European Journal of Soil Science

WILEY

RESEARCH ARTICLE OPEN ACCESS

Upscaling Models for the Large-Scale Assessment of Soil Functions

Alexandre M. J.-C. Wadoux[1,2] | Rachel E. Creamer[3] | Philippe Lagacherie[2] | Marko Debeljak[4]

[1]College of Science and Engineering, James Cook University, Cairns, Queensland, Australia | [2]LISAH, Univ. Montpellier, AgroParisTech, INRAE, IRD, L'Institut Agro, Montpellier, France | [3]Soil Biology Group, Wageningen University & Research, Wageningen, the Netherlands | [4]Department of Knowledge Technologies, Jozef Stefan Institute, Ljubljana, Slovenia

Correspondence: Alexandre M. J.-C. Wadoux (alexandre.wadoux@yahoo.fr)

Received: 17 January 2025 | **Revised:** 20 November 2025 | **Accepted:** 24 November 2025

Keywords: ecosystem services | multi-attribute modelling | multifunctionality | soil health | soil navigator

ABSTRACT

The characterization and assessment of soil functions is a prerequisite for agricultural and environmental policies aimed at soil health. However, there is a lack of satisfactory models for the assessment of soil functions supply to support national and intergovernmental initiatives. In this study we fill this gap by restructuring models developed to assess the multifunctionality of agricultural soils at the field scale. The multi-criteria decision models rely on soil properties, site characteristics and management information to assess the following five soil functions: (1) water regulation, (2) climate regulation, (3) nutrient cycling, (4) primary productivity and (5) provision of habitat for biodiversity. We develop models to assess soil functions supply at regional and national scales by adapting their structure to cope with the general lack of information on soil management at larger geographical scales. The restructured models are verified and a sensitivity analysis of the new model structure is performed. We further applied a comparison of the upscaled models with results from validated field-scale models using real data from 94 sites spanning across 13 European countries. We found that the upscaled models showed a similar sensitivity to the variability of the input data from the 94 sampling sites as the base models from which they were developed and that their overall supply is expected to be comparable. We describe the model structure of the upscaled models as well as their qualitative scales and integration rules. We propose the application of the models can serve for large-scale assessment of soil functions supply as part of soil health assessment for regional and national environmental and agricultural policies.

1 | Introduction

Soil is an essential part of terrestrial ecosystems because it provides habitats for biodiversity, supports plant growth and primary production, is a medium for the recycling of nutrients and regulates the quantity and quality of water flows (Blum 2005). Soil functions emerge from bundles of soil processes in interaction with soil properties (Bünemann et al. 2018) and, in turn, when considering the wider human demand, can determine the delivery of ecosystem services (Bouma 2014; Adhikari and Hartemink 2016). The notions of soil functions and services have been recognized in recent national and intergovernmental agricultural and environmental policies focused on the improvement of soil health. The European Union's proposed Directive on Soil Monitoring and Resilience, for example, aims to achieve soil health on a European scale by 2050 by 'maintaining or enhancing the ecosystem services provided by the soil without impairing the functions enabling those services' (European Commission 2023) and by establishing soil districts (Wadoux, Courteille, et al. 2024). The Global Soil Partnership of the Food and Agriculture Organization of the United Nations (FAO and ITPS 2015) is committed to global initiatives that recognize the contribution of soils to ecosystem services. Considering the need to support policy and management of land resources,

Highlights

- Adapted models from field-scale soil function assessment models.
- Models assess the supply of five soil functions.
- Models adapted for the regional or national scale evaluation of soil functions.
- Support assessment and implementation of environmental and agricultural policy.

the question arises as to how soil functions can be effectively characterized and their supply assessed at these policy decision-relevant levels.

Several methods for assessing soil functions are known, many of which have been developed under the umbrella terms of soil quality (Bünemann et al. 2018), soil health (Kibblewhite et al. 2008) and more recently soil security (Evangelista et al. 2023). Soil functions supply is usually estimated based on measured values of soil properties used as indicators of a given soil functional capacity. Popular examples of indicators include soil organic carbon content, nutrients, and bulk density (Van de Broek et al. 2019). Greiner et al. (2017) defined three approaches to soil function assessment. The first approaches are often referred to as indicator or static approaches, in contrast to the dynamic approach, which includes biophysical or process-based models. Using biophysical models is likely the preferred method for soil function assessment, as it better represents the underlying soil processes that deliver these functions. Examples of biophysical models are APSIM (Keating et al. 2003) and BODIUM (König et al. 2023). This approach is the most resource-intensive and time-consuming, as each case study requires substantial effort for data collection, processing, parameter calibration, mapping and validation. Despite some efforts (e.g. in Leip et al. 2008), outputs from static and indicator approaches are easier to communicate and are currently better suited for large-scale planning and scoping activities. In the indicator or static approaches, indicator values are normalized to a unitless value, usually between 0 and 1, and aggregated to a single estimate of either a particular soil function or, in some capacity, attempts have been made to derive a single index for soil health. In Halvorson et al. (1996), for example, six continuous indicators (e.g. electrical conductivity or total inorganic N) were measured at 220 locations. These continuous indicators were then transformed into indicators with nominal values depending on whether they exceeded a threshold value or not. Soil quality was considered satisfactory if no more than one indicator scored below its threshold value.

Soil functions supply is based on several indicators which are aggregated into a single value or index that describes the overall supply of the evaluated function. Rabot et al. (2017) classified aggregation methods into expert-based approaches in which scores according to thresholds define how a soil function is supplied (e.g. Lilburne et al. 2004), while statistical approaches utilize algorithms and statistical analyses for the selection of appropriate indicators from a wider set of parameters and the definition of scores and aggregation (e.g. Bastida et al. 2006). The first aggregation method leads to qualitative and the second to quantitative estimates, which can take various forms, such as decision trees, influence diagrams and multi-criteria decision models (MCDM). The MCDM has been recognized as a useful method for integrating different qualitative and quantitative indicators for evaluating variables in many application domains (e.g. Van Calker et al. 2006; Sinclair et al. 2015; Ikram et al. 2024).

This study builds on the work of Debeljak et al. (2019), who developed and validated a field-scale decision support system (DSS) for farmers to assess and manage the multifunctionality of their soils. The DSS called Soil Navigator (http://www.soilnavigator.eu/) is based on MCDM where Decision Expert (DEX, Bohanec et al. 2013) utilizes an integrative methodology. The resulting five qualitative MCDM corresponded to five soil functions described by Schulte et al. (2014) as (1) provision of food, fibre and fuel (primary productivity), (2) soil as a habitat for biodiversity (habitat provision), (3) the ability of a soil to receive, recycle and supply nutrients to plants (nutrient cycling), (4) water regulation and purification, and (5) the capacity of a soil to store carbon and reduce losses of greenhouse gases for climate regulation. Before the models were integrated into the DSS Soil Navigator, they underwent a verification and validation process carried out in a series of studies focusing on specific soil functions (the function soil biodiversity and habitat provisioning in Van Leeuwen et al. 2019, for example), while the synergies and trade-offs between these five functions were elaborated in Zwetsloot et al. (2021) and Vazquez et al. (2021). In these studies, in addition to soil properties and site characteristics, management information was also used to estimate soil functions supply, as they were originally developed as a tool that can be applied at a scale that meets the needs of farmers and farm advisors (Vazquez et al. 2021).

Building on the successful application of the methodology for the development of field-level soil function assessment models, this study aims to apply the same MCDM framework using the integrative DEX methodology for the development of models for the assessment of soil functions supply at the regional and national scales. Hereafter, scale refers to the geographical extent or areas under study. Field scale refers to the level of individual farms or plots, where data collection, monitoring or interventions are applied directly to these specific management units. Regional scale, used hereafter, refers to a broader geographic area that may encompass multiple fields, farms or even administrative zones (e.g. districts, provinces or watersheds). Regional assessments complement field-level analyses: they help identify spatial patterns, highlight local areas of interest and determine where targeted support may be most needed to maintain or enhance soil functions.

Our research has several objectives. First, we aim to adapt existing decision models for soil function supply assessment from the field scale to the regional scale. Detailed soil management information that is readily available at the field level is generally lacking at the regional and national levels, making the calibration and use of the developed models inappropriate. Next, we verify and perform a sensitivity analysis of the new model structures to iteratively refine their structure and achieve realistic outputs. We report the MCDM models that are designed to support regional and national decision makers in environmental and agricultural policy. Finally, we provide an overview of the strengths and weaknesses of the models and discuss the future potential of large-scale assessment of soil functions through qualitative multi-attribute modelling. In this way, we aim to bridge the gap between current and future research efforts in regional and national soil function supply assessment.

2 | Qualitative Multi-Criteria Decision Models

The Soil Strategy 2030 and the communication for a proposed Directive on Soil Monitoring and Resilience aim to improve the state of soils across Europe to a healthy status by 2050 (European Commission 2021, 2023). A healthy soil constitutes a soil that is not degraded and therefore has the capacity to provide its multiple functions and services (European Commission 2021). While assessing the multifunctionality of soils at the local scale has been the basis of many research papers (e.g. Calzolari et al. 2016; Zwetsloot et al. 2021; Vazquez et al. 2021), which combine information on soil properties with environmental factors and often management practices, this is more challenging at a pan-European scale. Assessing multifunctionality at the European scale is perceived as a difficult task, as it requires the amalgamation of information on soil parameters, environmental conditions and land management factors at a large spatial extent, and yet this information needs to remain meaningful in assessing the underlying relationships that define multi-functionality. While information exists on environmental conditions at larger spatial extents, detailed soil property information is limited to pan-European soil monitoring, such as the LUCAS topsoil survey (Tóth et al. 2013), which collects primarily soil chemical data with a small set of soil physical and biological data (the latter at a limited number of sites). The LUCAS Topsoil survey also provides information on land-cover parameters, but not on management practices applied. Thus, the application of models developed for the assessment of multifunctionality at the local scale is often too demanding for the data available at the European extent. This begs the question: what level of information is needed at a pan-European scale of assessment? Does it require detailed point-specific information that incorporates detailed management information at the field level, or should the model provide broad trends in the potential soil multifunctionality, considering the genoform (soil forming conditions) that can then be further investigated at a more appropriate scale of assessment in combination with management practices at the local scale? The search for regulatory and management measures for soil multifunctionality therefore remains a complex decision problem that is currently the basis for the proposed Directive on Soil Monitoring and Resilience, which aims to collect sufficient information at a pan-European scale to enable assessment of soil health (European Commission 2023).

To address this complex decision problem, we use multi-criteria decision analysis (MCDA, Greco et al. 2016) for the evaluation of soil functions. MCDA, which is an early form of artificial intelligence (Wadoux 2025), involves the formulation of complex decision problems, the identification of key objectives, the formulation of criteria, the development of multi-criteria decision models and their use for decision-making tasks such as the selection, evaluation, ranking and analysis of decision alternatives. Based on the specifics of a decision problem at hand, data and expertise availability and required features of soil function models, the DEX methodology of MCDA (Bohanec 2003) was chosen. DEX has been found particularly suitable for sorting and classification decision tasks aimed at assigning decision alternatives to predefined categories, which can be either preferentially ordered ('sorting') or unordered ('classification') (Craheix et al. 2015; Meunier et al. 2022). DEX is implemented through a MCDM where a decision model is developed first and independently from individual decision alternatives (Bohanec 2017). These alternatives are then evaluated by the model, first by scoring them for each criterion and then aggregating these evaluations into a global score (Bohanec 2003).

MCDM built by DEX methodology consists of hierarchically structured attributes. Attributes in a DEX model represent observable properties of the decision problem and decision alternatives. Each attribute is defined as an ordered set of qualitative (i.e. symbolic) values that rarely consist of more than five values. Scale values are represented by words (e.g. high, medium and low) rather than numbers, and they can be either ordered or unordered. Attributes are aggregated into a hierarchical structure. Attributes without parents are called roots and represent the main outputs of the model. Attributes without descendants are called basic (i.e. input) attributes and represent model inputs. Attributes with descendants and parents are referred to as aggregate attributes and are also considered partial intermediate outputs of the model. The structure is based on an aggregation function represented by decision tables, which serve for the evaluation of an aggregate attribute based on the values of its immediate descendants in the model structure. The decision table provides rules that define the elementary decision rules that aggregate child attributes into a parent attribute.

In the DEX methodology, utility functions, also referred to as aggregation or integration functions, combine values of lower-level qualitative attributes into higher-level evaluations within a hierarchical decision model. Formally, each DEX utility function is an aggregate function:

$$f: D_{x_1} \times D_{x_2} \times \cdots \times D_{x_n} \rightarrow D_y, \tag{1}$$

where D_{x_i} and D_y are finite, linearly ordered sets of qualitative values (e.g. low, medium, high or acceptable, good, excellent). These functions are defined using decision tables that comprehensively enumerate 'if–then' rules to specify the output for every possible input combination. In this way, DEX aggregation functions provide deterministic, complete and interpretable mappings that satisfy the formal definition of utility functions in multi-criteria decision-making theory (Bohanec 2022).

Once the DEX MCDM is developed, it serves for the evaluation and analysis of decision alternatives. Each alternative is represented by a set of values of input attributes describing the assessed item (e.g. the organic carbon content of a soil sample). Once the DEX model is populated by input data, the model provides an evaluation of the alternatives by the calculation of the output values. The evaluation is carried out as a bottom-up aggregation of model inputs towards its outputs, according to the hierarchical structure of attributes and associated aggregation functions. The main outputs are assigned to the root attribute, while values assigned to the remaining aggregate attributes provide additional information about the assessed alternative and help explain the main result (i.e. the value of the root attribute).

Since we are dealing with qualitative models, input data have to be transformed to a required format. In the case of numerical values of soil properties, data discretization has to be applied. The discretization requires a definition of thresholds. In case an input attribute is calculated or synthesized from several variables, the mathematical function for each synthesized attribute has to be predefined.

The DEX MCDM were built with the software modelling tool DEXi (Bohanec 2023a). DEXi is a desktop application for MS Windows that supports the interactive creation and editing of all components of DEX models (attributes, their hierarchy and scales, decision tables and alternatives) and provides methods for evaluating and analysing decision alternatives (what-if analysis, 'plus-minus-1' analysis, selective explanation, comparison of alternatives, option generator) (Bohanec 2017, 2022). There are also additional DEXi-related software tools that facilitate the use of DEXi models in different environments, such as command line, Java, C# and HTML (https://dex.ijs.si/dexiclassic/dexiclassic.html).

3 | Methods

3.1 | Base Models

We have used the concept of base models to develop decision models for the assessment of soil functions. Base models provide the core structure and underlying principles on which more specific and complex models can be built and adapted. In our study, we used the soil function assessment models developed by DEX methodology described in the previous section which are integrated into Soil Navigator DSS (Debeljak et al. 2019). Base models address cropland and grassland soil. More information on the models and structures as well as on validation can be found in the previously published studies of Sandén et al. (2019), Van Leeuwen et al. (2019), Schröder et al. (2016), Trajanov et al. (2019), Van de Broek et al. (2019) and Wall et al. (2020) for the primary productivity, habitat for biodiversity, nutrient cycling, climate regulation and water regulation functions, respectively.

Having outlined the general concept of the base models approach, the following section provides a brief overview of the individual base models of the five soil functions.

The base model for assessment of **primary productivity** consists of sub-models that describe the environmental conditions, the inherent soil conditions (physical, chemical, biological), the soil management and crop properties. Primary productivity, as the top attribute, integrates the sub-models, resulting in an assessment of the soil's ability to produce biomass. A detailed description of the primary productivity model can be found in Sandén et al. (2019) and Wenng et al. (2018).

The **nutrient cycling** base model uses three integrated submodules to assess a soil's ability to provide and cycle nutrients. These sub-modules address (i) the nutrient fertilizer replacement value, which indicates the extent to which nutrients from organic residues can replace manufactured fertilizers, (ii) the nutrient uptake efficiency of plants, which represents the effectiveness with which plants use the available nutrients and (iii) the harvest index, which reflects the proportion of nutrients taken up by plants that are ultimately removed from the field by harvesting (Schröder et al. 2016; Trajanov et al. 2019).

The base model for **climate regulation** comprises three modules: carbon sequestration, N_2O emissions and soil CH_4 emissions. The carbon sequestration module estimates the balance between carbon inputs, carbon losses and soil organic carbon concentration. The N_2O emissions module distinguishes between direct emissions that occur in agricultural fields and indirect emissions that result from emissions occurring from NO_3 and NH_3 losses. Finally, the CH_4 emissions module evaluates the effects of artificial drainage on organic soils. A more detailed description of the base model can be found in Van de Broek et al. (2019).

The base model for the **water regulation and purification** soil function integrates three modules that represent the primary water pathways in the soil: water storage, water runoff and infiltration. Water storage is determined by attributes that assess the water holding capacity and moisture deficit of the soil. Water runoff is estimated using attributes that consider water, sediment and nutrient losses. Finally, the water infiltration module uses attributes to assess the drainage of excess water beyond the storage capacity of the soil and the resulting nutrient leaching and losses (Wall et al. 2020).

The base model for **soil biodiversity and habitat provision** comprises four interlinked aspects: soil nutrients (assessing their status, trends, turnover and availability), soil biology (analysing the diversity, biomass and activity of soil organisms), soil structure considering soil properties at meso and macro levels and finally soil hydrology, which examines soil moisture and water flow pathways. A more detailed description of the base model can be found in Van Leeuwen et al. (2019).

The base models presented in Debeljak et al. (2019) for estimating different soil functions share the same basic structural features (e.g. hierarchical structure, number of attributes to be aggregated—up to three). For all five models, a DEX structuring methodology for a systematic decomposition of complex soil functions into manageable sub-components (e.g. modules) has been used. However, despite this common methodological framework, there are also differences between the models. As shown in Table 1, the structural features of the individual models differ. The water regulation and purification model and the biodiversity and habitat model are more complex than the other models. This reflects the inherent complexity of these two soil functions, which are influenced by a larger number of factors. In contrast, models for functions such as primary productivity or nutrient cycling may rely on a less extensive set of attributes and rules, reflecting their simpler relationships to specific soil properties. In addition, a set of 75 unique attributes across the five sets of input attributes is required to populate all five base models. These structural properties provide insight into the strengths and limitations of each base model in representing the

TABLE 1 | Summary of the structure for the five soil function models, from Debeljak et al. (2019).

Soil function	Total number of attributes	Number of aggregated attributes	Number of input attribute	Number of hierarchical levels	Number of integration rules
Water regulation	116	77	39	6	800
Climate regulation	54	21	19	5	301
Nutrient cycling	51	27	24	5	302
Primary productivity	42	16	25	4	294
Habitat for biodiversity	55	24	31	5	612

different soil functions supply and their ability to be scaled for application at the regional level.

3.2 | Refining Base Models for Regional Application

While the base models for Soil Navigator have been developed for application at the field level, their direct application at the regional level is constrained by the lack of detailed information on soil management. To overcome this limitation and ensure the applicability of the model across different assessment scenarios, we refined the base models described in the previous section by upscaling them for application at the regional level. This upscaling process involved an analysis of the base models and their potential for regional application. Such a review was crucial in identifying and refining the structure of the base models to ensure their functionality in the face of potentially limited regional data availability, while maintaining their ability to reliably assess soil functions supply at a larger (i.e. regional) scale.

The upscaled models were developed within the framework of MCDA using the DEX modelling methodology, as described in Section 2. We found that this approach is well suited to deal with complex decision problems such as the assessment of soil functions supply at the regional level. The implementation of MCDA through DEX modelling enabled the clear formulation of the main modelling objectives, the development of integration rules and the construction of upscaled multi-criteria models in the form of MCDM specifically tailored to the regional data availability and assessment needs.

Since the DEX models work with qualitative data, the numerical input data must be transformed through a discretization process that includes the definition of a threshold. For input attributes derived from multiple quantitative variables, mathematical functions have been predefined to ensure consistent calculations and their further discretization.

DEXi software was used to create, edit and analyse the upscaled DEX models. In addition, the functions of this decision modelling tool were used to evaluate and analyse the behaviour of the upscaled models (e.g. sensitivity, calibration and verification), to facilitate the interpretation of the results, and to support various tasks such as what-if analyses and selective explanations of assessed soil functions.

3.3 | Verification and Sensitivity Analysis of Upscaled Models

Once the upscaled models were structured, a verification was conducted to ensure that their internal operational logic and behaviour worked as intended. We simulated data from potential soil samples covering a wide range of input data variability. The models' results were compared with the expected supply of the soil functions. Where the model results differed from expectations, the integration rules were carefully reviewed and, if necessary, adjustments were made to the model structure itself.

Following verification, a sensitivity analysis was performed. The sensitivity of the DEX models is based on the contribution of each attribute to the results of the model, as expressed by attribute weights. Unlike traditional MCDM methods that rely heavily on weights to define the importance of attributes to model outputs (Greco et al. 2016), the DEX qualitative modelling method does not work with weights associated with qualitative attributes and decision rules. To achieve consistency between MCDM and DEX regarding attribute weights, DEX employs an estimation of the weights by approximate bi-directional transformations between weights and integration rules in decision tables. These transformations are explained in detail by Bohanec and Zupan (2004) and Bohanec (2020).

As the attributes in our models have different value scales (e.g. *Low*, *Medium* and *High*), the normalized weights (from 0% to 100%) were used to determine the relative importance of each attribute to its integrated attribute (local normalized weight) or the value of the top (root) attribute (global normalized weight) (Bohanec 2020). Attributes with negligible importance were removed from the model structure (i.e. with weights of $<1\%$), which required corresponding adjustments of the model structure and the rules within the integration tables. A verification and sensitivity analysis of such a refined model was repeated until the structure of the model was recognized as suitable for addressing its modelling tasks.

3.4 | Validation of Upscaled Soil Function Models

The validation of qualitative multi-attribute models for the assessment of regional soil functions poses a unique challenge, as a direct comparison of predicted values with known real observations on soil function supply at the regional scale is not possible because such data do not exist. To overcome this challenge, we used an approach adapted to the limitations of data availability. The approach consists of two steps. The first step is the sensitivity analysis of the upscaled soil function models with respect to the variability of the input data. Since regional soil properties show considerable spatial variability, we tested the sensitivity of the models with data from different pedoclimatic (soil and climate) and land-use conditions. We used the Landmark H2020 dataset (Saby et al. 2020), which includes data collected at 94 sites in 13 countries, representing five climate zones and two land use types (cropland and grassland). Detailed information on the selection of sampling sites, the sampling method used and the field and laboratory measurements can be found in Zwetsloot et al. (2021). Before using this dataset with the upscaled models, we ensured its applicability by checking and adjusting the consistency of the input attribute scales and their discretization thresholds with the input data requirements of the models. Once the dataset was harmonized for use by the upscaled models, the models were populated with the input data, and the results were collected. Note that missing measured data (e.g. tillage) was obtained from existing maps. This specific aspect is covered in the Discussion.

The second step of our approach was to compare the results of the upscaled models with the results of the validated base models applied to data from the same sampling sites using Soil Navigator (Debeljak et al. 2019). Although the base models work at the field level and the upscaled models at the regional level, this comparison provides valuable insights. As the base models are validated, similarities in the relative ranking of soil functional supply between the two scales (regional and field) argue in favour of the validity of the upscaled models. This comparison essentially utilizes the existing validation of the base models to provide confidence in the ability of the upscaled version to capture similar trends.

For all 94 sampling sites, we counted how often the results of the individual soil function models were categorized as *Low*, *Medium* or *High*. We did this for each of the five soil functions and for both types of land use (i.e. grassland and cropland). The distribution of these results was then compared with the distribution of results from Soil Navigator (Debeljak et al. 2019), which used data from the same sample sites. This approach that utilizes sensitivity analyses and comparison with base models enables some confidence in the results of the upscaled models for the assessment of regional soil functions. This method is of particular value because it solves the problem of the lack of ground-truth data needed to evaluate the performance of soil functions supply estimates at the regional level.

4 | Results

Based on the methodological steps described above, the following aspects of the models' each functions were described:

- The model structure, which is described by an overview of the hierarchical model, similar to Figure 2 for the water regulation function. It describes the number of input attributes and aggregated attributes highlighting the changes that have been made to the original base models to improve the estimation of soil function at a large area.
- Qualitative scales of both input and aggregated attributes.
- Utility functions (integration rules), which are used to combine information from different attributes to arrive at an overall assessment of the soil function.

By following this consistent structure, the descriptions for each upscaled model provide a comprehensive understanding of the strengths and limitations of each model. Furthermore, the structured description facilitates the comparison between the structure of developed soil function assessment models on a regional scale with the structural characteristics of the base models presented in Table 1.

4.1 | Water Regulation

The hierarchical structure of the upscaled model for an assessment of the water regulation function is shown in Figure 1. The model has 13 input attributes and 18 aggregated attributes, of which three are module attributes and one is the root attribute for the overall evaluation of the function. Five input attributes (i.e. precipitation in winter, clay and organic carbon content, artificial and natural drainage) are included in all three modules. The upscaled model has 50% fewer input attributes than the base model of Wall et al. (2020).

The upscaled model retains the same scales of attributes that were included in the original base model. Four types of qualitative scales are used in the model, the most common of which is the three-level scale of *Low*, *Medium* and *High*, with an ordering scale depending on the attribute (indicated with the red, black and green colours in the Supporting Information). In addition to this three-level scale, three binary scales are used 12 times, for example, to characterize the absence or presence (e.g. yes, no) or a threshold value (e.g. above or below rooting depth) of an input attribute feature.

Table 2 shows the utility functions represented as rules that are used to integrate the three modules' aggregated attributes into the top root attribute, which represents the soil water regulation function. The water regulation function is poorly supplied if one of the three attributes has a low value. A majority of the medium leads to a medium fulfilment, while a high fulfilment of the soil function always occurs with at least two high fulfilments of its sub-attributes, of which the remaining one must be medium or higher.

4.2 | Climate Regulation

Figure 2 shows the upscaled model for the assessment of the climate regulation function. The model has 10 input attributes and 15 aggregated attributes, including three module attributes and the root attribute for the soil function evaluation. Five input attributes (i.e. artificial drainage, total N and organic carbon content, annual precipitation and temperature) are used in more than one module. The upscaled model has 52% fewer

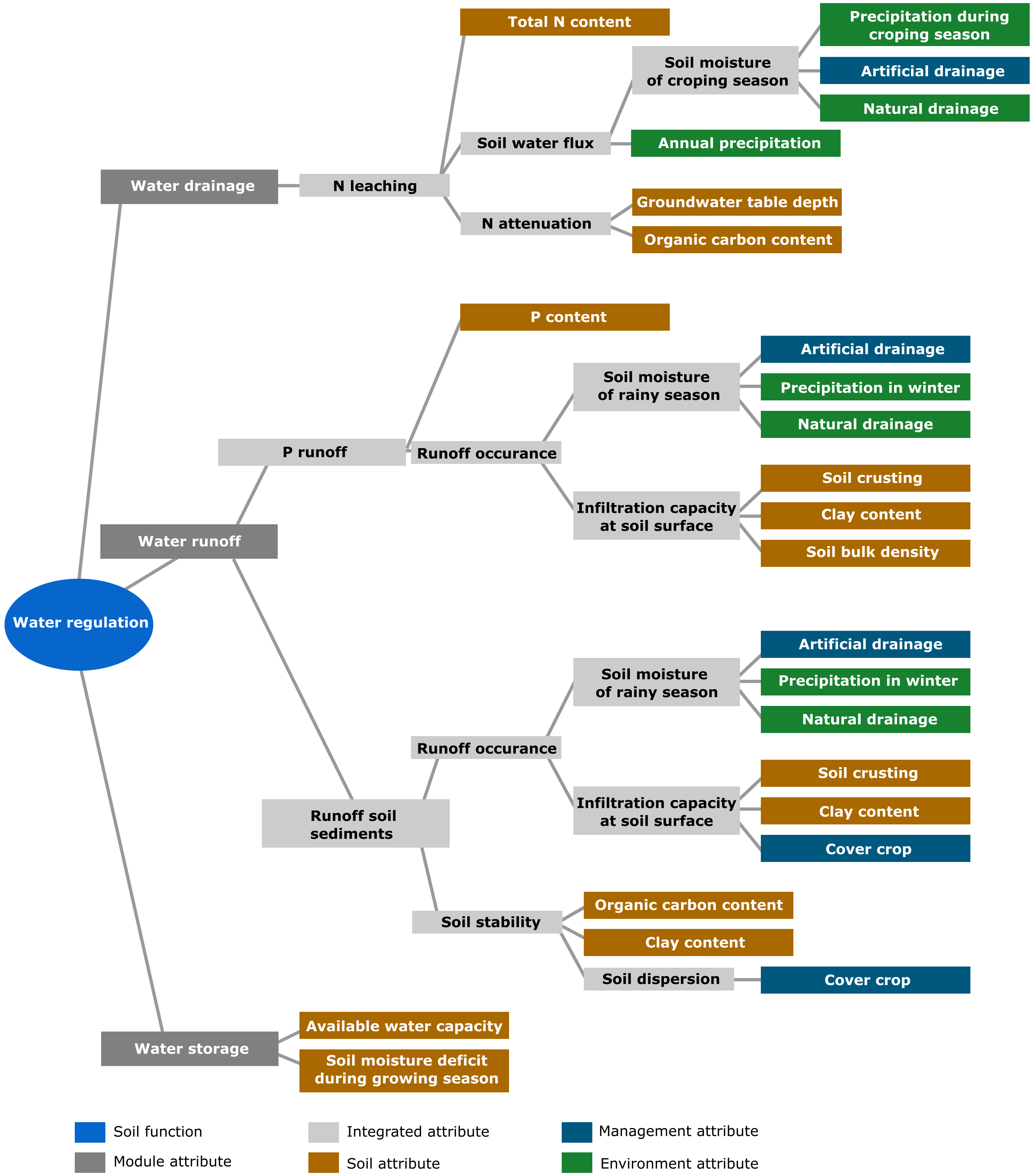

FIGURE 1 | Structure of the model for the water regulation function. Grey rectangles represent aggregated attributes, whereas coloured rectangles are soil, management or environmental attributes.

input attributes than the base model of Van de Broek et al. (2019) while other structural features of this model are listed in the Supporting Information.

The upscaled model has nine different qualitative scales (see also the Supporting Information) that were included in the original base model. The most common scale is the three-value scale composed of *Low*, *Medium* and *High*. This scale appears 17 times in total and is ordered in both ways (i.e. *Low* can be either positive or negative, see colours in the Supporting Information). In addition to this scale, eight attributes have a three-value scale (e.g. *Sand*, *Silt* or *Clay*), and four have binary scales (e.g. *Organic* or *Mineral*).

TABLE 2 | Utility functions relating the function soil water regulation to its three modules.

Water storage	Water runoff	Water drainage	Water regulation
Low	*	*	Low
*	High	*	Low
*	*	High	Low
Medium	Medium	≥ Medium	Medium
Medium	≥ Medium	Medium	Medium
≥ Medium	Medium	Medium	Medium
≥ Medium	Low	Low	High
High	≥ Medium	Low	High
High	Low	≥ Medium	High

Note: The asterisk '*' denotes any of the three values of the scale.

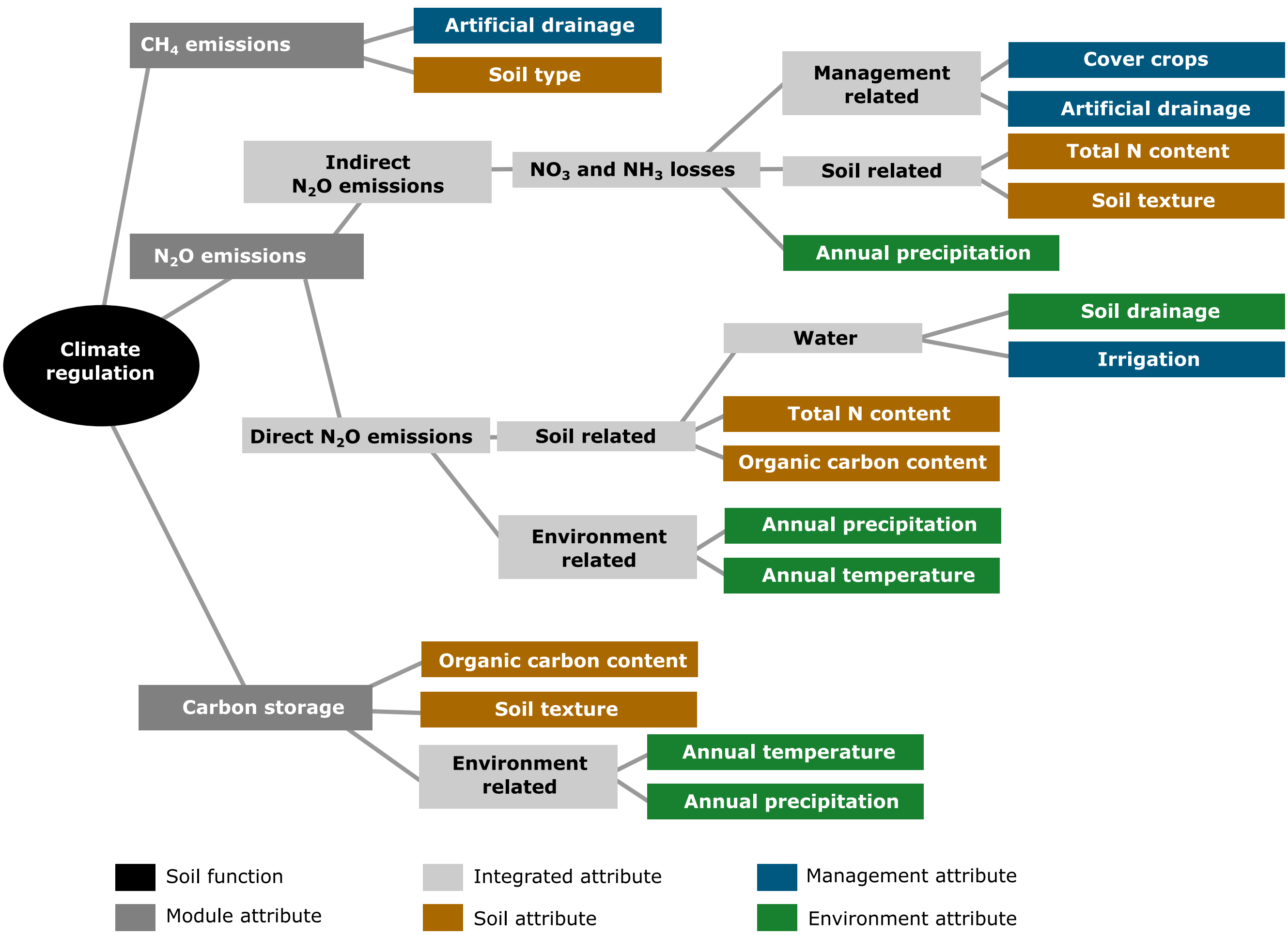

FIGURE 2 | Structure of the model for the climate regulation function. Grey rectangles represent aggregated attributes and coloured rectangles are soil, management or environmental attributes.

Table 3 shows the utility functions relating the climate regulation function to its three subordinate attributes. The climate regulation is poorly supplied when at least one of the attributes is poorly supplied too (e.g. high CH_4 emissions). A medium fulfilment is obtained when there is a majority of medium fulfilment, or when a balanced is obtained between high and low fulfilment between attributes. The climate regulation function of a soil is high when a majority of good fulfilment of the attributes occurs or when there is a high fulfilment of the carbon storage attribute with all other attributes supplied with medium or higher.

4.3 | Nutrient Cycling

The hierarchical structure of the upscaled model for nutrient cycling is shown in Figure 3. The model has 14 input attributes and 17 aggregated attributes, including the root attribute for

TABLE 3 | Utility functions relating the function soil climate regulation to its three module attributes.

Carbon storage	N_2O emissions	CH_4 emissions	Climate regulation
Low	$\leq$ Medium	*	Low
$\leq$ Medium	High	*	Low
*	High	High	Low
Low	Low	*	Medium
$\leq$ Medium	Low	$\leq$ Medium	Medium
*	Low	High	Medium
Medium	Medium	*	Medium
Medium	$\geq$ Medium	$\leq$ Medium	Medium
$\geq$ Medium	$\geq$ Medium	High	Medium
High	High	$\geq$ Medium	Medium
$\geq$ Medium	Low	Low	High
High	$\geq$ Medium	$\geq$ Medium	High

Note: The asterisk '*' denotes any of the three values of the scale.

the evaluation of the function and three module attributes. The input attributes soil texture, natural drainage, annual precipitation and days with average temperature above 5°C are used more than once as input to the model. The restructured model has 25% fewer input attributes compared to the original base model of Schröder et al. (2016) and Trajanov et al. (2019).

The upscaled model for the nutrient cycling function has six different qualitative scales, the most common of which is the three-value scale of *Low*, *Medium* and *High*, with an order changing depending on the attribute (see also the red and green colour in the Supporting Information). In addition to this three-value scale, there are seven attributes with another three-value scale (e.g. *Well drained*, *Moderately drained* or *Poorly drained*) and eight attributes with a binary scale (e.g. *Yes* or *No*).

Table 4 shows the utility functions for relating the nutrient cycling function to its three subordinate module attributes. The nutrient cycling function is poorly supplied when at least two attributes are poorly supplied too. Having one attribute with a scale of *Medium* or *Low* leads to *Medium* nutrient cycling. Having one attribute supplied at its maximum with the two other attributes at the scale *Medium* or higher leads to *High* fulfilment of the nutrient cycling function.

4.4 | Primary Productivity

Figure 4 shows the upscaled model for the evaluation of the primary productivity function. The model has 17 input attributes and 11 aggregated attributes, including the root attribute for the function evaluation and two module attributes. The restructured model has a reduction of 43% of input attributes from the based model.

The upscaled model for the primary productivity function has two different qualitative scales, the most common of which is the three-value scale of *Low*, *Medium* and *High*, with an order changing depending on the attribute (see also the red and green colour in the Supporting Information). In addition, another scale is composed of the three values denoted *Unsuitable*, *Neutral* and *Suitable* or *Optimal*. This scale occurs for seven attributes.

Table 5 shows the utility functions for relating the primary productivity function to its two subordinate module attributes. The primary productivity function has a low fulfilment when the soil is unsuitable or when the soil is neutral or worse and the environment is unsuitable. A medium soil function fulfilment is obtained when both soils and environment are neutral or when a balance is obtained with a suitable soil but unsuitable environment. A high primary productivity function fulfilment is obtained when either of the two attributes is optimal or suitable and the other is neutral.

4.5 | Habitat for Biodiversity

Figure 5 represents the upscaled model for the evaluation of the habitat for biodiversity function. The model has 12 input attributes and 12 attributes, including the root attribute for the evaluation of the function, and three module attributes. The restructured model has 61% fewer input attributes compared to the base model of Van Leeuwen et al. (2019).

The upscaled model for the habitat for biodiversity function has four different qualitative scales, the most common of which is the three-value scale of *Low*, *Medium* and *High*, with an order changing depending on the attribute (see also the red and green colour in the Supporting Information). In addition to this three-value scale, there are 10 attributes with another scale, either with three values (e.g. *Poor performance*, *Moderate performance* or *Good performance*) or with two values (e.g. *Yes* or *No*).

Table 6 shows the utility functions of the habitat for biodiversity function with its three subordinate module attributes. The habitat for biodiversity has a low fulfilment when at least two attributes have poor performance and the third one has moderate performance or lower. A medium fulfilment of the function is obtained when the majority of attributes have moderate performance or when a balance between poor and good performance is obtained. A high function fulfilment, conversely, is obtained for either two attributes with good performance or one attribute

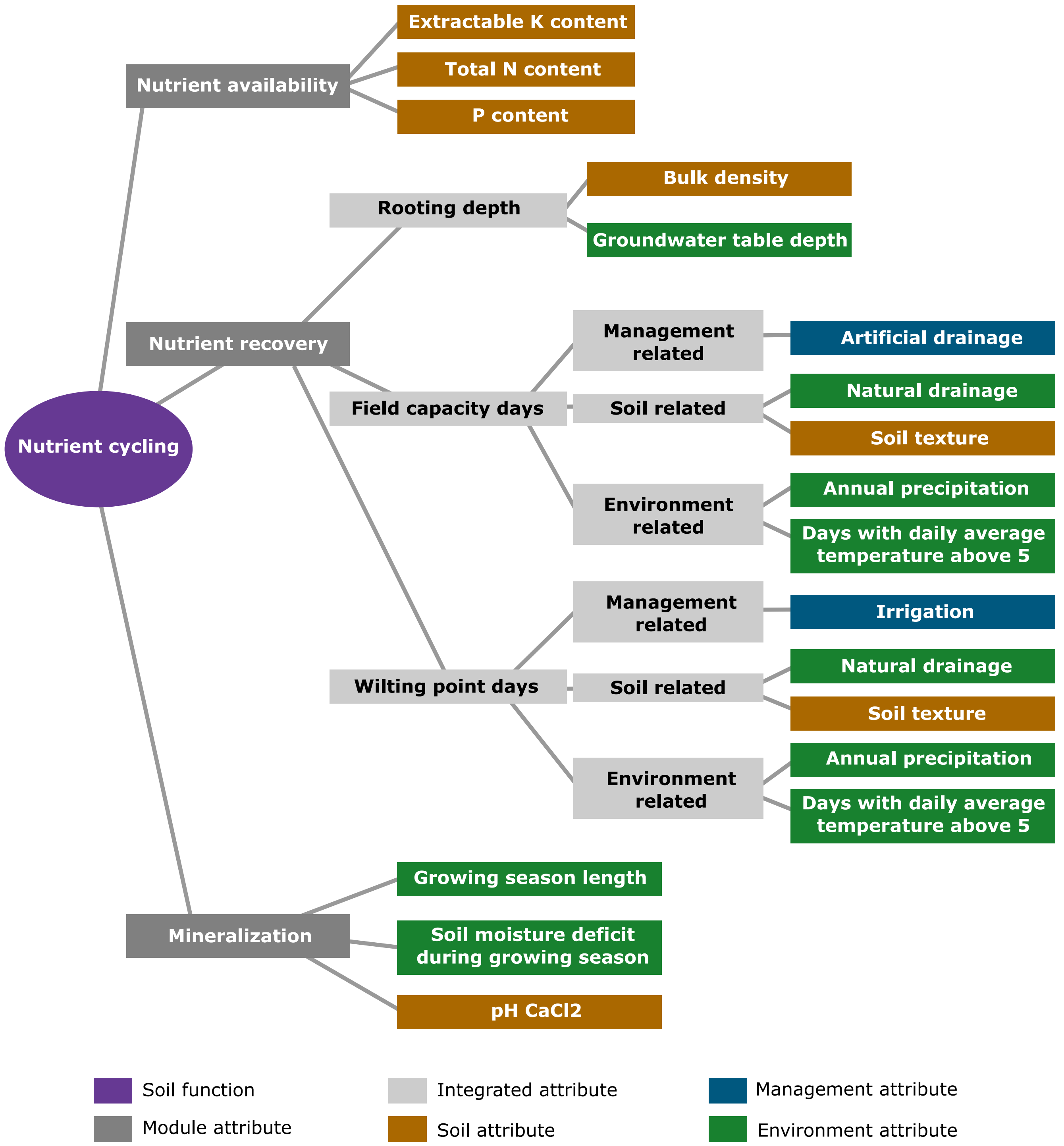

FIGURE 3 | Structure of the model for the nutrient cycling function. Grey rectangles represent aggregated attributes and coloured rectangles are soil, management or environmental attributes.

with high performance and the two others with moderate performance or higher.

4.6 | Verification and Sensitivity Analysis of Upscaled Models

The weights of the attributes in Table 7 show how differently the individual soil functions prioritize their contributing attributes (modules). Examining these variations reflects our understanding of the relative importance of each attribute for a given soil function, which was coded by integration rules formulated based on our knowledge of soil functions and the knowledge used in the construction of the base models.

In particular, the climate-regulating soil function is determined by a relationship between carbon sequestration and greenhouse gas mitigation. With the highest weight (43%) assigned to carbon storage, the model prioritizes the soil's ability to sequester carbon. However, N_2O emissions (39%) and CH_4 emissions

TABLE 4 | Utility functions relating the function nutrient cycling to its three module attributes.

Mineralization	Nutrient recovery	Nutrient availability	Nutrient cycling
Low	Low	*	Low
Low	*	Low	Low
*	Low	Low	Low
Low	≥ Medium	≥ Medium	Medium
≤ Medium	≥ Medium	Medium	Medium
Medium	*	Medium	Medium
≥ Medium	Low	≥ Medium	Medium
Medium	≥ Medium	≤ Medium	Medium
≥ Medium	≥ Medium	Low	Medium
≥ Medium	≥ Medium	High	High
High	≥ Medium	≥ Medium	High

Note: The asterisk '*' denotes any of the three values of the scale.

(17%) are also weighted significantly, which emphasizes their importance alongside carbon sequestration. The nutrient cycling soil function is determined almost equally by the modulus attributes included (mineralization 35%, nutrient availability 30% and nutrient recovery 35%). This even distribution of weights shows that the model considers all aspects of the nutrient cycle to be equally important for this soil function. For the primary productivity soil function, soil properties (63%) take precedence over environmental factors (38%) that influence plant growth. A higher weighting of soil properties indicates that the inherent characteristics of the soil itself, such as texture and organic matter content, were considered to be the most important factors for plants growth. The weights of the attributes that determine the water regulation soil functions are evenly distributed across all three modulus attributes. This balanced approach illustrates that the model considers all three aspects of water management, that is, storing sufficient water, preventing excessive runoff and promoting adequate drainage, to be equally important for this soil function. Finally, for the habitat for biodiversity soil function, nutrient availability and soil structure were recognized as the most important factors for promoting diverse soil communities. The highest weighting of nutrients (42%) indicates that the availability of nutrients is seen as the most important factor in supporting a diversity of soil organisms, as is good soil structure (35%) with its influence on suitable habitat conditions through soil aeration and water infiltration. Hydrology (23%), which stands for water availability for organisms, receives a slightly lower weighting but still plays an important role in creating suitable habitats.

4.7 | Comparison of Upscaled Soil Function Models Results

Figure 6 shows the distribution of results from Soil Navigator (Debeljak et al. 2019) compared to that of the upscaled models. The frequency distribution of the qualitative results of the upscaled and base models (Figure 6) shows that the upscaled models have a similar sensitivity to the base models of soil functions. Thus, the upscaled models successfully capture the variability of the input data from 94 sampling points in a similar way to the validated base models. However, some differences between the two distributions are visible, particularly in the relative frequency of certain qualitative classes for the primary productivity and climate regulation functions applied to grassland.

5 | Discussion

Upscaling models from the field to the regional level was a challenge, mainly because there is little detailed information on land management practices at large geographical scales. The Land Use and Coverage Area frame Survey (LUCAS) dataset (Orgiazzi et al. 2018), for example, is the largest harmonized soil database in the European Union but does not contain soil management information beyond the usual dynamic soil properties (e.g. organic carbon, bulk density). Similar types of large-scale datasets without detailed management information are found in the United States Soil Survey Geographic Database (SSURGO, Soil Survey Staff 2017) and Australian Soil Data Federator web API (Searle et al. 2021). We solved this problem by refining the base models and using DEX methodology, which has proven to be a flexible approach for the development of soil function assessment models (e.g. Sandén et al. 2019; Trajanov et al. 2019), especially in contexts where data availability is limited. Its hierarchical structure facilitates the decomposition of complex soil functions into manageable sub-components and enables the integration of both qualitative and quantitative data. This ability is especially useful when addressing the qualitative nature of soil function assessments and the scarcity of detailed data at the regional level. In our case, the restructuring of the models was also guided by the availability of management attributes at large scales, for example, tillage (Porwollik et al. 2019), artificial drainage Feick et al. (2005) and irrigation (Siebert et al. 2005), of which maps are available. For Europe, high-resolution information is available, such as the cover-crop map from Fendrich et al. (2023) and the global SoilGrids dataset of Poggio et al. (2021), while other regional or Europe-specific datasets can also be used. This ensures the applicability of the models to other areas where there is data within the European continent as this is the area on which they were evaluated in this study. If using maps as input to the base models for mapping purposes, it would be valuable to propagate map uncertainty to the model outputs. This could be done through Monte Carlo simulation of the map uncertainty, if such information is available.

Figure 6 reflects the capacity of the upscaled models to be similarly sensitive to the input data as the base models, as tested on a European dataset of 94 sites. Recall that the base and upscaled models used different input datasets. While the overall pattern in soil function assessment was similar, some expected

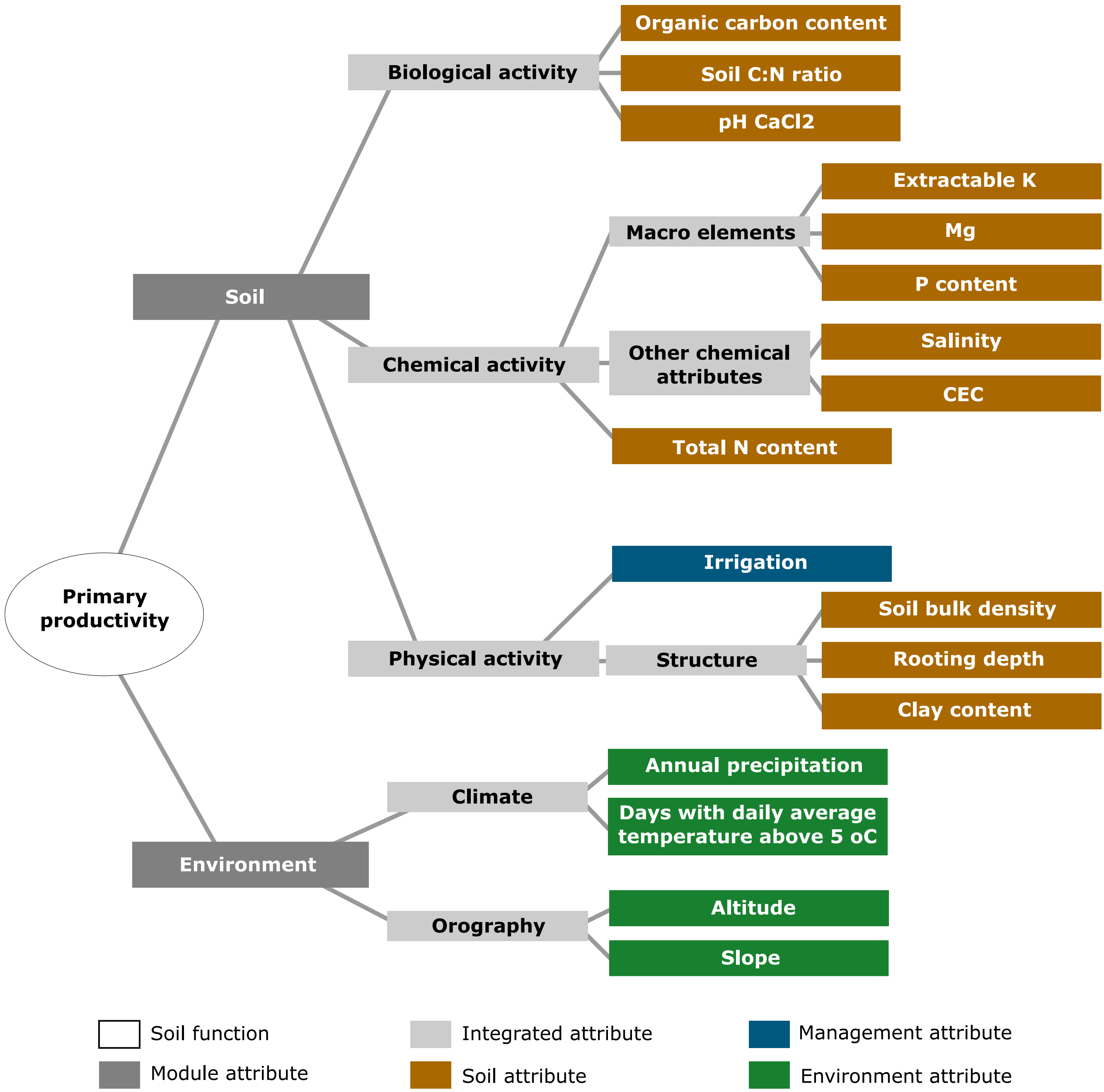

FIGURE 4 | Structure of the model for the primary productivity function. Grey rectangles represent aggregated attributes, and coloured rectangles are soil, management or environmental attributes.

TABLE 5 | Utility functions relating the function primary productivity to its three module attributes.

Soil	Environment	Primary productivity
Unsuitable	*	Low
$\leq$ Neutral	Unsuitable	Low
Neutral	Suitable	Medium
Suitable	Unsuitable	Medium
$\leq$ Neutral	Optimal	High
Suitable	$\leq$ Suitable	High

Note: The asterisk '*' denotes any of the three values of the scale.

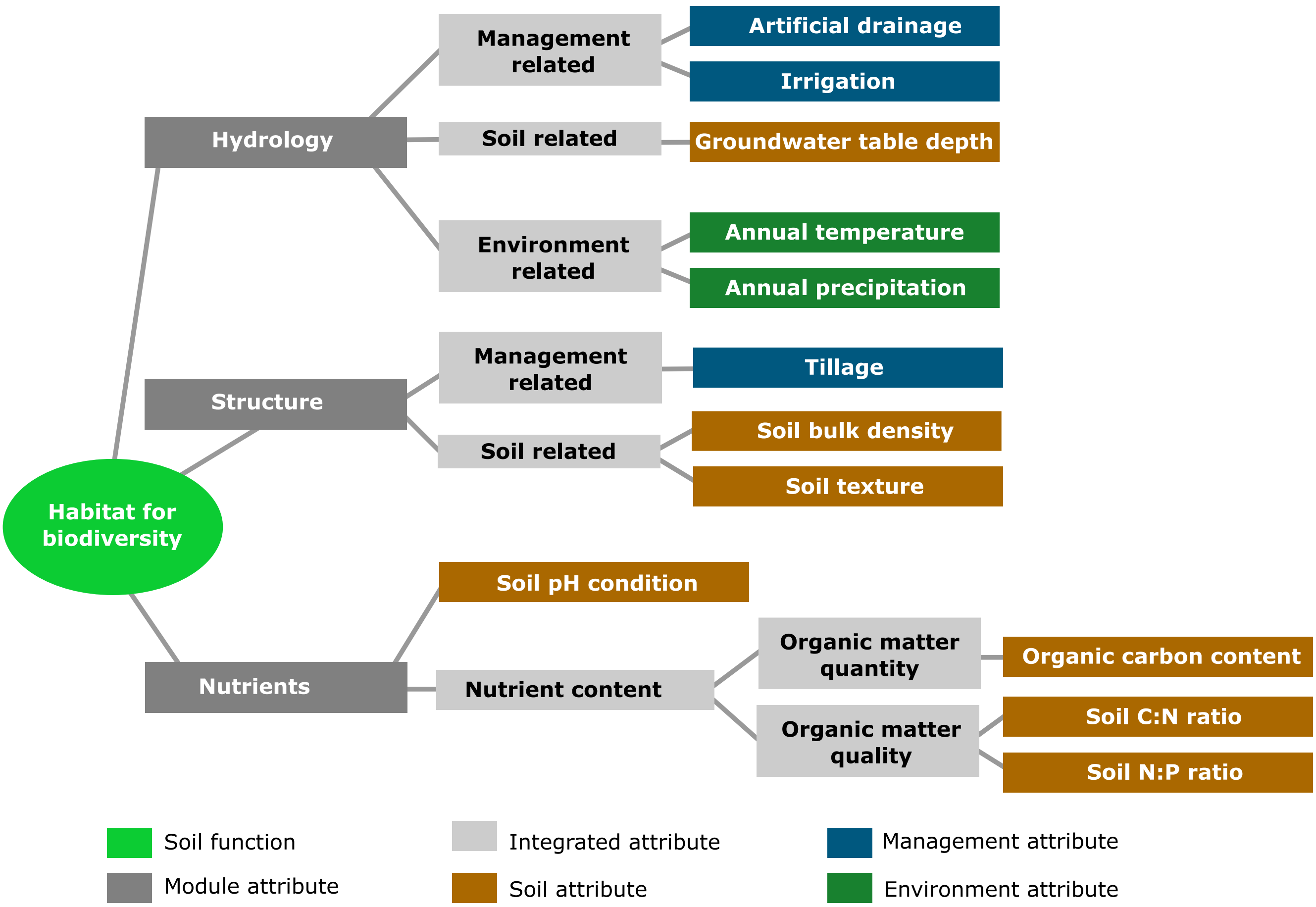

FIGURE 5 | Structure of the model for the habitat for biodiversity function. Grey rectangles represent aggregated attributes, and coloured rectangles are soil, management or environmental attributes.

TABLE 6 | Utility functions relating the function habitat for biodiversity to its three module attributes.

Nutrients	Structure	Hydrology	Habitat for biodiversity
Poor performance	Poor performance	*	Low
Poor performance	≤ Moderate performance	Poor performance	Low
≤ Moderate performance	Poor performance	≤ Moderate performance	Low
Poor performance	Moderate performance	≥ Moderate performance	Medium
Poor performance	≥ Moderate performance	Moderate performance	Medium
≤ Moderate performance	Moderate performance	Moderate performance	Medium
Poor performance	Good performance	≤ Moderate performance	Medium
≤ Moderate performance	Good performance	Poor performance	Medium
Moderate performance	Poor performance	Good performance	Medium
Moderate performance	Moderate performance	≤ Moderate performance	Medium
Moderate performance	≥ Moderate performance	Poor performance	Medium
Good performance	Poor performance	Poor performance	Medium
*	Good performance	Good performance	High
≥ Moderate performance	≥ Moderate performance	Good performance	High
≥ Moderate performance	Good performance	≥ Moderate performance	High
Good performance	*	≥ Moderate performance	High
Good performance	≥ Moderate performance	*	High

Note: The asterisk '*' denotes any of the three values of the scale.

differences reflected the effects of spatial generalization, differences in input data and model assumptions during upscaling. This comparison step was by no means a statistical validation of the upscaled models, as such validation would require observed values of the soil functions, which do not exist.

Although DEX utility functions operate on symbolic values, they can be quantitatively interpreted using techniques such as the Linear Approximation (LA) method (Bohanec and Zupan 2004; Bohanec 2023b). In this approach, each symbolic rule is represented in Euclidean space by assigning numerical ranks to qualitative values, and a least-squares hyperplane is fitted to the resulting dataset. The derived weights are obtained directly from the structure of the decision rules rather than being assigned subjectively, thereby enhancing both transparency and analytical rigour. This contrasts with the formulation used by Ng et al. (2024) within the Soil Security Assessment Framework (Evangelista et al. 2024), where utility functions are expressed as continuous transformations of quantitative indicators into normalized [0, 1] scores, typically using logistic, Gaussian or other fitted response curves based on expert expectations. While Ng et al. (2024)'s approach prioritizes numerical precision through curve fitting and DEX emphasizes rule-based symbolic reasoning, both share the fundamental aim of formalizing expert judgement within a structured multi-criteria aggregation process. In this sense, DEX utility functions are not *ad hoc* heuristics but rigorously defined, mathematically interpretable mappings that are fully consistent with the broader methodological principles articulated in Ng et al. (2024).

TABLE 7 | Contribution (weights) of the attributes for the results of the considered soil functions in the upscaled models.

Climate regulation		
Carbon storage	N_2O emissions	CH_4 emissions
39%	43%	17%
Nutrient cycling		
Mineralization	Nutrient recovery	Nutrient availability
35%	30%	35%
Primary productivity		
Soil	Environment	
63%	38%	
Water regulation		
Water storage	Water runoff	Water drainage
33%	33%	33%
Habitat for biodiversity		
Nutrients	Structure	Hydrology
42%	35%	23%

Note: The weights of all attributes for the five soil functions and the two land uses (i.e. grassland and cropland) can be found in the Supporting Information. The weights given here are the same for the two land use models. Weights are rounded to the nearest integer.

One limitation of the current approach is the subjectivity associated with defining the structure of assessment models and integration rules in decision tables. These methodological issues were addressed by using a panel of soil scientists with expertise in different soil functions and consulting them in the elaboration of the base models and integration rules. In addition to the expert-based definition of integration rules, best practices were used to check the obtained attribute weights and the selected thresholds for discretization on numerical input data, following Bohanec (2021) and Bohanec (2023b). We believe that this helped reduce the subjectivity involved the definition of the integration rules. In the literature, the integration of different sub-scores into a single index has been done similarly with expert knowledge and stakeholder involvement (Orgiazzi et al. 2016; Mendes et al. 2021). It was also done empirically using principal component analysis (e.g. Andrews et al. 2002) or sub-scores weighting (e.g. Wadoux, Dobarco, et al. 2024). It is often challenging to construct a set of decision rules for model integration. While it would be worthwhile to test continuous integration rules, as is commonly done in the literature,

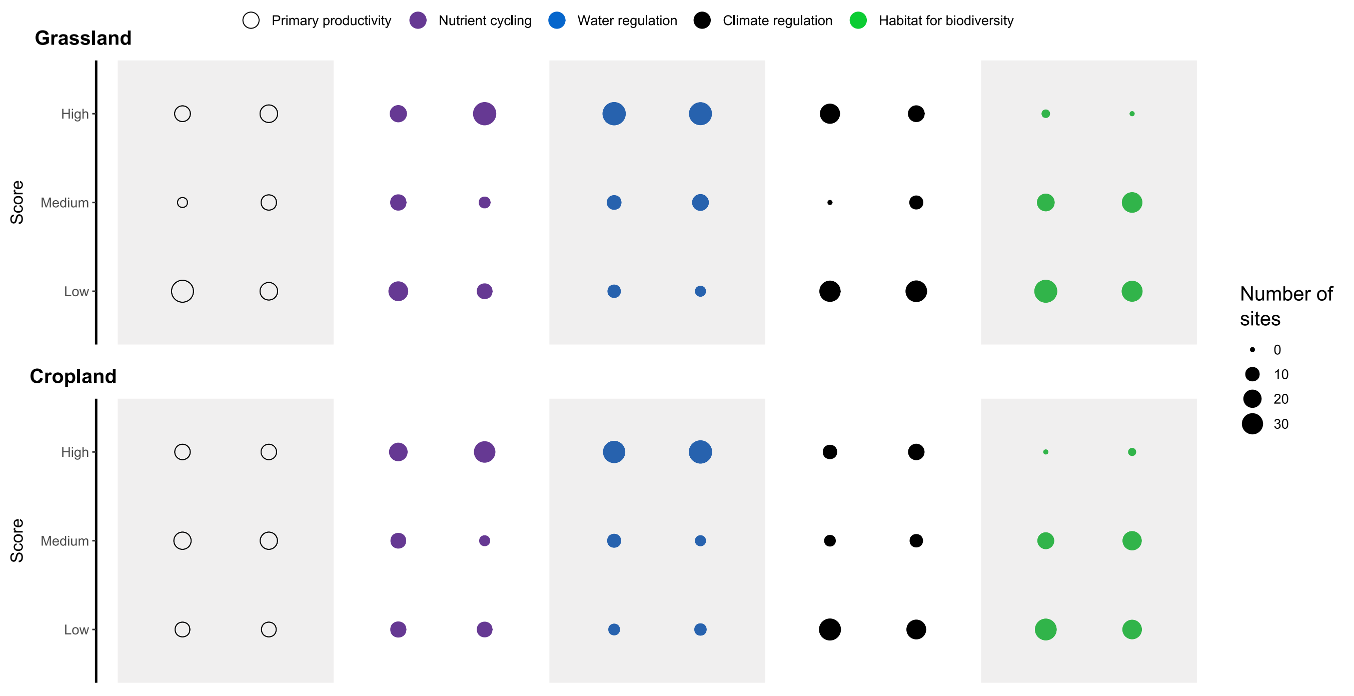

FIGURE 6 | Scores of the restructured model for the valuation of the five functions and two land uses (i.e. grassland on top, cropland at the bottom). The size of the dot indicates the number of sites within this class. For each soil function, the dots on the left side denote the output of the restructured model, whereas the dots on the right side represent the output of the original base models.

their potential to improve results is not straightforward and difficult to evaluate. This is due to significant uncertainty in defining the shape of these continuous functions and selecting appropriate thresholds. Moreover, such an approach does not resolve the problem of subjectivity involved in establishing the integration rules themselves. In future work, it may be more informative to assess the model sensitivity to rule sets defined by different experts. This could then be compared to the uncertainty propagated from the input data and help to identify which source of uncertainty has the greatest influence on model outcomes.

Another limitation is the static nature of the categorical outputs: a slight change in input might push a result from one category to another, even if the actual difference is small. As mentioned previously, these thresholds could be made continuous, although there is no obvious improvement in doing so, and evaluating this improvement is challenging. In our study, the thresholds varied between climate zones. This is surely an improvement over using the same threshold across all of Europe and for different land uses. In the future, we might want to test the use of site-specific thresholds or thresholds varying for each small unit (e.g. a field or a soil district). While this would be worthwhile, it would require a large number of high-quality, measured soil property values to define localized thresholds and validate their relevance. Without such data, the risk of introducing noise or bias may outweigh the potential benefits of having greater spatial specificity.

The application of the DEX methodology for the development of models at a regional scale illustrates its potential for wider use in agricultural and environmental research and management. This provides a tool for the regional assessment (general trends) of the capacity of differing soil genoforms (with the addition of very basic soil management information) to support the five soil functions. This could be utilized as a baseline for assessing soil health at larger spatial scales or analysing the environmental impacts of land use change at the regional scale. However, the lack of expertise and data availability at the regional level may require modifications to the DEX methodology to successfully address these specificities and ensure its effectiveness and use in decision modelling. The proposed Directive on Soil Monitoring and Resilience currently proposes a minimum indicator set, which focuses on the quantification of land degradation across Europe (See Supporting Information). However, it also provides an opportunity to collect indicators that form the basis of these models, which can define the spatial trends of soil functions in relation to soil genoforms at larger spatial extents, for example, for soil districts. This approach can then be further enhanced by the collection of soil management data within soil districts, which facilitates the quantification of soil multifunctionality and associated soil health at the local scale of assessment (Wadoux, Courteille, et al. 2024).

The primary changes in the aggregated attributes pertain to the input attributes available for large-scale studies. These include all basic measured soil properties and global datasets for which maps are available (e.g. irrigation and drainage). It is important to note that maps are predictions and generally less accurate than direct measurements and field observations. Therefore, whenever feasible, measured input attributes should be prioritized over maps. However, for the large-scale models developed in this study, we contend that incorporating maps as an additional source of input attributes is reasonable. This is because in the upscaled models the discretization of inputs for use in the rules means that small differences in input values may not change the modelled assessment. Typically, a minor change in the input attribute does not lead to a change in the aggregation rule's level. Future research could test this through a sensitivity analysis of the model output relative to the input attributes.

The evaluation of upscaled soil function models was another methodological challenge due to the lack of site-specific data on soil functions in European regions. Our approach offers an alternative to classical validation based on measured values at the field scale. By comparing the results of the upscaled model with those of a validated field-level model, we have shown that the sensitivity of the upscaled models to input variability generally follows the behaviour of the validated field-level model under comparable conditions, which increases confidence in the results of the upscaled models. Further, by comparing the model results at different scales (field vs. region), we gained insight into how the upscaled models respond to variability in the soil functions. These insights will be of use for further modelling improvements if needed. Our results are consistent with the experiences from other studies where proxy validation has been applied (Mezbahuddin et al. 2023; Eum and Gupta 2019). Although classical validation (i.e. the pairwise comparison of predicted vs. observed values) remains the ideal approach when feasible, it was not possible here. In some cases, the soil function can be measured (e.g. the biomass production) and so a validation using validation statistics may be employed.

Overall, the sensitivity analysis and the comparison approach have resulted in reliable upscaled models for the assessment of soil functions at the regional scale. Although we recognize the limitations of the DEX methodology and the lack of data availability at the regional scale, our research paves the way for the use of the developed models to support soil management and policy decisions, promote sustainable land use practices and monitor soil health. The development of the models in this study is a first step to assess soil multifunctionality in large areas, particularly in the European Union where a Soil Monitoring Law is under development. The application of the soil function models developed in this study on the LUCAS dataset would certainly make a valuable contribution to soil health assessment in Europe. In the future, we may explore uncertainty quantification of our approach to foster the inclusion of soil function assessment in soil monitoring initiatives. We also envision further application of the models for estimating changes in soil functions in response to threats and for projection of climate change, and to link the existing supply with the demand.

Finally, at the regional scale, the adapted model can provide decision-makers with an overview of the variability of soil functions across Europe using harmonized, continental-scale datasets. Such outputs can inform the design of national policies and the implementation of EU regulations by identifying priority areas for intervention and enabling the efficient targeting of resources. Beyond soil management, these results can support inter-sectoral policy development, linking soils to biodiversity conservation, ecosystem restoration and climate regulation objectives. For example, a policy-maker could use model outputs to determine where soil restoration measures would also deliver biodiversity benefits, thereby guiding integrated strategies. While the primary audience at this scale is policy-makers, indirect users include farm advisors, who can apply the regional insights to coordinate activities and align local management recommendations with broader policy objectives.

6 | Conclusions

We adapted existing base field-scale soil functions assessment models for use in a regional and national context. The restructure of the base models accounts for the general lack of management information available at large geographical scales. The new models were verified and tested for sensitivity using real soil data. From the results and discussion we draw the following conclusions:

- Five models for the large-scale assessment of soil functions are developed, corresponding to the five soil functions of water regulation, climate regulation, nutrient cycling, primary productivity and habitat for biodiversity.
- The models are specifically designed to assess soil functions over large geographical scale by requiring few management attributes as input.
- The developed DEX MCDMs successfully decompose a complex soil function evaluation problem into a hierarchical structure of less complex and therefore more manageable sub-problems, taking into account both qualitative and quantitative available input data.
- The definition of utility functions and threshold values is a critical step of the methodology. We used a expert-based approaches but empirical and data-driven approach exist.
- All upscaled models were verified and tested for sensitivity. Their response to a large range of values were similar to that of the field-scale base models.

Overall, the results suggest that the models are suited for application over large areas. In the future, we envision the application of the models to existing soil databases, for example, the European LUCAS dataset, in support of large-scale policy implementation and the estimation of soil change due to external factors (e.g. climate change, urbanization) or threats (e.g. acidification, erosion).

Author Contributions

Alexandre M. J.-C. Wadoux: conceptualization, investigation, funding acquisition, writing – original draft, methodology, validation, visualization, formal analysis, project administration. **Rachel E. Creamer:** conceptualization, investigation, writing – review and editing. **Philippe Lagacherie:** conceptualization, investigation, writing – review and editing, methodology, resources. **Marko Debeljak:** conceptualization, investigation, methodology, writing – review and editing, validation, software, data curation.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 Research and innovation programme under the Marie Skłodowska-Curie Grant agreement No. 101059012. The research has also been supported by the Slovenian Research and Innovation Agency (ARIS), (grant P2-0103). For the purpose of Open Access, a CC-BY public copyright licence has been applied by the authors to the present document and will be applied to all subsequent versions up to the Author Accepted Manuscript arising from this submission.

Funding

This project has received funding from the European Union's Horizon 2020 Research and innovation programme under the Marie Skłodowska-Curie Grant Agreement No. 101059012 and Slovenian Research and Innovation Agency (ARIS) P2-0103.

Data Availability Statement

The data that support the findings of this study are available in Landmark H2020 dataset at https://entrepot.recherche.data.gouv.fr/dataverse/LandmarkH2020, reference number H2020-SFS-2014-2: 635201. These data were derived from the following resources available in the public domain: Landmark H2020 dataset, https://entrepot.recherche.data.gouv.fr/dataset.xhtml?persistentId=doi:10.15454/MUTD4K.

References

Adhikari, K., and A. E. Hartemink. 2016. "Linking Soils to Ecosystem Services—A Global Review." *Geoderma* 262: 101–111.

Andrews, S. S., D. L. Karlen, and J. P. Mitchell. 2002. "A Comparison of Soil Quality Indexing Methods for Vegetable Production Systems in Northern California." *Agriculture, Ecosystems & Environment* 90: 25–45.

Bastida, F., J. L. Moreno, T. Hernández, and C. García. 2006. "Microbiological Degradation Index of Soils in a Semiarid Climate." *Soil Biology and Biochemistry* 38: 3463–3473.

Blum, W. E. 2005. "Functions of Soil for Society and the Environment." *Reviews in Environmental Science and Bio/Technology* 4: 75–79.

Bohanec, M. 2003. "Decision support." In *Data Mining and Decision Support*, edited by D. Mladenić, N. Lavrač, M. Bohanec, and S. Moyle, 1st ed., 23–35. Springer.

Bohanec, M. 2017. "Multi-Criteria DEX Models: An Overview and Analysis." *Paper Presented at the SOR'17 Proceedings (Ljubljana: Slovenian Society Informatika, Section for Operational Research)*, Ljubljana.

Bohanec, M. 2020. "*DEXi: Program for Multi-Attribute Decision Making User's Manual*. Version 5.04. IJS Report DP-13100, Jožef Stefan Institute, Ljubljana". http://kt.ijs.si/MarkoBohanec/pub/DEXiManual504.pdf.

Bohanec, M. 2021. "From Data and Models to Decision Support Systems: Lessons and Advice for the Future." In *EURO Working Group on DSS: A Tour of the DSS Developments Over the Last 30 Years*, edited by J. Papathanasiou, P. Zaraté, and J. de Freire Sousa, 191–211. Springer International Publishing.

Bohanec, M. 2022. "Dex (Decision EXpert): A Qualitative Hierarchical Multi-Criteria Method." In *Multiple Criteria Decision Making: Techniques, Analysis and Applications*, edited by A. J. Kulkarni, 39–78. Springer.

Bohanec, M. 2023a. "DEXi: A Program for Multi-Attribute Decision Making". https://kt.ijs.si/MarkoBohanec/dexi.html.

Bohanec, M. 2023b. "Inter-and Intra-Personal Differences, and Consistency of Decision Rules, in Multi-Criteria Modelling Method Dex: A Preliminary Study." In *Central European Conference on Information and Intelligent Systems*, Faculty of Organization and Informatics Varazdin, 43–48.

Bohanec, M., M. Žnidaršič, V. Rajkovič, I. Bratko, and B. Zupan. 2013. "Dex Methodology: Three Decades of Qualitative Multi-Attribute Modeling." *Informatica* 37: 49–54.

Bohanec, M., and B. Zupan. 2004. "A Function-Decomposition Method for Development of Hierarchical Multi-Attribute Decision Models." *Decision Support Systems* 36: 215–233.

Bouma, J. 2014. "Soil Science Contributions Towards Sustainable Development Goals and Their Implementation: Linking Soil Functions With Ecosystem Services." *Journal of Plant Nutrition and Soil Science* 177: 111–120.

Bünemann, E. K., G. Bongiorno, Z. Bai, et al. 2018. "Soil Quality–A Critical Review." *Soil Biology and Biochemistry* 120: 105–125.

Calzolari, C., F. Ungaro, N. Filippi, et al. 2016. "A Methodological Framework to Assess the Multiple Contributions of Soils to Ecosystem Services Delivery at Regional Scale." *Geoderma* 261: 190–203.

Craheix, D., J.-E. Bergez, F. Angevin, et al. 2015. "Guidelines to Design Models Assessing Agricultural Sustainability, Based Upon Feedbacks From the DEXi Decision Support System." *Agronomy for Sustainable Development* 35: 1431–1447.

Debeljak, M., A. Trajanov, V. Kuzmanovski, et al. 2019. "A Field-Scale Decision Support System for Assessment and Management of Soil Functions." *Frontiers in Environmental Science* 7: 115.

Eum, H.-I., and A. Gupta. 2019. "Hybrid Climate Datasets From a Climate Data Evaluation System and Their Impacts on Hydrologic Simulations for the Athabasca River Basin in Canada." *Hydrology and Earth System Sciences* 23: 5151–5173.

European Commission. 2021. "EU Soil Strategy for 2030. Reaping the Benefits of Healthy Soils for People, Food, Nature and Climate. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions European Commission. Brussels, Belgium".

European Commission. 2023. "Proposal for a Directive of the European Parliament and of the Council on Soil Monitoring and Resilience (Soil Monitoring Law). European Commission Brussels, Belgium". https://environment.ec.europa.eu/publications/proposal-directive-soil-monitoring-and-resilience_en.

Evangelista, S. J., D. J. Field, A. B. McBratney, et al. 2023. "Soil Security-Strategising a Sustainable Future for Soil." *Advances in Agronomy* 183: 1–62.

Evangelista, S. J., D. J. Field, A. B. McBratney, et al. 2024. "Soil Security—Strategizing a Sustainable Future for Soil." *Advances in Agronomy* 183: 1–70.

FAO ITPS. 2015. "Status of the World's Soil Resources—Main Report Food and Agriculture Organization of the United Nations and Intergovernmental Technical Panel on Soils Rome, Italy".

Feick, S., S. Siebert, and P. Döll. 2005. "A Digital Global Map of Artificially Drained Agricultural Areas Frankfurt Hydrology Paper. Germany".

Fendrich, A. N., F. Matthews, E. Van Eynde, et al. 2023. "From Regional to Parcel Scale: A High-Resolution Map of Cover Crops Across Europe Combining Satellite Data With Statistical Surveys." *Science of the Total Environment* 873: 162300.

Greco, S., M. Ehrgott, and J. R. Figueira, eds. 2016. *Multiple Criteria Decision Analysis*. Springer.

Greiner, L., A. Keller, A. Grêt-Regamey, and A. Papritz. 2017. "Soil Function Assessment: Review of Methods for Quantifying the Contributions of Soils to Ecosystem Services." *Land Use Policy* 69: 224–237.

Halvorson, J. J., J. L. Smith, and R. I. Papendick. 1996. "Integration of Multiple Soil Parameters to Evaluate Soil Quality: A Field Example." *Biology and Fertility of Soils* 21: 207–214.

Ikram, R. M. A., S. G. Meshram, M. A. Hasan, et al. 2024. "The Application of Multi-Attribute Decision Making Methods in Integrated Watershed Management." *Stochastic Environmental Research and Risk Assessment* 38: 297–313.

Keating, B. A., P. S. Carberry, G. L. Hammer, et al. 2003. "An Overview of APSIM, a Model Designed for Farming Systems Simulation." *European Journal of Agronomy* 18: 267–288.

Kibblewhite, M., K. Ritz, and M. Swift. 2008. "Soil Health in Agricultural Systems." *Philosophical Transactions of the Royal Society, B: Biological Sciences* 363: 685–701.

König, S., U. Weller, B. Betancur-Corredor, et al. 2023. "BODIUM—A Systemic Approach to Model the Dynamics of Soil Functions." *European Journal of Soil Science* 74: e13411.

Leip, A., G. Marchi, R. Koeble, M. Kempen, W. Britz, and C. Li. 2008. "Linking an Economic Model for European Agriculture With a Mechanistic Model to Estimate Nitrogen and Carbon Losses From Arable Soils in Europe." *Biogeosciences* 5: 73–94.

Lilburne, L., G. Sparling, and L. Schipper. 2004. "Soil Quality Monitoring in New Zealand: Development of an Interpretative Framework." *Agriculture, Ecosystems & Environment* 104: 535–544.

Mendes, I. C., D. M. G. Sousa, O. D. Dantas, et al. 2021. "Soil Quality and Grain Yield: A Win–Win Combination in Clayey Tropical Oxisols." *Geoderma* 388: 114880.

Meunier, C., M. Casagrande, B. Rosiès, et al. 2022. "Interplay: A Game for the Participatory Design of Locally Adapted Cereal–Legume Intercrops." *Agricultural Systems* 201: 103438.

Mezbahuddin, S., T. Nikonovas, A. Spessa, et al. 2023. "Accuracy of Tropical Peat and Non-Peat Fire Forecasts Enhanced by Simulating Hydrology." *Scientific Reports* 13: 619.

Ng, W., S. J. Evangelista, J. Padarian, et al. 2024. "Estimating Surrogates, Utility Graphs and Indicator Sets for Soil Capacity and Security Assessments Using Legacy Data." *Soil Research* 62, no. 2: SR23138.

Orgiazzi, A., C. Ballabio, P. Panagos, A. Jones, and O. Fernández-Ugalde. 2018. "LUCAS Soil, the Largest Expandable Soil Dataset for Europe: A Review." *European Journal of Soil Science* 69: 140–153.

Orgiazzi, A., P. Panagos, Y. Yigini, et al. 2016. "A Knowledge-Based Approach to Estimating the Magnitude and Spatial Patterns of Potential Threats to Soil Biodiversity." *Science of the Total Environment* 545: 11–20.

Poggio, L., L. M. De Sousa, N. H. Batjes, et al. 2021. "Soilgrids 2.0: Producing Soil Information for the Globe With Quantified Spatial Uncertainty." *Soil* 7: 217–240.

Porwollik, V., S. Rolinski, J. Heinke, and C. Müller. 2019. "Generating a Rule-Based Global Gridded Tillage Dataset." *Earth System Science Data* 11: 823–843.

Rabot, E., C. Keller, J.-P. Ambrosi, and S. Robert. 2017. "Revue des méthodes multiparamétriques pour l'estimation de la qualité des sols dans le cadre de l'aménagement du territoire." *Etude et Gestion Des Sols* 24: 59–72.

Saby, N. P., E. Micheli, J.-P. Chenu, et al. 2020. "Landmark H2020 Dataset". https://doi.org/10.15454/MUTD4K.

Sandén, T., A. Trajanov, H. Spiegel, et al. 2019. "Development of an Agricultural Primary Productivity Decision Support Model: A Case Study in France." *Frontiers in Environmental Science* 7: 58.

Schröder, J. J., R. P. O. Schulte, R. E. Creamer, et al. 2016. "The Elusive Role of Soil Quality in Nutrient Cycling: A Review." *Soil Use and Management* 32: 476–486.

Schulte, R. P. O., R. E. Creamer, T. Donnellan, et al. 2014. "Functional Land Management: A Framework for Managing Soil-Based Ecosystem Services for the Sustainable Intensification of Agriculture." *Environmental Science & Policy* 38: 45–58.

Searle, R., M. Stenson, P. L. Wilson, L. J. Gregory, R. Singh, and B. P. Malone. 2021. "Soil Data, United, Will Never Be Defeated—The SoilDataFederator".

Siebert, S., P. Döll, J. Hoogeveen, J.-M. Faures, K. Frenken, and S. Feick. 2005. "Development and Validation of the Global Map of Irrigation Areas." *Hydrology and Earth System Sciences* 9: 535–547.

Sinclair, S. J., P. Griffioen, D. H. Duncan, J. E. Millett-Riley, and M. D. White. 2015. "Quantifying Ecosystem Quality by Modeling Multi-Attribute Expert Opinion." *Ecological Applications* 25: 1463–1477.

Soil Survey Staff. 2017. "Natural Resources Conservation Service, United States Department of Agriculture. Web Soil Survey". https://websoilsurvey.nrcs.usda.gov/.

Tóth, G., A. Jones, and L. Montanarella. 2013. "The Lucas Topsoil Database and Derived Information on the Regional Variability of Cropland Topsoil Properties in the European Union." *Environmental Monitoring and Assessment* 185: 7409–7425.

Trajanov, A., J. Schröder, D. Wall, A. Delgado, R. Schulte, and M. Debeljak. 2019. "Assessing the Nutrient Cycling Potential in Agricultural Soils Using Decision Modelling." In *15th International Symposium on Operational Research, SOR 2019, Slovenia*, edited by L. Z. Stirn, M. K. Borstnar, J. Zerovnik, S. Drobne, and J. Povh, 23–27. Slovenian Society Informatika.

Van Calker, K. J., P. B. M. Berentsen, C. Romero, G. W. J. Giesen, and R. B. M. Huirne. 2006. "Development and Application of a Multi-Attribute Sustainability Function for Dutch Dairy Farming Systems." *Ecological Economics* 57: 640–658.

Van de Broek, M., C. B. Henriksen, B. B. Ghaley, et al. 2019. "Assessing the Climate Regulation Potential of Agricultural Soils Using a Decision Support Tool Adapted to Stakeholders' Needs and Possibilities." *Frontiers in Environmental Science* 7: 131.

Van Leeuwen, J. P., R. E. Creamer, D. Cluzeau, et al. 2019. "Modeling of Soil Functions for Assessing Soil Quality: Soil Biodiversity and Habitat Provisioning." *Frontiers in Environmental Science* 7: 113.

Vazquez, C., R. G. de Goe, M. Rutgers, T. J. de Koeijer, and R. E. Creamer. 2021. "Assessing Multifunctionality of Agricultural Soils: Reducing the Biodiversity Trade-Off." *European Journal of Soil Science* 72: 1624–1639.

Wadoux, A. M. J.-C. 2025. "Artificial Intelligence in Soil Science." *European Journal of Soil Science* 76: e70080.

Wadoux, A. M. J.-C., L. Courteille, D. Arrouays, et al. 2024. "On Soil Districts." *Geoderma* 452: 117065.

Wadoux, A. M. J.-C., M. R. Dobarco, W. Ng, and A. B. McBratney. 2024. "Spatial Evaluation of the Soils Capacity and Condition to Store Carbon Across Australia." *Geoderma* 442: 116805.

Wall, D. P., A. Delgado, L. O'Sullivan, et al. 2020. "A Decision Support Model for Assessing the Water Regulation and Purification Potential of Agricultural Soils Across Europe." *Frontiers in Sustainable Food Systems* 4: 115.

Wenng, H., H. Spiegel, M. Debeljak, et al. 2018. "Key Indicators and Management Strategies for Primary Productivity. LANDMARK Report 3.1". www.landmark2020.eu.

Zwetsloot, M. J., J. van Leeuwen, L. Hemerik, et al. 2021. "Soil Multifunctionality: Synergies and Trade-Offs Across European Climatic Zones and Land Uses." *European Journal of Soil Science* 72: 1640–1654.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting Information.