan based on a small sample of data. It is subject to change when the full dataset is received. An expert consultation process is also planned to input into and refine the approach.

Before analysis, ASV counts will be rarified to account for differences in sequencing depth between samples, which is a common issue posed with metabarcoding data. Non-metric multidimensional scaling (NMDS) will identify community clustering by land cover type and soil properties (e.g. pH, carbon, nitrogen, iron, phosphorus, bulk density). Where possible, land cover will be grouped into a reduced number of broad categories, adhering to NMDS clustering. This will help ensure broad land-use types (e.g. grazing land, arable land) still have similar communities of biodiversity. This will enable analysis of alpha diversity using the Shannon diversity index across taxa and land cover types in a bar graph with ranges, which will form part of the key results output.

To develop a headline indicator score, it is planned that the maximum alpha diversity score for each taxon and land cover will be used to scale diversity scores between 0 and 1, grouped by land cover type, or potentially soil variables if there is clear clustering in the NMDS (see Equation 1).

$$\frac{\alpha\ diversity}{Max\ \alpha\ diversity} = Normalised\ score\ by\ land\ use\ type$$

The average of the normalised scores for the five taxonomic groups (bacteria, nematodes, fungi, metazoans and earthworms) will allow comparison between land cover types recognising inherent differences in biodiversity across ecosystems. Acknowledging that not all taxa will be ‘better’ for soil health as some organisms will have a neutral or negative impact (e.g. pathogens), certain taxonomic groups (e.g. bacteria, fungi) or individual taxa (e.g. important fungi groups) can be assigned an increased weighting after normalisation. This can be applied with expert and literature consultation particularly for individual species or families, based on NMDS if soil properties are significantly correlated with specific taxonomic groups, or correlational analysis between taxa and important properties for soil health. The latter method can be used to infer statistically significant indicator taxa, which can also infer weightings.

Due to the scaling and averaging of results, even with increased weightings the maximum score for soil biodiversity will be 1 and minimum will be 0. This aligns with the presentation of modelled results for other ecosystem services and allows easy comparison across ecosystems and time.

We note the following caveats related to this approach, and will seek options to mitigate them in subsequent development work:

- NMDS is subjective and under the current proposed approach would be down to visual interpretation.
- Outliers can impact normalisation, which may require excluding outliers or using percentile-based scaling.
- There would be no consideration of functional diversity.
- There would be a need to incorporate earthworms, which are not included within the metabarcoding directly, separately. The same approach of normalization by land cover type could potentially be used for this.
- Rarification of metabarcoding to correct for different sequencing depths may obscure some trends if also normalising by taxa and land cover types. Further investigation into this issue is required.
- There are likely to be amplification issues relating to taxonomic coverage with primers and databases.
- Presence/absence and number of ASVs in metabarcoding data are not directly related to abundance.
- There will likely be seasonal differences relating to samples taken at different points in the year.

4. Limitations, assumptions and uncertainty

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

- Limitations of the interim field datasets that are being used in this initial, interim publication:
    - The EES operates as a five-year rolling survey, with monads (1 km^2 sampling units) selected through stratified random sampling based on ITE Land Class and adjusted for rare classes of interest. Certain areas – such as dense urban zones, large water bodies (> 2 ha), NFI woodlands, and land below Mean High Water - are excluded. Interim results may over- or under-represent some land classes until the cycle is complete. Potential sampling bias arising from landowner permission has not yet been assessed. This dataset reflects only a partial subset of the full set of samples planned in the survey's strategic sample design and is supplied as a partial dataset for experimental use. Additional years of data collection and publication will follow, at which point a fully representative sample will be available. Thus, this interim dataset is not entirely representative of the whole target population and may contain an element of bias, which may make it not suitable for all intended analytical purposes. In addition, the modelling works on the assumption that the EES's representativeness by land type can be equated to representativeness of soil types, which may not necessarily be the case and should be investigated in further work. No weightings to correct for this have been applied in the current work, so results should be treated as demonstrative only at this stage.
    - At the analysis stage, for the purposes of this statistic, some further land types, including saltmarsh, fen and littoral land types, are additionally excluded in the current results due to low numbers of sampling points, meaning specifying their different functionalities within the models was not efficient. Additionally, woodland soil data are being collected through a separate NCEA monitoring programme (NFI+), which we intend to integrate into the indicator in future but is not included at this stage.
- 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 cover in the carbon models is grouped into 'tree cover', 'shrub/grassland' and 'cropland', and soil moisture into 'high,' 'medium' and 'low'. The models are 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 thresholds to define these categorical states have been defined based on literature review and expert input, based on current conditions. It is planned that

future development work will consider the appropriateness of these thresholds in the context of projected future changes, such as climate change.

- 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 processes. As described in Section 3.1.1, the general assumptions are that the relationships between parent and child nodes are 'linear' (in terms of step changes between the categories for each variable), and that the combined effect of parent variables on the ecosystem service is additive. Exceptions to these assumptions are accounted for where evidence was found to justify this. For example, if it is found that variable 'a' interacts with variable 'b' to give a non-linear response, then this has been defined. Details of these relationships are given in Appendices 1 to 3.
- Unless the literature review or expert panel process pointed to differences in the magnitude of impacts between variables, then they are assumed to be equal to one another (e.g. variables 'c', 'd', 'e' have an equal effect on ES delivery because there is no evidence to suggest otherwise). However, if it is considered that variable 'x' has twice as large an effect size on ES delivery as variable 'y', this has been defined.
- The (absolute and relative) magnitudes and direction of effect of each individual node in the model, as well as any interactions (which combine to generate the final model results) were first determined by literature review and the expert panel process, and later calibrated by experts, as described in Section 3.1.1 (see in particular the paragraphs describing the CPTs). These effect sizes cannot be directly measured. Therefore ultimately, the results represent probability estimates of soils' contribution to ecosystem service delivery, based on model dynamics seen as plausible and defensible by experts (and as suggested by literature review), rather than precise or 'true' probabilities.
- 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 are not considered within the current results.
- The models combine spatial and non-spatial data, and assume that these data can be treated in the same way. For example, sampled spatial data are used to derive the probability of a given location 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.
- Variables not covered by the EES have been supplemented by using location data for EES plots to extract values for spatial data at those locations using terra's "extract" function on raster datasets (Hijmans 2025) and sf's "st_join" function on vector datasets (Pebesma 2018). There are inherent uncertainties associated with these functions and with the accuracy of both the plot location data and the spatial input datasets. This is mitigated through a data cleaning process that removes data that were considered impossible to achieve on EES locations, such as rock land cover types and bog land cover types with mineral soils.

- The models are fit to the input data by creating CPTs for root nodes that follow the distribution of the input data (for example, if 30% of the input data for the node has value “high”, the CPT assigns the data a 30% probability of being “high”). However, no method was found in the functions used to allow the model to incorporate the likelihood of certain combinations of data - for example, that crop rotation will always be ‘absent’ on non-cropland land cover types, or that there are no instances of locations with land cover type ‘bog’ with ‘mineral’ soils. To mitigate against this limitation (whereby when simulations of the model are generated for the querying functions they may include runs with instances of these ‘impossible’ combinations together), the water and carbon models are each run on different subsets of the full dataset (see the model diagrams in Figures 5 and 6 and associated descriptions for further details on these models). This method of running the model on subsetted data also means that the conditional relationships in the water model are captured in accurate proportions. For example, there is a conditional relationship between land cover and peaty/mineral soil type whereby the impact that land cover has on model results is dependent on whether that land cover is found on peaty or mineral soil types. 'Peaty' soils with ‘tree cover’ as the land cover, for example, are less likely to contribute to reduction of runoff risk than ‘mineral’ soils with 'tree cover'. While these are two separate nodes in the model, the CPTs are constructed so that they effectively work as one node with a combined effect on model results. Doing two separate water model runs with different input datasets (peaty and mineral) means that the land cover types are distributed accurately across the peaty and mineral datasets (e.g. if there were 5 data points for tree cover in the peaty data and 50 in the mineral data, the corresponding model run (peaty/mineral) would be fit only to the relevant data, rather than all 55 of the tree cover data points being randomly matched up to either peaty or mineral soil types in a combined model run). Consequently, this conditional relationship is represented in the correct proportions. Alternative methods to overcoming these potential limitations are also being investigated, such as running the model on a site-by-site basis by setting the evidence in the query to the input data values at each plot location.
- In some cases, inputs use quite variable dates. This is based on the most recent data that are available but does present an additional caveat around how representative results are of the time period being analysed.
- There is some inconsistency in how each of the three models are run compared to each other. This is due to differences in scope between what each cover and is explained in further detail in Section 3.

5. Next steps

The planned next steps for the work are as follows:

- **Further development work.** Work is planned to increase and test the sensitivity of the models, and to integrate more factors of relevance. For example, the initial, interim models used here are of most relevance to cropland systems; 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 cover 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 now available and will be integrated into the next release of the statistic. 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. Work will also continue on the development of soil biodiversity metrics.
- **Publication of a final baseline statistic in ~2030.** It is planned that this will be based on data from the full five-years of EES data collection, and so will be nationally representative (for land cover types within scope).
- **Publication of data for subsequent timepoints on the graph.** This will take place once further data collection has been completed, expected each ~5 years. 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.

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Weblinks

Table 2. Full URLs of 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
EU's planned Soil Observatory Indicator Dashboard	https://joint-research-centre.ec.europa.eu/eu-soil-observatory-euso/eu-soil-observatory-dashboard-indicators_en
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 Under 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 3. Glossary of terms used in the report.

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.

Term	**Definition**
Dashboard	A tool displaying data in an easy-to-understand manner.
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 Services (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	An England-wide survey of soils, vegetation and landscape to produce a baseline that change can be detected from, being undertaken by Natural England. Part of the Natural Capital and Ecosystem Assessment 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.

Term	Definition
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.
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 a new time series of data on soil condition with extended soil parameters to include soil biodiversity..
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 surface water 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

Term	Definition
	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 30cm.
Sustainable crop provision	The ability to produce high crop yields 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 the data sources used, how variables were categorised and relationships between them and the final ecosystem service defined. 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). It is planned that the thresholds for categorisation will remain constant throughout time, to allow for eventual assessment of change over time. However, these may change further during the development phase of the project as further calibration exercises are undertaken.

For any variables included that are based on EES data, averages across the soil depths for which data were available (typically 0–15 cm, 15–30 cm and 30–40 cm) were used, unless otherwise stated.

Variables included in the model

Earthworm counts

- **Justification for inclusion:** The expert panel suggested that this should be added, although recommended for this to be 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). For this initial, interim release, data on all earthworms have been included, as data providing a breakdown into ecotype are not yet available. However, this will be changed to anecic earthworm counts in future years once NCEA have published this breakdown. Similarly, whilst data on biomass were found to be preferable to counts in the literature review, only count data were recorded by NCEA and so those have been used here. The possibility of using count data to estimate biomass was explored but not considered robust by the expert panel.
- **Data source:** NCEA data (EES). Data are divided into categories of ‘high’ (> 15 earthworms per sample), ‘medium’ (5 to 15 earthworms per sample), and ‘low’ (< 5 earthworms per sample). These categories are loosely based on the AHDB scorecard categories, although averaging (and rounding) the values provided for cropland with the values provided for grassland (as the model requires a single set of categories as its input, and whilst *expected* earthworm counts vary by land cover, the model assumes that *functional* thresholds do not). This merging was reviewed by experts through the calibration exercise. Each sample is 20 x 20 x 20 cm.
- **Relationships with other variables and final ecosystem service:** Higher earthworm counts are considered to increase infiltration rate (and through this reduce surface runoff, thereby increasing the probability that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff). At the site level (i.e. considering a single set of model inputs), high earthworm counts would increase model results (the probability that current soil conditions will lead to mitigated surface water flood risk) by ~approximately 4.9% relative to low earthworm counts (or ~2.5%

relative to medium earthworm counts, all else being equal). See example in Figure 8 to aid interpretation of these values, and Table 4 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

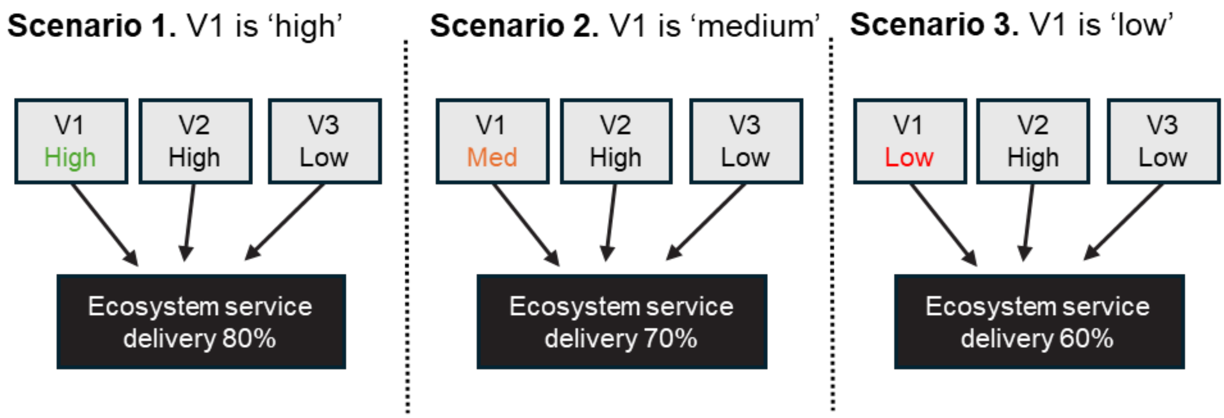

Figure 8. An illustrative example of model run scenarios to demonstrate what is meant by % effect sizes of variables on ecosystem service delivery. These scenarios are described as 'site-level' because there is a single set of model inputs in each case (variables are set as either 'high', 'medium' or 'low' rather than there being multiple inputs for each variable, as would be the case when fitting the model to a dataset with multiple sites). Scenarios 1 to 3 demostrates that high variable 1 would increase model results (the probability of ecosystem service delivery) by 20% relative to low V1 (scenario 1 versus 3) or 10% relative to medium V1 (scenario 1 versus 2). We say, in these examples, that 'all else is equal' because the states of variables 2 and 3 are the same in all three scenarios. Therefore the change in likelihood of ecosystem service delivery between scenarios is due to the change in state of V1 only.

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). The key aspect of land cover of relevance is vegetation cover. The expert panel process also noted a conditional relationship with soil type (mineral versus peaty soils), and particularly the significance of degraded peatlands where infiltration rates are expected to be very low.
- **Data source:** UKCEH 2023 Land Cover Map (LCM) – 25 m resolution, sampled at plot locations where NCEA data (EES) were collected with land cover categories aggregated into 'tree cover', 'shrub/grassland', 'bog' and 'cropland'. Note that EES data do not cover urban areas, and EES points with extracted land cover values of water, rock, sand, and urban/suburban were excluded due to the likelihood of this being an error. In addition, for the water model, points with land cover type "fen" were excluded due to the low numbers of samples in these categories meaning it was not worthwhile developing specific CPTs for them at this stage. All other data points were kept and grouped into the node state categories as set out in Appendices 1 to 3. The

UKCEH LCM was considered the best data source available at the time of the initial model development. The production team are aware that Living England have since produced a higher resolution map which will be considered for use in future publications.

- **Relationships with other variables and final ecosystem service:** This variable interacts with soil type. Infiltration is considered to be highest in tree cover on mineral soils (and through this reduce surface runoff, thereby increasing the probability that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff). At the site level (i.e. considering a single set of model inputs), all else being equal, tree cover on mineral soils would increase model results by:
  - ~1.8% relative to shrub/grassland on mineral soils;
  - ~3.7% relative to bog on peaty soils;
  - ~5.5% relative to cropland on mineral soils; and
  - ~30.7% relative to tree cover or shrub/grassland or cropland on peaty soils (all of which are assumed to represent degraded peatland).

Note that while land cover and soil type are separate nodes in the model network, they can be considered as working as a single node due to this conditional relationship, which is defined in the CPTs. See Table 4 for the full list of % effect sizes for each variable in the model.

Peaty versus mineral soils

- **Justification for inclusion:** This is included to interact with land cover, based on expert panel advice.
- **Data source:** NCEA data (EES) at 0–15 cm preferentially, or at 0–30 cm if no data is available at 0–15 cm. The data are divided into peaty soils and mineral soils. We align with the NE Peat Map (Kratz *et al.* 2025) definition of peaty soils, (i.e. soils with at least 20% organic matter), or 25% where there is more than 50% clay.
- **Relationships with other variables and final ecosystem service:** Interacts with the land cover node; see the land cover section for details and Table 4 for the full list of % effect sizes for each variable in the model. Soil type is also captured separately in the two rainfall acceptance nodes (the categories of which are 'heavy', 'medium', 'light', and 'peaty'). The reason for the inclusion in two separate places in the DAG is because each are allowing for different conditional relationships to be defined in the CPTs. Note that the input data for the water model was subsetted into peaty sites and mineral sites, and the model was fit to each of these two datasets separately, before combining results based on the proportions of peaty and mineral samples in the overall dataset, as outlined in Section 3.2.2.

Soil organic matter (SOM)

- **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). For light soils, the data are divided into categories of 'high' (> 5% SOM), 'medium' (2–5% SOM) and 'low' (< 2% SOM). For all other soils, they are divided into categories of 'high' (> 4% SOM), 'medium' (2–4% SOM) and 'low' (< 2% SOM). These categories reflect input from the expert panel, simplified alignment with the AHDB scorecard categories, and information from the literature (Oldfield 2019, 2020, 2022; Bhogal *et al.* 2022).
- **Relationships with other variables and final ecosystem service**: Higher soil organic matter is considered to increase infiltration rate (and through this reduce surface runoff, thereby increasing the probability that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff). At the site level (i.e. considering a single set of model inputs), high soil organic matter would increase model results by ~4.9% relative to low soil organic matter (or ~2.5% relative to medium soil organic matter, all else being equal). See Table 4 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

Soil moisture

- **Justification for inclusion:** In the proof-of-concept study (Harris *et al.* 2023), 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), sampled at plot locations where NCEA data (EES) were collected (mean across the year). The COSMOS dataset was also considered, but the Copernicus data were found to have greater spatial resolution and to provide deeper data. The data are divided evenly into categories of 'high' (>62%), 'medium' (58-62%) and 'low' (<58%), based on splitting the 2024 Copernicus Soil Water Index data for England into categories of approximately equal size. In future, the aim is to recalculate these thresholds based on more years of data.
- **Relationships with other variables and final ecosystem service:** Higher soil moisture is considered to reduce infiltration rate (and through this increase surface runoff, thereby decreasing the probability that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff). At the site level (i.e. considering a single set of model inputs), low soil moisture would increase model results by ~14.7% relative to high soil moisture (or ~7.4% relative to medium soil moisture, all else being equal). See Table 4 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

Rainfall acceptance of surface soil (< 30 cm)

- **Justification for inclusion:** Both the panel and the literature provided evidence for the inclusion of soil texture to represent a soil's rainfall acceptance, 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). Combining information on soil texture with other soil properties such as drainage was also considered important; we hope to be able to integrate this in future iterations of the model.

- **Data source:** NCEA data from samples taken at depths of between 0 cm and 30 cm (EES), grouped into high runoff risk / low rainfall acceptance ('heavy' and 'peaty' soils), moderate runoff risk / medium rainfall acceptance ('medium' texture soils) and low runoff risk / high rainfall acceptance ('light' soils). For the purposes of this classification preference was given to the texture classification at samples of depth 0–15 cm, then to depth 15–30 cm if no texture classification was available at depth 0–15 cm. We align with the NE Peat Map definition of peaty soils (Kratz *et al.* 2025), i.e. soils with at least 20% organic matter, or 25% where there is more than 50% clay. We align with the concordance table published in Annex 3 of Harris *et al.* (2023) to group textures into the other three categories. In future, we hope to replace the texture data with data from EA's Alert tool, which additionally takes into account factors such as drainage, if scoping work considers this feasible.
- **Relationships with other variables and final ecosystem service:** Heavier and peaty soil textures are considered to increase surface runoff (thereby decreasing the probability that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff). At the site level (i.e. considering a single set of model inputs), light soil texture would increase model results by ~19.7% relative to peaty soils, ~16.9% relative to heavy soils (or ~8.5% relative to medium soils, all else being equal). See Table 4 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England. The effect of slope is dependent on this variable, as described in the slope section, below.

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:** The OS Terrain 50 data (a Digital Terrain Model generated on a 50m grid to the nearest 0.1m height) is used, sampled at plot locations where NCEA data (EES) were collected. The data are divided into categories of 'steep,' 'medium' and 'flat,' aligning with those used in the ALERT tool (< 3 degrees = low, 3–7 degrees = medium, and > 7 degrees = high).
- **Relationships with other variables and final ecosystem service:** The expert panel noted that slope would have no effect on surface runoff on peaty soils. Therefore, steeper slope is considered to increase surface runoff (thereby decreasing the probability that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff) for mineral soils ('heavy', 'medium' and 'light') only (note that the categories in the rainfall acceptance of surface soil node are 'heavy', 'medium', 'light', and 'peaty'). At the site level (i.e. considering a single set of model inputs), slope being 'flat' on mineral soils would increase model results by ~5.6%

relative to steep slope (or ~2.8% relative to medium slope, all else being equal). Peaty soils are unaffected by slope, and they have roughly the same effect on runoff risk as heavy soil textures on a medium slope, which is they reduce model results by around 19.7% compared to light soil textures (as noted above under 'Rainfall acceptance of surface soil (<30 cm)'), all else being equal. This is equivalent to the 16.9% reduction driven by heavy soils compared to light soils, plus a further 2.8% reduction driven by medium slope rather than flat. Note that while slope and rainfall acceptance of shallower soils are separate nodes in the model network, they can be considered as working as a single node due to this conditional relationship, which is defined in the CPTs. See Table 4 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

Rainfall acceptance of deeper soil (> 30 cm)

- **Justification for inclusion:** 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). Combining information on soil texture with other soil properties such as drainage was also considered important; we hope to be able to integrate this in future iterations of the model. Literature review found that the effects of subsurface runoff are secondary to surface runoff, so this variable has a smaller impact than the rainfall acceptance of shallower soil (< 30 cm) node on model results.
- **Data source:** NCEA data from samples taken at depths greater than 30 cm (EES), grouped into high runoff risk / low rainfall acceptance ('heavy' and 'peaty' soils), moderate runoff risk / medium rainfall acceptance ('medium' texture soils) and low runoff risk / high rainfall acceptance ('light' soils). We align with the NE Peat Map definition of peaty soils (Kratz *et al.* 2025), i.e. soils with at least 20% organic matter, or 25% where there is more than 50% clay. We align with the concordance table published in Annex 3 of Harris *et al.* (2023) to group textures into the other three categories. In future, we hope to replace the texture data with data from EA's Alert tool, which additionally takes into account factors such as drainage, if scoping work considers this feasible.
- **Relationships with other variables and final ecosystem service:** Heavier and peaty soil textures are considered to increase subsurface runoff (thereby decreasing the probability that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff). At the site level, i.e. considering a single set of model inputs, light soil texture would increase model results by ~5.0% relative to peaty or heavy soils (or ~2.5% relative to medium soils, all else being equal). See Table 4 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

Bulk density to represent surface compaction (< 30 cm)

- **Justification for inclusion:** The expert panel considered compaction an essential variable to include, but suggested representing this with bulk density as this is available as part of the NCEA data. Whilst VESS (Visual Evaluation of Soil Structure) 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). Whilst this was initially only included for sub-surface compaction, expert input during the calibration exercise identified that bulk density samples taken at shallower depths would be relevant to both surface compaction as well.

- **Data source:** NCEA data (EES) from samples taken at depths of between 0 cm and 30 cm, with preference given first to depths 0–15 cm then to depths 0–30 cm. For mineral soils, the data are divided into categories of 'high' (> 1.3 g/cm^3), 'medium' (0.85–1.3 g/cm^3) and 'low' (< 0.85 g/cm^3), based on the 25th percentile, middle 50 percentiles and 75th percentile of the bulk density data in Panagos *et al*. (2024). For peaty soils, the data are divided into categories of 'high' (> 1 g/cm^3), 'medium' (0.85–1 g/cm^3) and 'low' (< 0.85–g/cm^3), with the adjusted 'high' category based on trigger values from Merrington *et al*. (2006) and Bhogal *et al.* (2008).
- **Relationships with other variables and final ecosystem service:** Higher bulk density is considered to reduce infiltration rate (and through this increase surface runoff, thereby decreasing the probability that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff). At the site level, i.e. considering a single set of model inputs, low bulk density would increase model results by ~12.3% relative to high bulk density (or ~6.1% relative to medium bulk density, all else being equal). See Table 4 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

Bulk density to represent subsurface compaction (> 30 cm)

- As above, except from EES samples taken at depths of greater than 30 cm. Literature review found that the effects of subsurface runoff are secondary to surface runoff, so this variable has a smaller impact than the bulk density (shallow) node on model results.
- **Relationships with other variables and final ecosystem service:** Higher bulk density is considered to reduce infiltration rate (and through this increase surface runoff, thereby decreasing the probability that current soil conditions will lead to mitigated surface water flood risk, through changes in runoff). At the site level, i.e. considering a single set of model inputs, low bulk density would increase model results by ~5.0% relative to high bulk density (or ~2.5% relative to medium bulk density, all else being equal). See Table 4 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

Table 4. Summary of relative % effect each variable state has on final model results (the probability that current soil conditions will lead to mitigated surface water flood risk) at the site level, i.e. considering a single set of model inputs. The final column indicates the relative model results for the alternative state compared to the optimal state, all else being equal. For example if two theoretical sites, A and B, are represented in exactly the same way as each other in the model (all variable states are the same), except site A has 'high' earthworm counts and site B has 'low' earthworm counts, then the modelled result for site B would be 4.9% lower than the result for site A.

Variable(s)	Optimal state for this variable	Alternative state	Model results for alternative compared to optimal state
Earthworm counts	High	Low	-4.9%
		Medium	-2.5%
Land cover / soil type (peaty versus mineral)	Tree cover on mineral soil	Tree cover or shrub/grassland or cropland on peaty soil (all of which are assumed to represent degraded peatland)	-30.7%
		Cropland on mineral soil	-5.5%
		Bog on peaty soil	-3.7%
		Shrub/grassland on mineral soil	-1.8%
Soil organic matter	High	Low	-4.9%
		Medium	-2.5%
Soil moisture	Low	High	-14.7%
		Medium	-7.4%
Rainfall acceptance of surface soil (< 30 cm)	Light	Peaty	-19.7%
		Heavy	-16.9%
		Medium	-8.5%
Slope (effect on mineral soils only i.e. when rainfall acceptance of surface soil is heavy, medium or light. Peaty soils are unaffected by slope).	Flat	Steep	-5.6%
		Medium	-2.8%

Variable(s)	Optimal state for this variable	Alternative state	Model results for alternative compared to optimal state
Rainfall acceptance of deeper soil (> 30 cm)	Light	Peaty or heavy	-5.0%
		Medium	-2.5%
Bulk density (< 30 cm)	Low	High	-12.3%
		Medium	-6.1%
Bulk density (> 30 cm)	Low	High	-5.0%
		Medium	-2.5%

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 versus 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 depth**: The panel suggested inclusion of soil depth data, with the logic that deeper soils would be able to store more water than shallow soils. This was initially supported by targeted reading and a relevant data source was found. However, further research and consultation relating to the data source identified that there is likely to be a general trend of the underlying geology of shallow soils being more permeable than the underlying geology of deep soils. To avoid potential for confusion and sending the opposite signal to that intended, this node has therefore been cut for the current iteration of the model, but further consideration will be made of this point in future development work.
- **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 models

This appendix provides information about the variables that were included in, and considered but excluded from, the carbon storage models illustrated in the main report (Figure 6), including justification and references for doing so. It also provides additional information about data sources used, how variables were categorised and relationships between them and the final ecosystem service defined. 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). It is planned that the thresholds for categorisation will remain constant throughout time, to allow for eventual assessment of change over time. However, these may change further during the development phase of the project as further calibration exercises are undertaken.

Note that while there are two separate carbon models (arable and non-arable), the 'scores' for variables which appear in both models have been calibrated such that they have equivalent impacts on results in each model. So, for example, the % effect on model results of changing soil texture from 'light' to 'heavy' (all else being equal) is the same in both models. Therefore, for variables included in both models, the 'relationships with other variables and final ecosystem service' are only described once but can be interpreted as applying to both models. Similarly, the 'justification for inclusion' and 'data sources' are applicable to both models.

For any variables included that are based on EES data, averages across the soil depths for which data were available (typically 0–15 cm, 15–30 cm and 30–40 cm) were used unless otherwise stated.

Variables included in the 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), grouped into 'heavy', 'medium', 'light' soils, based on the classes outlined in Annex 3, Table 4 of Harris *et al.* 2023. We align with the concordance table published in Annex 3 of Harris *et al.* (2023) to group textures into these three categories. Peaty soils are currently excluded. We align with the NE Peat Map definition of peaty soils (Kratz *et al.* 2025), i.e. soils with at least 20% organic matter, or 25% where there is more than 50% clay. To select one texture across depths per plot location, the most frequent texture across depths was used, or if there was one different texture per depth the texture at depth 15–30 cm was used.
- **Relationships with other variables and final ecosystem service:** Heavier soil classes are considered to increase the probability that current soil conditions will lead to long-term carbon storage. At the site level (i.e. considering a single set of model inputs), heavy soil texture would increase model results (the probability that current soil conditions will lead to long-term carbon storage) by ~28.6% relative to light soil

texture (or ~14.3% relative to medium soil texture, all else being equal). See example in Figure 8 (Appendix 1) to aid interpretation of these values, and Table 5 for the full list of % effect sizes for each variable in the models. The indicator is based on input data from sites across England. Peaty soils are excluded from this 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.

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), averaged across all depths provided and sampled at plot locations where NCEA data (EES) were collected (mean across the year). The COSMOS dataset was also considered, but the Copernicus data were found to have greater spatial resolution and to provide deeper data. The data are divided evenly into categories of ‘high’ (> 62%), ‘medium’ (58–62%) and ‘low’ (< 58%), based on splitting the 2024 Copernicus Soil Water Index data for England into categories of approximately equal size. In future, the aim is to recalculate these thresholds based on more years of data.
- **Relationships with other variables and final ecosystem service:** Increased soil moisture is considered to increase carbon inputs (thereby increasing the probability that current soil conditions will lead to long-term carbon storage). At the site level, i.e. considering a single set of model inputs, high soil moisture would increase model results by ~11.1% relative to low soil moisture (or ~5.6% relative to medium soil moisture, all else being equal). See Table 5 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

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 at a larger spatial scale (Quine & Van Oost 2007).
- **Data source:** Pan European Soil Erosion Risk Assessment – PESERA (described in Kirkby *et al.* 2004; 2008), sampled at plot locations where NCEA data (EES) were collected. The data are divided into categories of ‘high’ (>1 T per ha per year based on the threshold of soil loss considered tolerable in Switzerland; Verheijen *et al.* 2009),

'medium' and 'low', with the equal width method applied to the rest of the dataset to distinguish between 'medium' and 'low'.

- **Relationships with other variables and final ecosystem service:** Increased erosion risk is considered to increase carbon turnover (thereby decreasing the probability that current soil conditions will lead to long-term carbon storage). At the site level (i.e. considering a single set of model inputs), low erosion risk would increase model results by ~1.7% relative to high erosion risk (or ~0.9% relative to medium erosion risk, all else being equal). See Table 5 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England. 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 cover) are already accounted for within the dataset being used. As such, the effect on model results is consistent no matter the state of other variables within the model.

Land cover

- **Justification for inclusion:** Evidence from the literature review was conclusive (and found that the difference between each land cover 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:** UKCEH Land Cover Map (LCM), sampled at plot locations where NCEA data (EES) were collected, and aggregated into 'cropland', 'tree cover', and 'shrub/grassland'. Data points for land cover types typically found on peaty soils (bogs, fens) are excluded from this initial interim output, as our current literature review focused on mineral soils. The UKCEH LCM was considered the best data source available at the time of the initial model development. The production team are aware that Living England have since produced a higher resolution map which will be considered for use in future publications.
- **Relationships with other variables and final ecosystem service:** Based on Figure 2a of Ostle *et al*. (2009), cropland leads to lower soil carbon content (in our model this is mediated via both inputs and turnover), thereby decreasing the probability that current soil conditions will lead to long-term carbon storage, compared to the other land cover categories. At the site level (i.e. considering a single set of model inputs), model results for tree cover or shrub/grassland land covers would be ~44.1% higher than a cropland site with all management nodes optimised (i.e. crop rotation, cover crops and manure application all present, and no tillage; see below), all else being equal. See Table 5 for the full list of % effect sizes for each variable in the model. Cropland sites always have lower model results than the other two land cover types, no matter the other node states. For example, a cropland site in the 'best possible condition' for long term carbon storage (according to our model inputs) has a ~55.9% probability that its soil conditions will lead to long term carbon storage compared to a ~58.6% probability for a non-cropland site in the 'worst possible condition'. The indicator is based on input data from sites across England.

Crop rotation (arable model only)

- **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). This is further backed up by findings from [Conservation Evidence](https://www.conservationevidence.com/).

- **Data source:** Data presented in Upcott (2023), which groups rotation by broad crop types based on the UKCEH Land Cover plus Crops dataset. For the initial interim release, crop rotation is assessed categorically as either ‘present’ or ‘absent’ for samples from cropland. Crop rotation is categorised as present only for diverse rotations with 3 or more broad crop types within a 6-year rotation. This is a different categorisation to the arable crop model as the literature suggests benefits to carbon storage result from diverse rotations of multiple different crop types (Schjønning *et al.* 2007; Zani *et al.* 2023), hence the lower proportion of crops subject to a high carbon rotation compared to rotations which are beneficial for the sustainable provision of food within the arable crop model. Ongoing work will continue to search for improved and updated datasets, including a grass or ley period.
- **Relationships with other variables and final ecosystem service:** Presence of crop rotation is considered to increase carbon inputs (thereby increasing the probability that current soil conditions will lead to long-term carbon storage). As spatial data are not available, this is presented at a fixed proportional value and assigned randomly across all samples (in this case, 37.3% of samples will be assumed to use crop rotation). At the site level (i.e. considering a single set of model inputs), presence of crop rotation would increase model results by ~5.5% relative to crop rotation being absent (all else being equal). As recommended by expert input, this is the management variable with the greatest effect on model results. See Table 5 for the full list of % effect sizes for each variable in the model. Whilst the proof-of-concept project weighted this node in a way that considered the interactions between this and other management factors, 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 were unable to include this level of nuance in the initial indicator due to data constraints.

Manure application (arable model only)

- **Justification for inclusion:** Evidence from both the literature review and the expert panel process was in agreement that solid manure application increases soils’ contribution to long term carbon storage (Gross & Glaser, 2021; Maillard & Angers, 2014; Poulton *et al.* 2018; Powlson *et al.* 2012). This is further backed up by findings from [Conservation Evidence](https://www.conservationevidence.com/). 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 British Survey of Fertiliser Practice (Defra 2024). Manure application is assessed categorically as 'present' (when cattle farmyard manure (FYM), pig FYM, layer manure, and other farm manure are applied), or 'absent'.
- **Relationships with other variables and final ecosystem service:** Presence of manure application is considered to increase carbon inputs (thereby increasing the probability that current soil conditions will lead to long-term carbon storage). As spatial data are not available, this is presented at a fixed proportional value and assigned randomly across all samples (in this case, 17% of samples are assumed to apply manure). At the site level (i.e. considering a single set of model inputs), presence of

manure application would increase model results by ~3.7% relative to manure application being absent (all else being equal). See Table 5 for the full list of % effect sizes for each variable in the model. Whilst the proof-of-concept project weighted this node in a way that considered the interactions between this and other management factors, 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.

Tillage (arable model only)

- **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). The importance of including tillage is further backed up by findings from Conservation Evidence. 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:** Farm Practices Survey (2010). This provides data for a single point in time so is 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 is assessed categorically as ‘conventional’, ‘minimum’ or ‘no tillage’.
- **Relationships with other variables and final ecosystem service:** Higher levels of tillage are considered to increase carbon turnover (thereby decreasing the probability that current soil conditions will lead to long-term carbon storage). As spatial data are not available, this is presented at a fixed proportional value and assigned randomly across all samples (in this case, 56% of samples will be assumed to have conventional tillage, 40% minimum, 4% no tillage). At the site level, i.e. considering a single set of model inputs no tillage would increase model results by ~3.5% relative to conventional tillage (and ~1.7% compared to minimum tillage, all else being equal). See Table 5 for the full list of % effect sizes for each variable in the model. Whilst the proof-of-concept project weighted this node in a way that considered the interactions between this and other management factors, 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.

Cover crops (arable model only)

- **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). This is further backed up by findings from Conservation Evidence.
- **Data source:** British Survey of Fertiliser Practice (Defra, 2024). This has been used for the initial, interim statistic, but only provides data for a single point in time, so 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). For this initial release, cover crops have been assessed categorically as either ‘present’ or ‘absent’ for samples from cropland.

- **Relationships with other variables and final ecosystem service:** Presence of cover crops is considered to increase carbon inputs (thereby increasing the probability that current soil conditions will lead to long-term carbon storage). As spatial data are not available, this is presented at a fixed proportional value and assigned randomly across all samples (in this case, 10% of samples are assumed to have cover crops). At the site level, i.e. considering a single set of model inputs presence of cover crops would increase model results by ~1.8% relative to cover crops being absent (all else being equal). See Table 5 for the full list of % effect sizes for each variable in the model. Whilst the proof-of-concept project weighted this node in a way that considered the interactions between this and other management factors, 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.

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

- **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 are therefore presented alongside outputs from the model, but not included within the model network itself.
- **Data source:** Calculated from NCEA data (EES) on soil organic carbon and bulk density, reporting the median average absolute values of tonnes of carbon per hectare of soil.
- **Relationships with other variables and final ecosystem service:** N/A – not part of the model.

Table 5. Summary of relative % effect each variable state has on final model results (the probability that current soil conditions will lead to long-term carbon storage) at the site level (i.e. considering a single set of model inputs). The final column indicates the relative model results for the alternative state compared to the optimal state, all else being equal. For example if two theoretical sites, A and B, are represented in exactly the same way as each other in the model (all variable states are the same), except site A has 'heavy' soil texture and site B has 'light' soil texture, then the modelled result for site B would be 28.6% lower than the result for site A. All % effect changes reported are applicable to both carbon models, unless otherwise stated.

Variable	Optimal state for this variable	Alternative state	Model results for alternative compared to optimal state
Soil texture	Heavy	Light	-28.6%
		Medium	-14.3%
Soil moisture	High	Low	-11.1%
		Medium	-5.6%
Erosion	Low	High	-1.7%
		Medium	-0.9%
Land cover	Tree cover or shrub/grassland	Cropland with management nodes optimised (i.e. crop rotation, cover crops and manure application all present, and no tillage)	-44.1%
Crop rotation (arable model only)	Present	Absent	-5.5%
Manure application (arable model only)	Present	Absent	-3.7%
Tillage (arable model only)	No tillage	Conventional	-3.5%
		Minimum	-1.7%
Cover crops (arable model only)	Present	Absent	-1.8%

Variables that were considered, but excluded from the models

- **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 affecting 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.
- **Ratio of respiration and microbial biomass:** This was suggested for inclusion 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). However, it was not possible to obtain relevant data as whilst EES is measuring respiration rates, it is not measuring microbial biomass and it is the interaction between the two that is pertinent. Development work will continue to investigate possibilities for its inclusion in future.
- **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 cover and many of the other variables also included within the model, so has been excluded.

Appendix 3: Supplementary detail on the arable crop model

This appendix provides information about the variables that were included in, and considered but excluded from, the food model illustrated in the main report (Figure 7), including justification and references for doing so. It also provides additional information about the data sources used, how variables were categorised and relationships between them and the final ecosystem service defined. 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). It is planned that the thresholds for categorisation will remain constant throughout time, to allow for eventual assessment of change over time. However, these may change further during the development phase of the project as further calibration exercises are undertaken.

This model is currently run for data from arable land covers only.

For any variables included that are based on EES data, averages across the soil depths for which data were available (typically 0–15 cm, 15–30 cm and 30–40 cm) were used unless otherwise stated.

Variables included in the model

ALC (proportion of Best and Most Versatile Land)

- **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 an approach of using ALC in place of these other factors, although highlighted that it would only be appropriate for an agricultural context. The model's scope currently only considers potential for agricultural production, but additional follow-up discussions with Forest Research and subsequent reading landed on use of Ecological Site Classification combined with biomass tables from the Woodland Carbon Code as an equivalent approach that could be used for forested areas. This will be integrated in future iterations of the model, with the scope of the model being expanded to cover food and fibre, rather than only food.
- **Data source:** The initial interim statistic makes use of the existing ALC 'Likelihood of Best and Most Versatile Agricultural Land' maps (Natural England, 2017). These maps show the best available estimate of agricultural land quality at the date of compilation expressed in terms of the proportion of land likely to classified as 'best and most versatile' ('BMV') i.e. Grades 1, 2, 3a in the Defra Agricultural Land Classification (revised 1988). Future work will consider the imminent release of the predictive ALC dataset, and 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 use the existing groupings of 'high', 'moderate' and 'low' likelihood of BMV land.

- **Relationships with other variables and final ecosystem service:** Higher proportion of Best and Most Versatile Land is considered to increase the probability that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields. At the site level, i.e. considering a single set of model inputs, high BMV would increase model results (i.e. the probability that current soil conditions could lead to sustainable arable crop provision) by ~35.3% relative to low BMV (or ~17.7% relative to medium BMV, all else being equal). See example in Figure 8 (Appendix 1) to aid interpretation of these values, and Table 6 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

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). The data are divided into categories of 'high' (>1.29 g/cm^3), 'medium' (0.85-1.29 g/cm^3) and 'low' (<0.85 g/cm^3), based on the 25th percentile, middle 50 percentiles and 75th percentile of the bulk density data in Panagos *et al*. (2024).
- **Relationships with other variables and final ecosystem service:** Higher bulk density is considered to decrease nutrient uptake and increase risk of soil borne pathogens and disease (both thereby decreasing the probability that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields). At the site level (i.e. considering a single set of model inputs), low bulk density would increase model results by ~15.7% relative to high bulk density (or ~7.9% relative to medium bulk density, all else being equal). See Table 6 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

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). In future, the use of data on functional groups will be incorporated, with thresholds adjusted to take diversity into account rather than simply total counts, but these data were not available in time for use in the current model iteration.
- **Data source:** NCEA data (EES). Data are divided into categories of 'high' (>9 earthworms per sample), 'medium' (4-8 earthworms per sample), and 'low' (<3 earthworms per sample). These categories are based on the AHDB scorecard categories for cropland. Each sample is 20x20x20 cm.
- **Relationships with other variables and final ecosystem service:** Higher earthworm counts are considered to increase the probability that current soil conditions could lead

to sustainable arable crop provision, through estimated changes in long-term yields. At the site level (i.e. considering a single set of model inputs), high earthworm counts would increase model results by ~5.9% relative to low earthworm counts (or ~2.9% relative to medium earthworm counts, all else being equal). See Table 6 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England. The results from the model do not currently cover forestry, but it is planned that in future development work the conditional probabilities tables will be constructed in a way that interacts with land cover (which will also be added as a node), so that earthworm counts have no effect on forestry land. This is based on evidence that this is a factor of relevance to agricultural crops but not to timber production.

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). 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). The data are divided into categories of ‘high’ (> 1 T per ha per year based on the threshold of soil loss considered tolerable Switzerland; Verheijen *et al.* 2009), ‘medium’ and ‘low’, with the equal width method applied to the rest of the dataset to distinguish between ‘medium’ and ‘low’.
- **Relationships with other variables and final ecosystem service:** Higher erosion risk is considered to reduce nutrient uptake (thereby decreasing the probability that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields). 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 cover) are already accounted for within the dataset being used. As such, changes to erosion risk have a consistent effect no matter the state of other variables within the model (i.e. it does not interact with other model variables). At the site level (i.e. considering a single set of model inputs), low erosion risk would increase model results by ~2.7% relative to high erosion risk (or ~1.4% relative to medium erosion risk, all else being equal). See Table 6 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

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. 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). The data are divided into categories of 'high', 'medium' and 'low', based on the AHDB soil health score card values, with <= 9 mg/L or >= 71 mg/L considered to be low, 9–16 mg/L (non-inclusive) and 45-71 mg/L (non-inclusive) considered to be medium, and 16–45 mg/L (inclusive)to be high. Since the EES reports its Olsen P in units of mg/kg, a unit conversion was carried out using the bulk density measurements before applying these thresholds. 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.
- **Relationships with other variables and final ecosystem service:** Higher Olsen P is considered to increase nutrient uptake (thereby increasing the probability that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields). At the site level (i.e. considering a single set of model inputs), high Olsen P would increase model results by ~5.4% relative to low Olsen P (or ~2.7% relative to medium Olsen P, all else being equal). See Table 6 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

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). Data have been grouped into sites with an optimal 'neutral' pH (6.5–7.5) and sites with a sub-optimal ('acidic' or 'alkaline') pH (< 6.5, and > 7.5).
- **Relationships with other variables and final ecosystem service:** A neutral pH is considered to increase nutrient uptake (thereby increasing the probability that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields). At the site level (i.e. considering a single set of model inputs), neutral pH would increase model results by ~8.0% relative to acidic or alkaline pH, all else being equal. See Table 6 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

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 (~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 loss on ignition). The data are divided into categories of 'high' (> 4%), 'medium' (2–4%) and 'low' (< 2%). These categories are based on the AHDB scorecard categories, using the values for mid-texture soils in mid-rainfall regions (as the model requires a single set of categories as its input).
- **Relationships with other variables and final ecosystem service:** Higher SOM is considered to increase the probability that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields. At the site level (i.e. considering a single set of model inputs), high SOM would increase model results by ~14.7% relative to low SOM (or ~7.4% relative to medium SOM, all else being equal). See Table 6 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

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), sampled at plot locations where NCEA data (EES) were collected and averaged across all depths provided (mean across the year). The COSMOS dataset was also considered, but the Copernicus data were found to have greater spatial resolution and to provide deeper data. The data are divided evenly into categories of 'high' (> 62%), 'medium' (58–62%) and 'low' (< 58%), based on splitting the 2024 Copernicus Soil Water Index data for England into categories of approximately equal size. In future, the aim is to recalculate these thresholds based on more years of data.
- **Relationships with other variables and final ecosystem service:** Higher soil moisture is considered to increase the risk of soil borne pathogens and diseases (thereby decreasing the probability that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields). At the site level (i.e. considering a single set of model inputs), low soil moisture would increase model results by ~2.3% relative to high soil moisture (or ~1.2% relative to medium soil moisture, all else being equal). See Table 6 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England. It should be noted that soil moisture is also one of the climatic factors considered in the ALC (BMV) node under 'wetness' and 'droughtiness', but its inclusion here relates to a different mechanism.

Crop rotation

- **Justification for inclusion:** Targeted reading following expert panel discussions identified this as a 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:** Data presented in Upcott (2023), which groups rotation by broad crop types based on the UKCEH Land Cover plus Crops dataset. For the initial interim release, crop rotation is assessed categorically as either 'present' or 'absent'. 'Present' refers to presence of crop rotation with mixed crop types (e.g. mixed cereals & oilseed rape), which are considered beneficial for sustainable crop provision, whilst 'absent refers to rotations with the same crop type only (e.g. short spring cereals). This is a different categorisation to the carbon model as the literature suggests benefits relating to disease suppression result from avoiding monoculture, hence the more flexible categorisation of beneficial rotations (Bullock, 1992; Peralta *et al.*, 2018). As spatial data are not available, this variable is presented at a fixed proportional value and assigned randomly to samples (in this case, 77.6% of cropland will be assumed to use crop rotation (Upcott 2023)). Whilst some literature review evidence flagged that the optimum crop-rotation system will vary between contexts, we are unable to include this level of nuance in the initial indicator due to data constraints. Ongoing work will continue to search for improved datasets.
- **Relationships with other variables and final ecosystem service:** As spatial data are not available, this is presented at a fixed proportional value and assigned randomly across all samples (77.6% of samples will be assumed to have crop rotation). Presence of crop rotation is considered to decrease the risk of soil borne pathogens and diseases (thereby increasing the probability that current soil conditions could lead to sustainable arable crop provision, through estimated changes in long-term yields). At the site level (i.e. considering a single set of model inputs), presence of crop rotation increases model results by ~10.0% relative to absence of crop rotation, all else being equal. See Table 6 for the full list of % effect sizes for each variable in the model. The indicator is based on input data from sites across England.

Table 6. Summary of relative % effect each variable state has on final model results (the probability that current soil conditions will lead to sustainable arable crop provision, through estimated changes in long-term yields) at the site level (i.e. considering a single set of model inputs). The final column indicates the relative model results for the alternative state compared to the optimal state, all else being equal. For example if two theoretical sites, A and B, are represented in exactly the same way as each other in the model (all variable states are the same), except site A has a 'high' proportion of BMV and site B has a 'low' proportion of BMV, then the modelled result for site B would be 35.3% lower than the result for site A.

Variable	Optimal state for this variable	Alternative state	Model results for alternative compared to optimal state
ALC class (represented by proportion of BMV)	High BMV	Low BMV	-35.3%
		Medium BMV	-17.7%
Bulk density to represent compaction	Low	High	-15.7%
		Medium	-7.9%
Earthworm counts	High	Low	-5.9%
		Medium	-2.9%

Variable	Optimal state for this variable	Alternative state	Model results for alternative compared to optimal state
Erosion	Low	High	-2.7%
		Medium	-1.4%
Olsen P	High	Low	-5.4%
		Medium	-2.7%
pH	Neutral	Acidic or alkaline	-8.0%
Soil organic matter	High	Low	-14.7%
		Medium	-7.4%
Soil moisture	Low	High	-2.3%
		Medium	-1.2%
Crop rotation	Present	Absent	-10.0%

Variables that were considered, but excluded from the model

- **Land cover:** The current scope of the model is restricted to arable crops so all land covers are 'cropland' and this is redundant. However, development work in future years will aim to expand the model(s) to describe all food/fibre provision, including integrating data and variables of relevance to perennial crops, timber from forestry and meat from grazing land, at which point a land cover node may be required.
- **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.
- **Nitrogen:** 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. However, EES are only collecting data on total %N, which experts subsequently highlighted is not a good proxy for available / potentially mineralizable nitrogen. It has therefore been excluded but future work will investigate proxies and alternatives for inclusion.

- **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.