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DOI
10.1016/j.envsoft.2024.106116

Publication date
2024

Document Version
Final published version

Published in
Environmental Modelling and Software

Environmental Modelling and Software 179 (2024) 106116

Contents lists available at ScienceDirect

Environmental Modelling and Software

journal homepage: www.elsevier.com/locate/envsoft

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ARTICLE INFO

Handling Editor: Daniel P Ames

Keywords:
Model framework
Land-use change
Carbon sequestration
Drought
Landscape functions
Soft coupling
Environmental modelling

ABSTRACT

This study addresses the challenging task of analysing multifunctional landscapes through an innovative integrated modelling approach. Acknowledging the limitations of disciplinary models in assessing diverse landscape functions, we present a conceptual framework for their integration. Demonstrating the feasibility and effectiveness of this approach in a Netherlands case study, we assess alternative land use changes for drought and carbon sequestration. Results underscore the framework's efficacy in elucidating the intricate relationship between carbon and water across multiple model runs and iterations. Notably, the alternative land use scenario reveals an average increase in soil moisture during dry periods and an increase in soil organic carbon content across four model runs. This softly coupled approach offers valuable insights into environmental modelling, facilitating navigation of complex integration challenges for researchers and practitioners. Furthermore, it enhances modelling transparency by elucidating variable representation and processes, providing a foundation for informed decisions in sustainable landscape management.

1. Introduction

There is increasing attention for the concept of multi-functionality within landscapes (Bolliger et al., 2011; Herspberger et al., 2021; Wang et al., 2022). The concept of landscape multi-functionality, moves away from the traditional management of a single function landscape (e.g., for agricultural production), to a landscape offering multiple environmental, social and economic benefits (O'Farrell et al., 2010). Additionally, multi-functionality of landscapes, underscores the diversified use of natural resources by humans and primarily characterizes the service capacity of landscape functions in areas such as carbon cycling, habitat provision, water supply and soil conservation (Griffiths, 2018; Hart et al., 2016) and their interactions (Li et al., 2020).

Societies grapple with the multi-functionality of landscapes and shift towards landscape-focused approaches (Hersperger et al., 2021). To address complex environmental issues and deal with multiple landscape functions, new integrated solutions are proposed. A good example is the increased attention for nature-based solutions (Chausson et al., 2020; Seddon et al., 2020, 2021). Evidence suggests that well-designed nature-based solutions can support the provision of landscape functions and their synergy (Chausson et al., 2020; Keesstra et al., 2018; Seddon et al., 2020). For instance, protecting and restoring habitats in upper catchments or along shorelines can enhance climate change adaptation and mitigation by safeguarding communities and infrastructure from flooding and erosion, while also boosting carbon sequestration and preserving biodiversity (Smith et al., 2017).

Environmental models are central to the effective planning and implementation of interventions and policies aimed at harnessing the benefits of landscapes through their landscape functions (Hamilton et al., 2015; Moriasi et al., 2012; Tan et al., 2018; Teng et al., 2017). These models serve as invaluable tools for conducting ex ante evaluations, offering insights into the potential outcomes of diverse interventions and policies before they are put into practice (Basco-Carrera et al., 2017; Voinov et al., 2016). Over the past decades many disciplinary environmental models have been developed. Within the various disciplines, these models are extensively calibrated, validated and have shown great model performance. Good examples include hydrological models (Kumar et al., 2021; Teng et al., 2017), soil carbon models (Doetterl et al., 2016; Liu et al., 2021; Nabiollahi et al., 2019) and soil erosion models (Deeks et al., 2012; Morgan et al., 1998). These

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https://doi.org/10.1016/j.envsoft.2024.106116
Received 24 December 2023; Accepted 12 June 2024
Available online 15 June 2024

disciplinary models often look at one or a few related functions, however, as soon as we are interested in multiple functions and integrated solution pathways, the disciplinary models are not suitable as one landscape function (e.g. water provision), could have a fundamental effect on another landscape function (e.g. carbon storage) (Huang, 2017).

Integrated modelling is a promising approach to bringing together diverse types of information, theories and data, allowing for the landscape to be seen as a whole with its diverse landscape functions. A lot of integrated models already exist. One such model is the general ecosystem model (GEM) designed to simulate a variety of ecosystem types ranging from wetlands to upland forests providing at least two useful functions in synthesizing our broader understanding of ecosystem properties (Fitz et al., 1996). However, integrated modelling presents growing challenges beyond the requirement for increased computational power, additional resources, and a specific level of proficiency in the modelled landscape processes - with regards to the concept of digital twins, (Blair, 2021), but also the software used (Castelletti et al., 2012; Voinov and Fishwick, 2018) and the transparency of the calculations. They often require extensive amounts of input data and deal with processes that we might not be interested in and one can wonder whether the full complexity of these models is always required, especially in cases where we deal with very specific (or exploratory) questions on landscape functions (e.g. in urban planning or environmental outlook studies).

The goal of this research is to explore an approach to address this challenge. This approach seeks to bridge the gap between existing disciplinary models and the imperative for integrated modelling showcasing the multifunctionality of landscapes. To illustrate the feasibility and effectiveness of this approach, we present a case study centred on a catchment in the Netherlands—a landscape that encapsulates a diverse array of landscape functions and challenges.

We first provide a conceptual framework for model integration when at least one disciplinary model is available. Subsequently we explore the practical use of the framework where we look at the application of integrated modelling for the ex-ante evaluation of nature based solutions to deal with drought and carbon sequestration through land use change.

2. Integrated environmental modelling

For almost all landscape functions a multitude of models are available that describe the system. However, these models differ considerably in terms of the spatial and temporal scales at which they operate. In additions, they may vary in the processes that they model and in the level of detail of the model.

In this research we define integrated environmental modelling as a model study in which multiple landscape functions from different disciplines are analysed.

If a particular study deals with multiple landscape functions that do not interact with each other, one can argue that the models describing the landscape functions can be run independently from each other. However, for the purpose of consistency in an application it may be necessary that the data used in both models (including the definition of scenarios) are consistent. For example, if two models make use of a digital elevation model one would like to use the same digital elevation model. Similarly, it may be useful if both models operate on the same temporal and spatial scale. However, in environmental modelling, this may be an exception rather than a rule. In most cases, there will be some interaction between the landscape functions.

For the theoretical discussion, we will look at a simplified case, that we will analyse in 5 steps. Imagine two landscape functions LF_A and LF_B. As mentioned in the introduction, multiple models for both landscape functions may be available.

Step 1 of the conceptual framework is **model selection** for both landscape functions that match in terms of their temporal and spatial scales. When linking existing disciplinary models, it is crucial to examine their variables, scales and resolutions (Voinov and Cerco, 2010). In practice, one of the models may already be available (calibrated and/or validated) after which a second model needs to be selected. For example, a model A is already available for LF_A and a model B is selected for LF_B based on the spatial and temporal scales of model A and the specific requirements of the study (e.g., in terms of the level of detail). Additionally, in this step it is also vital to define the variables of both models. A and B make use of a specific set of *exogenous* and *endogenous* variables. The *exogenous variables* (v_{ex}) are those variables that are kept fixed, they do not change within the model whereas the *endogenous variables* (v_{end}) are those that are being modelled, whose values are determined within the model (Minot, 2009).

Given the above definitions, we can assume for the purposes of this paper that one can always resort to the general formulation:

$$LF_A = f(v_{A,ex}, v_{A,end}) \tag{1.A}$$

$$LF_B = g(v_{B,ex}, v_{B,end}) \tag{1.B}$$

For example, a hydrological model may simulate groundwater tables which is mostly used as an endogenous variable in the model. However, soil properties like soil organic matter are often exogenous to the hydrological model although they may change as a consequence of changes in hydrology.

Step 2 includes an **analysis of the variables.** If there is no overlap between the variables in both models, then integration is not necessary and the models can run independent from each other. However, if there are variables that are endogenous to both models and/or exogenous variables of one model are endogenous in the other model, there should be some level of model integration. However, it may well be that variables are used in a model, but that the model results are not very sensitive (Step 3, Fig. 1) to changes in the exogenous variable(s). For example, a hydrological model may include the groundwater table as a variable, but in the study area, groundwater tables may be so deep, that changes do not influence the model results. Therefore, it may not be necessary to go through the burden of model integration.

In Step 3 **model sensitivity** is tested, specifically the case when there are overlapping populations between the model A and B variables. In this step it is relevant to test whether the endogenous variables from one model are sensitive or not to the endogenous variables of the other model. If they are not, then model integration is not necessary. If they are, the next step (Step 4: **Integration of model A and B**) is to decide on which modeling strategy to use for A and B. Full model integration means that both models A and B have some endogenous variables that overlap, for example, simulating water quantity, A is one dimensional and simulates the water movement in the main channels, and B is two or even three dimensional and simulates the water movement in the floodplains and the soil, and they are sensitive to each other because the water quantity in the main channels has an impact on the water quantity both in the floodplains and the soil, then we need to fully integrate these two models into a new model C. Full integration increases complexity and makes it harder to isolate or modify individual variables without affecting the entire system and it is used only when the two models need to work seamlessly together.

If the endogenous variables from A and B are not overlapping (Step 4), however we see that the endogenous variable(s) from one model are the exogenous variable(s) from the other model, and they are also sensitive to each other, we need to choose between a tight and loose coupling strategy. The choice between these two strategies comes down to few factors. The choice of coupling should consider how well the

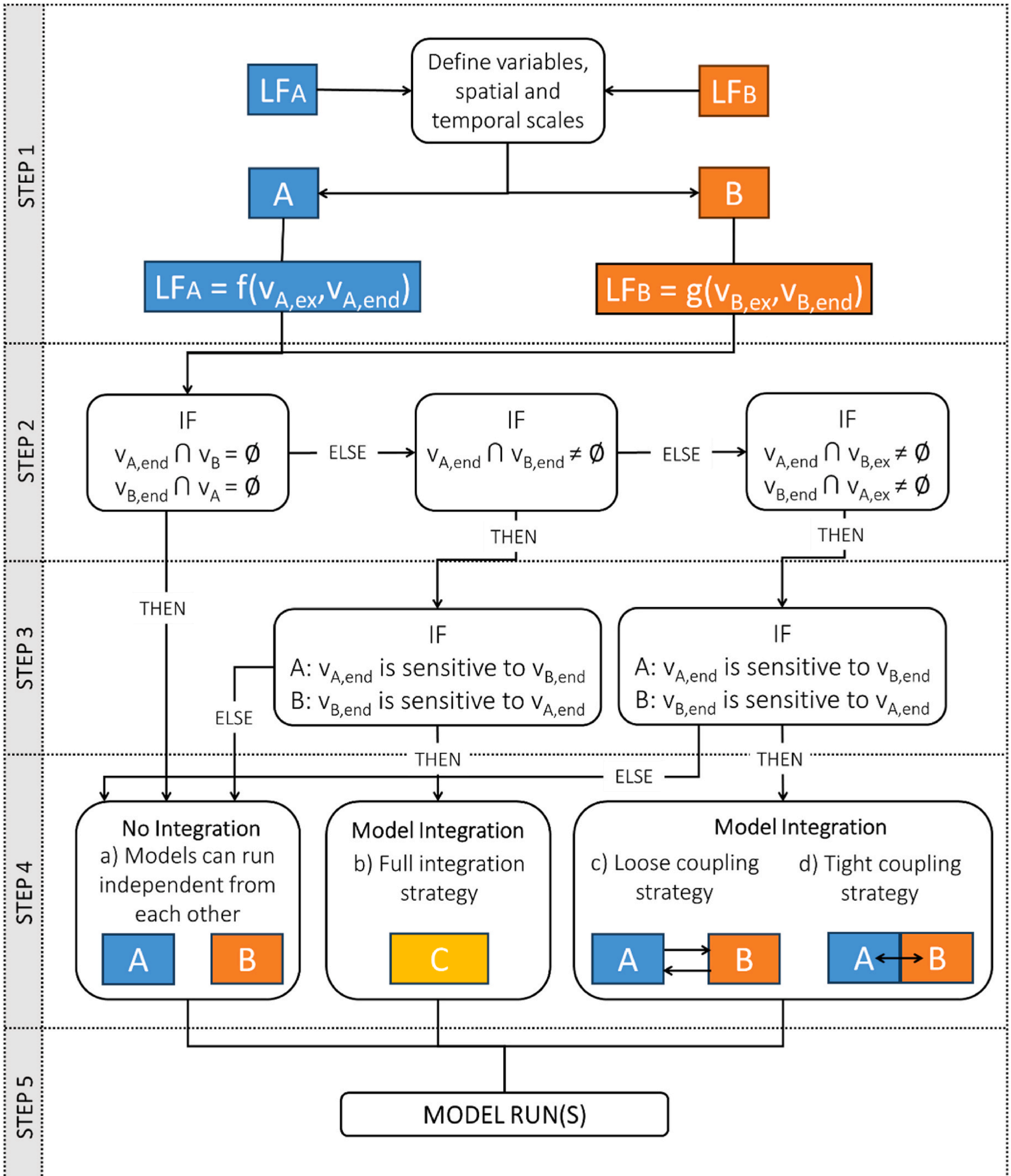

Fig. 1. Conceptual framework for integrated environmental modelling. Step 1: Model selection; Step 2: Analysis of variables and their overlapping populations; Step 3: Sensitivity Analysis; Step 4: Integration of model A and B and Step 5: Model Runs.

components need to interact and share information. Tight coupling is suitable when two models need to closely collaborate, sharing significant amount of variables, and must operate as a single unit. This can make the system more challenging to maintain and less flexible to changes. Loose coupling is often the choice when we do not want a formal software mechanism involved for coupling as the endogenous variable from one model is sent to the other model as an exogenous variable and vice versa.

The last and final step (Step 5) includes the **model runs**. This will demonstrate the effect of the coupling strategy and usually a specific application is added so that the effects can be analysed from using this integrated environmental modeling approach.

3. Materials and methods

We chose a case study in the Netherlands to illustrate the practical application of our conceptual framework for integrated environmental modelling. Specifically, we selected the Aa of Weerijs catchment due to the interest in analysing multiple landscape functions, particularly water provision and carbon sequestration.

In this case, there is an existing, calibrated, and validated disciplinary (hydrological) model that serves as a starting point for our framework application. The Aa of Weerijs catchment is interesting because there is a need to connect disciplinary models, given ongoing discussions on how nature-based solutions in the landscape can enhance resilience against droughts and contribute to carbon storage.

The integration of models in this catchment would not only contribute to catchment-specific discussions but also align with the general call for climate action, emphasizing the need for adaptation and mitigation interventions (IPCC et al., 2023). The ultimate goal is to use this framework and integration approach to engage in valuable discussions with stakeholders.

To achieve this, we plan to test the coupled models through our stepwise framework for integrated modelling, with scenarios involving alternative land use changes (Fig. 2, d), comparing them to existing land use changes (Fig. 2, c). Alternative land use change in this case includes changing the dominating agricultural land use category to mixed forest. This comparative analysis aims to illustrate the possibility of modelling nature-based solutions in the future such as reforestation.

3.1. Case study description

The catchment Aa of Weerijs spans across Belgium and The Netherlands and it is a transboundary area. The river flows from its source in Belgium Flanders and eventually joins the canals in the Netherlands near the city of Breda. Originally, the rolling landscape was a vast wetland with drier uplifted heights of cover sand. The wetlands were later reclaimed in the fourteenth century and further expanded for agriculture in the nineteenth century. Many waterways were

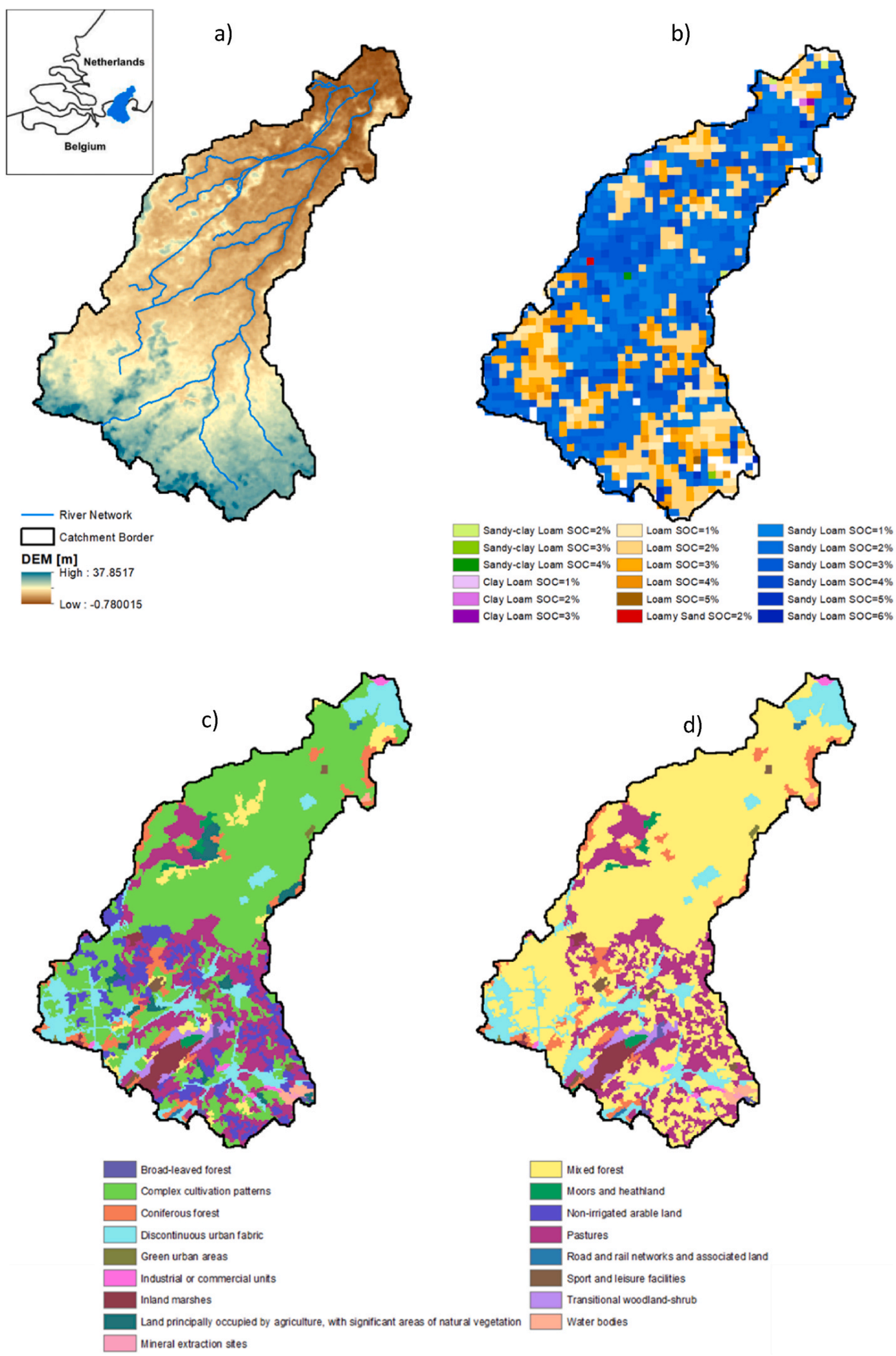

Fig. 2. The Aa of Weerijs catchment: a) digital elevation model (DEM) with the river network (CLMS, n.d.); b) the soil map (Ballabio et al., 2016); c) current land use change (CLMS, 2018) and d) alternative land use change.

constructed during this time, leading to the present stream valley landscape in the catchment (Fig. 2, a). The predominant soil type in the area is sandy loam, characterized by soil organic carbon contents (SOC) within the range of 1–6%. Additionally, loamy soils are present, featuring SOC levels ranging from 1 to 5% (Fig. 2, b). Over time, several streams were straightened to facilitate faster drainage of excess rainwater. Agriculture is the primary land use, with grassland being the most common, followed by arable farming and tree cultivation (Fig. 2, c). The stream valley width is around 3 km, and the catchment area is about 346 km^2. Main tributaries are the Kleine Beek, Bijloop and Tufvaart (Beers et al., 2018).

The Aa of Weerijs catchment is facing a severe threat of drought, mainly due to agricultural practices. Climate change impacts, including rising temperatures and more frequent and intense rainfall, are further exacerbating the water quality and quantity issues in the catchment. As a result, the river discharge is expected to decrease during summer months (Beers et al., 2018).

As mentioned before, nature-based solutions (NbS) are discussed in the context of Aa of Weerijs catchment for improving the landscape multifunctionality and tackle environmental challenges namely drought. Additionally, due to ongoing catchment discussions on drought mitigation and the need for more carbon sequestration (IPCC et al., 2023), it is important that within the landscape, the landscape function of carbon sequestration is also improved, specifically due to vast historical land use changes contributing to carbon emissions (Ruyssenaars et al., 2021; Timmer, 2022). Moreover, it is important make the carbon-water model linkage due to the fundamental influence of soil organic carbon (SOC) to various soil-centred water processes such as water infiltration, evaporation, soil moisture and root uptake (G. Sun and Mu, 2022; P. Sun et al., 2019; Zhao et al., 2020).

3.2. Step 1: model selection

3.2.1. Model A – MIKE hydrological model

Hydrological models play a pivotal role in understanding complex hydrological phenomena (Zhang et al., 2021). Various distributed models, such as the Topography-Based Hydrological Model (TOPMODEL) (Beven and Kirkby, 1979), Variable Infiltration Capacity (Lohmann et al., 1998), the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998), and the MIKE System Hydrological European (MIKE-SHE) model (Abbott et al., 1986) and MIKE Hydrologic Modelling System (MIKE-HMS) (Ruelland et al., 2008), have been widely employed in addressing practical scientific issues.

MIKE SHE, a physically-based model, stands out due to its extensive reliance on various physical parameters encompassing precipitation, evaporation, interception, river flow, saturated and unsaturated groundwater flow, and other hydrological cycle processes (Abbott et al., 1986). Its versatility is evident in its applicability to both small and large catchments, enabling simulations related to land-use changes, water resource management, and groundwater interactions (Abbott et al., 1986; Aredo et al., 2021; Im et al., 2009; Paudel and Benjankar, 2022; Sahoo et al., 2006). Additionally, MIKE SHE incorporates MIKE 11 to simulate channel flow, offering comprehensive capabilities for modelling intricate channel networks, lakes, reservoirs, and river structures, including gates, sluices, and weirs (Butts and Graham, 2005a). MIKE SHE's grid-based, spatially distributed nature allows for the incorporation of spatial variability in physical and meteorological parameters, distinguishing it from lumped models such as SWAT (Arnold et al., 2010) and HEC-HMS (Ruelland et al., 2008).

In this study, we illustrate the potential for integrating the water and carbon dynamics using a recently developed MIKE SHE model for the Aa of Weerijs catchment. This model, previously established, calibrated, and validated (Ali et al., 2023; Sardar, 2023), serves as our illustrative example and we will use it as model A.

The model has a spatial distribution in the form of a grid with the size of 500m × 500m, utilizing readily available data on topography, precipitation, potential evapotranspiration, land use, surface water, soil texture, and groundwater. We classify this data as endogenous and exogenous variables (Table 2, MIKE-SHE) along the criteria on the conceptual framework (Fig. 1). The temporal scale is a time period of 10 years, from September 15, 2009 until December 31, 2019 with an initial basic time step of 1h. The model delivers gridded results such as: water content in the unsaturated zone, depth of overland flow, infiltration to unsaturated zone, average water content in the rootzone and many others using a daily time step. On each location in the grid, it is also possible to calculate time series results.

The MIKE-SHE model incorporates the Mualem van Genuchten soil hydraulic parameters defining soil retention curves and hydraulic conductivity (Dourado Neto et al., 2011). What sets this model apart is that these variables are exogenous. It is not uncommon that alternative approaches, like the Rosetta model (Van Genuchten et al., 2001), can be used to determine these soil hydraulic parameters, sometimes disregarding the influence of SOC. However, one can argue that when implementing interventions such as nature-based solutions, SOC does not remain the same; and it has an impact on the soil hydraulic parameters. Consequently, this affects the soil's retention curves and hydraulic conductivity, which, in turn, influence the overall hydrology of the landscape.

3.2.2. Model B – soil organic carbon model

Following the conceptual framework (Fig. 1), when we already have an existing disciplinary model A, the next step is to analyse whether there is an existing model B, used for the analysis of the landscape function – carbon sequestration.

The significant quantity of existing disciplinary SOC models, as highlighted in Campbell and Paustian's 2015 review, underscores their significance and the intricate nature of SOC modelling. Various models are well-suited to distinct scenarios, encompassing diverse factors such as land use, management practices, climate conditions, soil characteristics, and both temporal and spatial scales. These models exhibit varying limitations or prerequisites, including data availability and simulation objectives, and may be structured using different process types, each involving a specific set of parameters and input data requirements, as noted in studies by Campbell and Paustian (2015) and Garsia et al. (2023). Nonetheless, the challenge remains on selecting an appropriate soil organic carbon simulation model (Garsia et al., 2023). To avoid the complication of reviewing all these models (more than 64 models validated for multiple ecosystems)(Garsia et al., 2023), we studied few SOC models, specifically their conceptual frameworks, variables and scales.

The CENTURY Model is a biogeochemical model used to study carbon and nutrient cycling in ecosystems over the long term. It assesses the impact of land management practices on carbon sequestration and nutrient dynamics (Parton et al., 1993). The RothC Model is a process-based carbon model focused on estimating carbon dynamics in agricultural soils. It helps analyse the effects of agricultural practices on soil carbon storage (Jenkinson, 1990). Both CENTURY and RothC models, have soil texture, specifically the percentage clay (C) as an exogenous variable used to directly calculate the soil moisture (Table 2). The clay content (%) is an exogenous variable that in temperate regions, does not change due to interventions such as nature-based solutions nor can be modelled seen as a endogenous variable.

A third potential model is The Daisy Model. Daisy is a dynamic simulation model that examines interactions between plants, soil, and the atmosphere. It aids in understanding carbon sequestration potential and the effects of climate change on ecosystem carbon cycling (Abrahamsen and Hansen, 2000). Compared to CENTURY and RothC, Daisy uses the soil moisture as an exogenous variable for calculating the mineralization rate of carbon turnover. Additionally, Daisy is specifically designed to facilitate interaction with other models, either by replacing individual Daisy processes (e.g. soil carbon turnover) or by using Daisy as a part of a larger system (Abrahamsen and Hansen, 2000).

Daisy has been previously integrated with MIKE SHE, by taking over the unsaturated zone and vegetation/ET processes within the modelling framework (Butts and Graham, 2005a), usually for simulating the nitrogen dynamics within the system for assessing groundwater quality (Styczen and Storm, 1993; Thirup, 2013), macropore flow and transport processes modelling (Skovdal Christiansen et al., 2004) and integration of remote sensing in agro-hydrologic modelling (Boegh et al., 2004). This first coupling, where DAISY was fully coupled with MIKE SHE, turned out to be too difficult to maintain and was abandoned (Thirup et al., 2014). However, until now, an integration between MIKE-SHE and Daisy has not been reported in the context of coupling the hydrological and carbon processes neither for assessing climate adaptation and mitigation strategies.

After reviewing few SOC models, their conceptual frameworks, scales and variables, we opted for developing a new meta-model called CARBI that would fit the scales and variables of MIKE. This decision was based on the following observations.

1. Most SOC models use the same conceptual framework assuming an equilibrium state approach:

$$I_{OC} \bullet D_R = SOC \bullet M_R \tag{2}$$

where I_{oc} = input of organic carbon [kg/ha] D_R = decomposition rate [%] and M_R = mineralization rate [%], SOC = soil organic carbon [kg/ha].

2. Their main difference is the level of detail namely on the number of pools/compartments they use and how they are modelled;
3. The mineralization rate does not change directly due to changes in hydrology.

The CARBI model is a static meta model using the conceptual framework from a plethora of SOC models and makes the following assumptions and estimations.

Firstly, the developed model CARBI only focuses on one soil organic carbon pool. This is because otherwise it would be difficult to calibrate the model due to the lack of measurements of different SOC pools in the Netherlands and Belgium. The calculation of the mineralization rate, was taken from the bigger SOC model Daisy, because of the direct link with hydrology, in contrast to other reviewed models (Table 1). Three factors are used for predicting the mineralization rate (M_R) (Eq. (3)). The equation includes the clay factor (C_F), temperature factor (T_F) and pressure potential factor (PP_F) factors which are multiplied by the base mineralization rate (bM_R) (Hansen, 2002). The equation takes the simple product form:

$$M_R = bM_R \bullet C_F \bullet T_F \bullet PP_F \tag{3.A}$$

$$C_F = f(C);\ T_F = f(ST)\ ;\ PP_F = f(\theta) \tag{3.B}$$

where bM_R = base mineralization rate [%]; C_F = clay factor; T_F = temperature factor; PP_F = content soil water pressure potential factor; C = clay [%] and ST = soil temperature [°C] (Hansen, 2002).

Table 1
SOC models selected variable comparison.

Data		Roth C	CENTURY	Daisy
Weather	Precipitation	Ex	Ex	–
	Potential Evapotranspiration	Ex	–	–
	Air temperature	Ex	Ex	–
	Soil temperature	–	–	Ex
Soil	Soil texture (Clay)	Ex	Ex	Ex
	Input of organic carbon	–	Ex	Ex
	Soil Organic Carbon Content	En	En	En
Water Movement	Soil Moisture in Unsaturated Zone	–	–	Ex

Secondly, the mineralization rate (M_R) is estimated to be 2% based on an MIT – model parameters at standard conditions (optimum soil moisture, no clay content and soil temperature of 10 °C) and there is no need to use any equations (Hansen, 2002). However, for values different than the optimum ones, we need to calculate the clay (C_F), temperature (T_F) and pressure potential (PP_F) factors using abiotic functions for adjustment of the mineralization rates, and then we multiply these values with the base mineralization rate bM_R (2%) to get the actual mineralization rate for that soil profile (Eq (3)).

Thirdly, we took into account the scales of model A for developing static model with the same grid size of 500 × 500 m. Furthermore, from MIKE-SHE, we use the topsoil variables which correlates to the soil profile for the unsaturated zone up to 30 cm depth, hence we estimate that we have one carbon stock block of 30 cm. This is where most of the changes in terms of carbon turnover happen, if we implement specific interventions such as nature-based solutions. From a temporal point of view, we can state that carbon turnover is a relatively slow process in contrast to the rapid hydrological fluctuations that are quite relevant to analyse in short term. That is why the hydrological model is dynamic, with a temporal scale of 10 years, and this is not necessary with the carbon model, so we assume that the system is in equilibrium (Eq. (2)) and develop a static model.

The first exogenous variable, to this carbon stock is the organic carbon input which is the organic carbon that enters the system with estimated 50% decomposition rate (D_R). The value of organic carbon input is dependent on crop and grass residues including roots, animal manure and compost (Conijn and Lesschen, 2015) and it is calculated as an average per vegetation type (land use type) using the soil clay content (%) and organic carbon measurements (kg/ha) from the soil surveys (n = 3768) in Belgium and the Netherlands dating from the 1980s.

3.3. Step 2: analyzing the variables and their overlapping populations

This step will select relevant variables and illustrate their overlapping populations. Based on this, and whether there is a need for a sensitivity analysis or not (Fig. 1, Step 3), a coupling strategy will be determined.

3.4. Step 3: sensitivity analysis

3.4.1. Model A – MIKE-SHE hydrodynamic model

Previous studies have identified key variables that significantly impact the performance of MIKE-SHE in groundwater and surface water hydrology, including hydraulic conductivity, specific yield, initial potential head of aquifer, soil bypass coefficient, Manning's roughness, evapotranspiration parameters, leakage coefficient, and detention storage (Butts and Graham, 2005b; Moriasi et al., 2012; Paudel and Benjankar, 2022).

However, to assess the landscape functions, specifically carbon sequestration, in addition to enhancing drought resilience, we aim to investigate MIKE-SHE's response to changes in carbon content, specifically within the top 30 cm of the unsaturated zone. Soil organic carbon technically not a variable in this model (Table 2), however the Mualem van Genuchten soil hydraulic parameters and the bulk density (BD) are. In theory, by changing SOC, the soil hydraulic parameters and the bulk density will also change. That is why, because MIKE-SHE has not be analysed for this specific variable sensitivity, we need to conduct our own sensitivity analysis where we will change the SOC content and keep the other parameters fixed. For recalculation of the Mualem-van Genuchten soil hydraulic parameters and the bulk density, we will use the pedo-transfer functions, as these might affect the model's performance. To achieve this, we have conducted tests using the already calibrated and validated base model, representing the existing catchment conditions. We manually increased carbon content by 2% and 4% following the rationale for the '4 per 1000' initiative (Soussana et al., 2019). This resulted in new Mualem van Genuchten and bulk density (BD) variables

Table 2
Selection of relevant variables to illustrate the overlapping populations between models A (MIKE-SHE) and B (CARBI); (–) variable not available in the model.

Data type	Variable	Data Source	MIKE - SHE	CARBI
Weather	Rainfall	Ginneken, Zundert and Loenhout stations	Ex	–
	Potential evapotranspiration	Gilze-Rijen station	Ex	–
	Soil Temperature	Average value from Beerse station	–	Ex
Topography	Digital Elevation Model	EU DEM (CLMS, n.d.)	Ex	–
	River Network		Ex	–
Vegetation	Land Cover	Corine Land Cover 2018; CLMS, 2018)	Ex	Ex
	Leaf area index and root depth	Crop parameters of guide crops in the Netherlands as defined by NHI (NHI, 2008)	Ex	–
Soil	Input of organic carbon	Dutch and Belgian soil survey data (Oorts et al., 2019; WUR, 1983)	–	Ex
	Soil texture	USDA soil texture based on LUCAS topsoil database (Ballabio et al., 2016)	Ex	Ex
	Soil hydraulic parameters (Mualem van Genuchten parameters)	Calculated pedo-transfer functions (Wösten et al., 1999) based on soil texture (Ballabio et al., 2016) (Eqs. (5)–(9))	Ex	Ex
	Bulk Density	Calculated pedo-transfer functions (Wösten et al., 1999) based on soil texture (Ballabio et al., 2016) (Eq. (4))	Ex	Ex
	Soil Organic Carbon Content	–	–	En
Water Movement	Soil Moisture in Unsaturated Zone	–	En	Ex
	Overland Flow	–	En	–
	Actual evapotranspiration	–	En	–
	Ground water head elevation	–	En	–

using the pedo-transfer functions (Eqs (4)–(9)). Subsequently, we updated the soil maps with these variables and executed two new simulations in MIKE-SHE covering the period from September 15, 2009 to December 31, 2019.

3.4.2. *Model B – soil organic carbon model*

To assess the CARBI model's sensitivity, we need to compare the base model with variations that involve changes in the exogenous variables and see the effect on the endogenous parameter, the soil organic carbon turnover. Specifically, we are interested in analysing how the changes in hydrology, will influence changes in the soil organic carbon turnover. Thus increasing the overlapping variable, which is the pressure potential, expressed through the soil moisture. We will analyse the increase of 10% and 20% in soil moisture based on an analysis of the retention curve used for calculating the moisture content in model A and the soil moisture deficit trends for the Netherlands and Belgium (EEA, 2019).

3.5. *Step 4: integration of model A and B*

Following the steps of the conceptual framework for integrated environmental modelling, we need to couple the carbon model CARBI (Model B), with the hydrological model MIKE-SHE (Model A). By defining the endogenous and exogenous variables of both the hydrological model (Table 2, MIKE) and the possible carbon models (Table 1), we recognised that there is an intersection between them. This is evident namely because the hydrological model simulates the soil moisture, specifically in the unsaturated zone and this is seen as its endogenous variable. We are interested in carbon sequestration which is identified as our second landscape function (LF_B), so we need to see whether soil organic carbon content is a variable in MIKE-SHE. On first look, this does not appear to be the case (Table 2). However, by having a deeper look and understanding of the soil hydraulic parameters, which are an exogenous variable in MIKE-SHE, and are calculated using the pedotransfer functions, we can conclude that SOC is necessary for calculating the exogenous variables in MIKE-SHE, specifically the soil hydraulic Mualem van Genuchten (vG) and bulk density (BD) variables (Eqs. (4)–(9)). Based on this, the two variables which create overlapping populations between model A and model B are the soil moisture (θ) and the soil organic carbon content (SOC) through the Mualem van Genuchten parameters (vG) and the pedo-transfer functions (PTF) (Fig. 3). Next steps would include choosing a model coupling strategy. This depends on the results of the sensitivity analysis of both models, and their spatial and temporal scales and requirements.

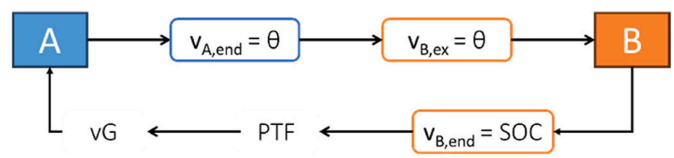

Fig. 3. Variables and equations for A and B model linkage.

3.6. *Step 5: model runs*

After choosing the coupling strategy based on the outcomes of the previous steps, it is important to conduct multiple model runs and look at the difference in results between them, to understand the influence of the model coupling. Because our interest are the landscape functions, water provision for analysing droughts and carbon sequestration for analysing the soil organic carbon changes, we will specifically compare the impact of the model runs on: i) drought – dry period and ii) soil organic carbon – average over the model run of 10 years. We will conduct these model runs for both the existing land use change scenario (Fig. 2, c) and for the alternative land use change scenario (Fig. 2, d).

4. Results

4.1. *Step 1: model selection*

The hydrological model is an existing calibrated and validated model. Its variables and spatial scales were already pre-defined and are explained chapter 3.2.1.

The soil organic carbon model was developed based on the methodology presented in chapter 3.2.1. Furthermore, we calibrated the CARBI model, with regards to the input of organic carbon (I_{OC}) and the base mineralization rate. The input of soil organic (I_{OC}) carbon depends on the crop and grass residues, animal manure and compost. For the calibration of the carbon model, we used 3768 soil survey points. Each soil observation point is assigned with the land use value, based on its location. Because the soil survey was conducted in 1980, for the consistency, we used the earliest available Corine Land Cover Map from 1990. For each of the point, the I_{OC} is calculated using the assumption that the system is in equilibrium (Eqs. 1). Consequently, for each land use type, we chose one average value and we calibrated it using the SOLVER function.

Additionally, we calibrated the CARBI model with regards to the base mineralization rate (bM_R). The bM_R is directly dependant on the texture class, SOC is more stable in clay soils and the content of SOC is also higher in clay soils rather than sandy soils. Consequently we developed a look up table for the bM_R on the base of the texture class. There is a total of 17 texture classes for clay contents from 0% to 85% and bM_R ranging from maximum 2.5 up to 1. The look up table is also developed using the clay contents from the 3768 soil measurement data and it is calibrated using the SOLVER function.

4.2. Step 2: analysing the variables and their overlapping population

The exogenous and endogenous variables of both models, the existing MIKE hydrological model and newly developed meta soil organic carbon model CARBI are presented in Table 2.

The soil data exogenous variables in MIKE are in the form of indexed raster maps with associated look-up tables that link the soil indexes (soil texture + SOC%) to the soil properties specifically the soil hydraulic properties used for calculating the retention curve and hydraulic conductivity. These indexes represent homogeneous soil units having univocal set of soil parameters. At the study area, soil maps and tables were built based on the texture and soil organic carbon classifications from the LUCAS topsoil database (Ballabio et al., 2016).

As pointed out previously, the soil organic carbon is not a direct exogenous variable in MIKE. However, for the purpose of analysing both the hydrological response and soil organic carbon sequestration, we opted for using the Mualem-van Genuchten parameters, because these parameters are calculated on the base of the pedo-transfer functions that require the carbon contents (%). By doing this, the carbon content can be viewed in the model A as an indirect exogenous variable. Aside from the Mualem-van Genuchten parameters, the retention curve in MIKE can be calculated using tabulated values and the Campbell equations, and the hydraulic conductivity using the: tabulated values, Averjanov, Campbell/Burdine equations.

The empirical pedo-transfer functions allowed calculating the Mualem-van Genuchten parameters, used for modelling the unsaturated zone of the model domain. They were applied to each soil index and are based on the soil texture (C - clay and S - silt) and soil organic carbon (OC). Specifically for the bulk density (BD) the empirical Eq. (4) for sandy soils from Wösten (1997) and the Mualem-van Genuchten parameters for calculating the retention curve and hydraulic conductivity the empirical Eqs. (5)–(9) from Wösten et al. (1999), calibrated for European soils were applied:

$$1/BD = -1.984 + 0.03174 \bullet OC + 0.032 \bullet topsoil + 0.00003576 \bullet C^2 + 67.5 \bullet M50^{-1} + 0.424 \bullet \ln(M50) \tag{4}$$

$$\theta_S = 0.719 + 0.001691 \bullet C - 0.29691BD - 0.000001491 \bullet S^2 + 0.000244 \bullet OC^2 + 0.02427 \bullet C^{-1} + 0.01113 \bullet S^{-1} + 0.01472 \bullet \ln(S) - 0.000126 \bullet OC \bullet C - 0.000619 \bullet BD \bullet C - 0.00204 \bullet BD \bullet OC - 0.0001664 \bullet topsoil \bullet S \tag{5}$$

$$\alpha^* = -14.96 + 0.03135 \bullet C + 0.0351 \bullet S + 1.114 \bullet OC + 15.29 \bullet BD - 0.192 \bullet topsoil - 4.671 \bullet BD^2 - 0.000781 \bullet C^2 - 0.0204 \bullet OC^2 + 0.026 \bullet OC^{-1} - 0.0663 \bullet \ln(S) - 0.0807 \bullet \ln(OC) - 0.04546 \bullet BD \bullet S - 0.8365 \bullet BD \bullet OC + 0.00673 \bullet topsoil \bullet C \tag{6}$$

$$n^* = -25.23 - 0.02195 \bullet C + 0.0074 \bullet S - 0.3344 \bullet OC + 45.5 \bullet BD - 7.24 \bullet BD^2 + 0.0003658 \bullet C^2 + 0.008575 \bullet OC^2 - 12.81 \bullet BD^{-1} - 0.1524 \bullet S^{-1} - 0.01136 \bullet OC^{-1} - 0.2876 \bullet \ln(S) - 0.0386 \bullet \ln(OC) - 44.6 \bullet \ln(BD) - 0.02264 \bullet D \bullet C + 0.1545 \bullet BD \bullet OC + 0.00718 \bullet topsoil \bullet C \tag{7}$$

$$l^* = 0.0202 + 0.0006193 \bullet C^2 - 0.003376 \bullet OC^2 - 0.1261 \bullet \ln(OC) - 0.03544 \bullet BD \bullet C + 0.00283 \bullet BD \bullet S + 0.0841 \bullet BD \bullet OC \tag{8}$$

$$K_S^* = 7.755 + 0.0352 \bullet S + 0.93 + topsoil - 0.967 \bullet D^2 - 0.000484 \bullet C^2 - 0.000322 \bullet S^2 + 0.001 \bullet S^{-1} - 0.0434 \bullet OC^{-1} - 0.643 \bullet \ln(S) - 0.01398 \bullet BD \bullet C - 0.2884 \bullet BD \bullet OC + 0.02986 \bullet topsoil \bullet C - 0.03305 \bullet topsoil \bullet S \tag{9}$$

where θ_S is a model parameter, a*, n*, l* and K* are transformed model parameters in the Mualem-van Genuchten equations; C = clay [%], S = silt [%]; OC = organic carbon [%]; topsoil and subsoil are qualitative variables having the value 1 and 0; and ln = natural logarithm.

4.3. Step 3: sensitivity analysis

For both models we conducted a sensitivity analysis where we test how is the endogenous variable – soil moisture (θ) sensitive in MIKE to changes in the exogenous variable, which is an endogenous variable of CARBI – soil organic carbon (SOC) (Fig. 3)and vice versa. The results from the sensitivity analysis both in MIKE and CARBI are presented in Table 3.

From Table 3, we can conclude that with increase of 2% and 4% of soil organic carbon in MIKE resulted in an increase of the mean value of the soil moisture in a dry period, seen as an average for the whole catchment with around 22–37%. The increase of 10% and 20% of soil moisture in CARBI resulted in an increase of the mean value of SOC with around 3.8%–7.3%.

4.4. Step 4: integration of model A and B

We have an existing calibrated model A – MIKE for a landscape function LF_A – water provision/hydrology, and a developed meta model B - CARBI for the landscape function LF_B – carbon sequestration. With the sensitivity analysis we established that the models A and B are sensitive to each other, by testing them for the variables that would exchange between the models. The next vital step is establish a linkage between the hydrological model A, specifically in the unsaturated zone, and model B, representing the topsoil layer of a catchment up to a depth of 30 cm. To achieve this, we have developed a simplified static carbon meta model named CARBI fitted to the spatial and temporal scales of model A. CARBI utilizes the endogenous variables from the hydrological model as exogenous variables and provides new exogenous variables to the hydrological model in a gridded (spatially distributed) form. Based on our conceptual framework for integrated modelling (Fig. 1), in a case when the endogenous variables of model A, become exogenous in model B and vice versa, the best is to employ a loose (soft) coupling strategy.

Table 3
Model A and B Sensitivity (standard deviation between brackets).

θ			SOC [%]		
Base Model	Model +2% SOC	Model +4% SOC	Base Model	Model +10% θ	Model +20% θ
0.27 (0.05)	0.33 (0.04)	0.37 (0.04)	3.40 (1.13)	3.53 (1.23)	3.65 (1.37)

We chose a loose over a tight coupling strategy because we wanted to develop an easy and straightforward approach without the added complexity of requiring a software that would create the exchange between the models and their variables.

The main endogenous variable from model B is the SOC (%) which is in the form of indexed soil raster maps, keeping the same form as the indexed soil raster maps in model A. This goes back to model A as a new exogenous variable and through the lookup tables containing the different combinations of soil types in model A, provides this model with new soil hydraulic parameters – the Mualem van Genuchten parameters which influence the overall hydrology of the model.

4.5. Step 5: model runs

In total, four model runs were conducted in MIKE as the initial model, followed by three runs in CARBI (see Fig. 4). The first MIKE run utilized a soil map (SOC 1.0) based on the USDA soil texture from the LUCAS topsoil database (Ballabio et al., 2016), where soil hydraulic variables and bulk density were calculated using pedo-transfer functions (Eqs. (4)–(9)).

Firstly, we will examine the results arising from the model coupling by comparing mean and standard deviation values over the entire catchment for both the current and alternative land use scenarios. From Fig. 4 and Table 4, it becomes evident that the most substantial increase in SOC occurred for both the current (68%) and alternative land use (73%) scenarios between step 1, where soil organic carbon is not modelled but utilized from an existing European database, and step 2, where we model soil organic carbon using the CARBI model and incorporate the initial model output, soil moisture (θ1.0), from MIKE. The differences between subsequent steps are smaller, approximately 3.6% between the second and third steps, with no change between the third and fourth steps, indicating carbon stabilization in the current land use scenario. For the alternative land use scenario, these model runs resulted in a difference of 1.44% between the second and third steps and 10.8% between the third and fourth steps.

The results for soil moisture in the current land use scenario demonstrate an increasing trend between steps one and two (6.4%) and steps two and three (3%). In the alternative land use scenario, this increase is more pronounced at 13.8% between steps two and three and 15.15% between steps three and four.

Subsequently, we will inspect the results relating to the current and alternative land use scenarios. Specifically, we aim to compare how the models respond to distinct land use changes. Furthermore, this analysis seeks to illustrate the potential application of the model integration

Table 4
Spatial mean and standard deviation values for the modelling steps for the current and the alternative land use.

	Current land use		Alternative land use	
	SOC [%]	Soil Moisture θ [(.)]	SOC [%]	Soil Moisture θ [(.)]
Run 1	2.00 (0.86)	0.31 (0.05)	2.00 (0.86)	0.29 (0.05)
Run 2	3.36 (1.13)	0.33 (0.05)	3.46 (1.10)	0.33 (0.05)
Run 3	3.48 (1.40)	0.34 (0.06)	3.51 (1.40)	0.38 (0.03)
Run 4	3.48 (1.50)		3.89 (1.40)	

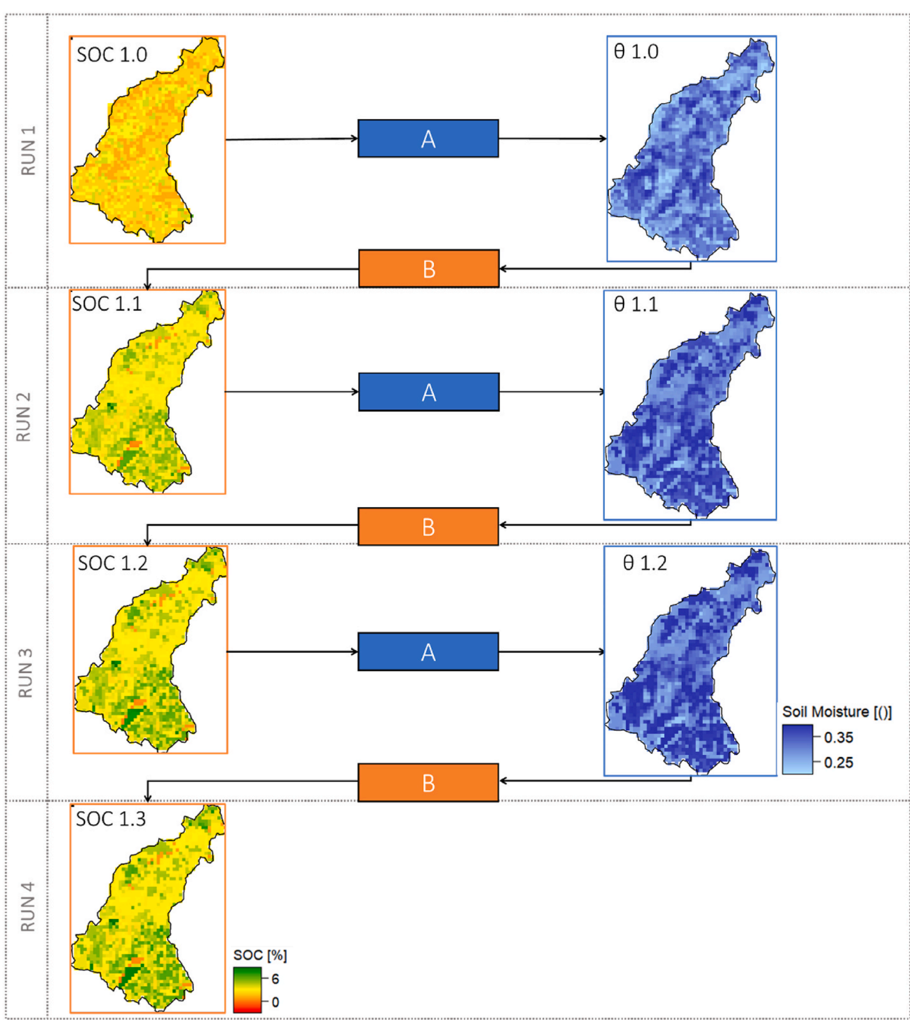

Fig. 4. Schematic representation of the loose coupling strategy between model A and B and their model runs for the current land use scenario.

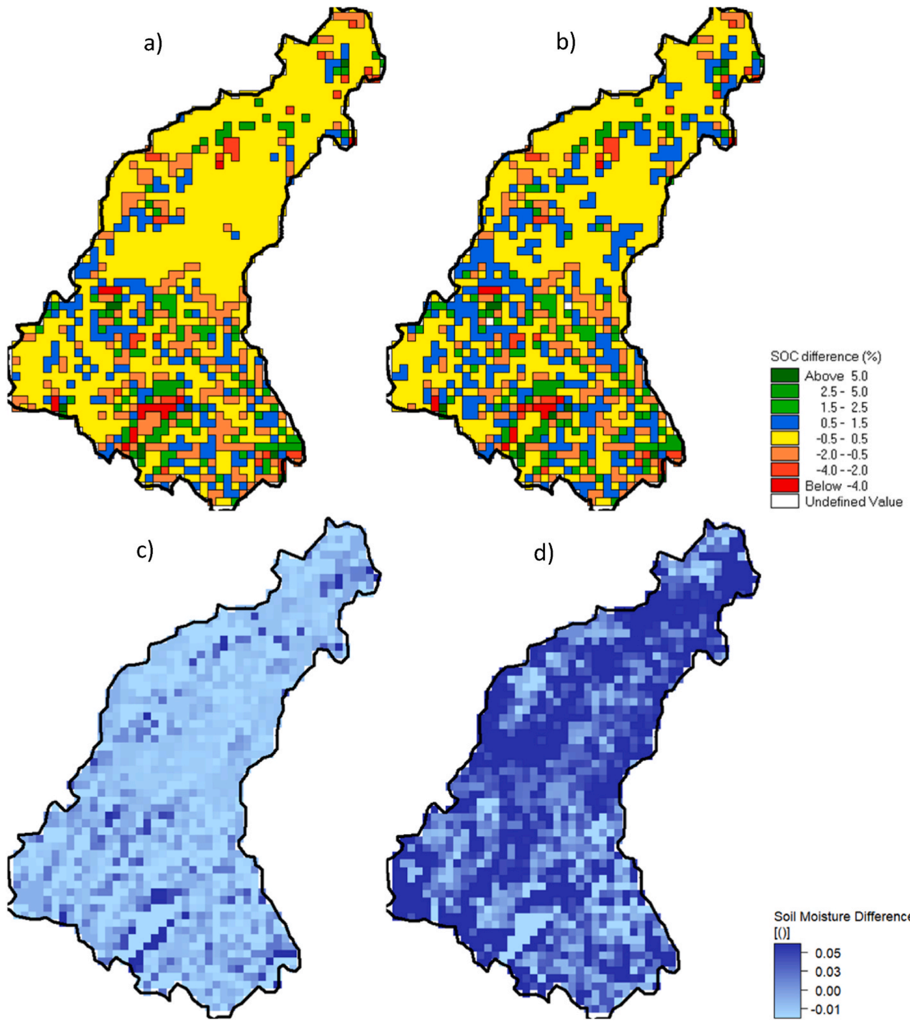

Fig. 5. Effects of land use change on drought and soil organic carbon sequestration. Difference between the alternative and current land use between a) run 4 and run 3; b) run 4 and run 4; c) run 3 and run 2; d) run 3 and run 3 consequently.

framework, particularly the water-carbon coupling strategy, in demonstrating the implementation of nature-based solutions through land use change.

Fig. 5 presents the spatial variation in the effects of land use change. Land use changes resulted in considerable changes in SOC contents that varied throughout the catchment (Fig. 5a and b). The predominant impact of land use change is upstream in the Belgian part, contrasting with the middle and downstream Dutch sections of the catchment. Comparing the change between the third and fourth model runs for alternative land use with the last model run for current land use (Fig. 5a and b), locations showing SOC loss largely remain consistent, while some with minor SOC increases continue to intensify with the additional model run.

Soil moisture results from land use change indicate an increasing trend across the majority of the catchment, particularly in the last (third) model run (Fig. 5d), contrasting with the second run (Fig. 5c).

In terms of model integration, the coupling of models reveals a direct dependency between soil organic carbon and soil moisture. The increase in soil organic carbon corresponds to elevated soil moisture, and vice versa. Additionally, the θ-SOC grid by grid relationship is non-linear and the resulting slopes become less steep due to the difference in their relationships arising from the increase in SOC (%) and the vicinity to the soil moisture saturation (Supplementary Material 1, Fig. 1). The impact of alternative land use change has a more pronounced effect on increasing soil moisture in the catchment, particularly in the last run. Regarding carbon sequestration, the effects of alternative land use are location-dependent. Changing agriculture to forest may exhibit tendencies for carbon sequestration in some locations, while others may experience potential carbon losses. The θ-SOC relationship for alternative land use is similar to the current land use (Supplementary Material 1, Fig. 2).

5. Discussion

Using multiple, disciplinary models is not always straightforward. This paper provides a framework to determine the level of integration that is required if we want to use multiple models in a single study. Through the integration of diverse models, it becomes possible to interpret results in a manner that is more effective for addressing intricate inquiries (between processes and their variables) compared to relying solely on a single pre-existing model. Loose or soft coupling is often a necessary approach for linking disciplinary models for analysing the multi-functionality of landscapes, particularly when rapid (ex-ante) decisions are needed.

A known standard for model linkage in the water domain is The Open Modelling Interface and Environment (OpenMI), developed by a consortium of universities and private companies (Harpham et al., 2019). Their standard defines an interface that allows already existing or new fully developed time-dependent models to exchange data at runtime. However, when rapid decisions are needed, this might contribute to the rationale behind increased complexity, which is in contrast to our suggested stepwise framework. In the agricultural domain, a similar effort for linking the climate, crop, and economic modelling communities with information technology for producing improved crop, economic and climate projection models, is the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013; Ruane et al., 2017). Such modelling frameworks can often require the collection of extensive data that might make the integration process slower.

The proposed framework adopts a somewhat modular approach, wherein disciplinary models are carefully chosen (or designed) to interact in a manner that preserves the integrity of the original model (MIKE) or employs an even more streamlined version (CARBI model) which was designed to be linked. This concept resembles the 'plug and play' paradigm prevalent in contemporary software development, where model components engage seamlessly through standard communication protocols (Papajorgji, 2005).

This integrated modelling approach could be used for modelling the impact of potential nature-based solutions, including but not limited to meandering, ditch blocking, peatland and forest restoration, as well as the implementation of cover crops for even more fruitful discussions with stakeholders. However, the application of this modelling approach in this paper is intended to primarily take an exploratory approach.

Another noteworthy finding from this research underscores the necessity for increased transparency in models. It is not always readily apparent which data is utilized and what limitations are associated with them. This observation stems from the soil data requirements in MIKE, where Soil Organic Carbon (SOC) is not inherently treated as an exogenous factor, and MIKE can run without considering it. If one opts for the Mualem van Genuchten method to calculate soil hydraulic parameters, which significantly impacts the hydrology, especially in the unsaturated zone, carbon may be entirely overlooked. This oversight occurs despite the fact that pedo-transfer functions cannot compute the Mualem van Genuchten parameters without incorporating carbon, as evident in equations (4)–(9).

6. Conclusion

In this study, we introduce a stepwise conceptual framework to determine the level of integration that is necessary for integrated environmental modelling, using the Aa of Weerijs catchment as a case study. The study emphasizes the significance of coupling hydrological and carbon models and to demonstrate the potential utility of this approach for examining the effects of land use change in future discussions with stakeholders. The model coupling was achieved through a stepwise framework, involving an initial analysis of variables and scales, an exploration of their overlapping populations leading to a necessary sensitivity analysis, and adopting a loose coupling approach.

Environmental models play a central role in the effective planning and implementation of interventions and policies aimed at harnessing the benefits of landscapes. While disciplinary models have historically focused on specific functions, the need for integrated solutions has become apparent. Our research contributes to addressing this challenge by proposing a conceptual framework that bridges the gap between using existing disciplinary models and the imperative for integrated modelling, particularly showcasing the multifunctionality of landscapes.

The application of the case study and subsequent model runs reveals substantial differences between runs for both current and alternative land use scenarios when considered separately. Notably, the most significant difference arises between the initial carbon map used in the first MIKE run, derived from an existing database, and the subsequently modelled carbon map, entirely based on the CARBI model designed to fit the spatial scale of MIKE. While an overall increasing trend is observed between other runs, the final runs indicate carbon stabilization, with soil moisture continuing to show considerable increments. This highlights the interconnectedness of carbon and hydrology, underscoring the importance of comprehending the dynamics of these processes, which is challenging with separate disciplinary models. A relatively loose model integration was established in which the models were run iteratively.

Concerning alternative land use, distinct from current land use, the results suggest increased water storage in the unsaturated zone, particularly during dry periods, contributing to our understanding of the model's effectiveness in assessing drought conditions. In terms of carbon sequestration, the results are location-dependent, with some areas experiencing an increase leading to sequestration, while others exhibit a decrease resulting in emissions. These findings contribute valuable insights into the intricate interactions within the system and underscore the potential of the proposed modelling framework for informing discussions on environmental management and land use planning.

Software and data availability

1. Name of software for Hydrological model: MIKE SHE and MIKE 11 Flow Model

Developer: Danish Hydraulic Institute (DHI)
Contact information: https://www.mikepoweredbydhi.com.
Hardware and software requirements: e at least a 2 GHz CPU, 8–16 GB of RAM and 100–500 GB of free disk space.
Availability: https://www.mikepoweredbydhi.com/download/mike-2023.
Cost: license necessary.
The use data can be found in Table 2and the following sources: weather data (https://www.knmi.nl/), topography data - EU DEM at (CLMS, n.d.), vegetation data – Land Cover (CLMS, 2018) and crop parameters (NHI, 2008), soil data (https://esdac.jrc.ec.europa.eu/resource-type/datasets) based on (Ballabio et al., 2016).

2 Name of software for Carbon Model: CARBI (Linking module)

Developer: Borjana Bogatinoska Contact information: borjana.bogatinoska@ou.nl.
Year first available: 2023.
Program language: Excel.
Cost: free under Microsoft Office license.

Software availability

1 model run is showcased in the Supplementary Material 2.
The use data can be found in Table 2 and the following sources: weather data (https://www.weerstationkempen.be/template/indexDesktop.php), soil survey data for the Netherlands (https://bodemdata.nl/) and for Belgium (https://www.dov.vlaanderen.be/) and soil texture data from (https://esdac.jrc.ec.europa.eu/resource-type/datasets) based on (Ballabio et al., 2016) and vegetation data – Land Cover (CLMS, 2018).

CRediT authorship contribution statement

Borjana Bogatinoska: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft. **Angelique Lansu:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing. **Jean Hugé:** Supervision, Writing – review & editing. **Muhammad Haris Ali:** Investigation, Software. **Stefan C. Dekker:** Conceptualization, Supervision, Writing – review & editing. **Jetse Stoorvogel:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:
Borjana Bogatinoska reports financial support was provided by

European Union's Horizon 2020 research and innovation programme. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data is explained in the research article and submitted additionally as supplementary material

Acknowledgement

The authors greatly acknowledge the financial support by the European Union's Horizon 2020 research and innovation programme: the "EIFFEL project" (Grant No. 101003518) and the Interreg 2 Seas programme: the "Co-Adapt project" (Grant No. 2S06-023).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2024.106116.

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