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Quantifying spatially explicit LCA midpoint characterization factors to assess the impact of specific farming practices on ecosystem services

Sara Lago-Oliveira^{*}, Maria Teresa Moreira, Sara González-García

CRETUS, Department of Chemical Engineering, School of Engineering, University of Santiago de Compostela, 15782 Santiago de Compostela, Spain

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ABSTRACT

The Life Cycle Assessment (LCA) methodology is a scientifically sound tool, endorsed by the European Commission, for conducting environmental assessments. Despite its standardized approach, certain areas require improvement, particularly concerning impacts on ecosystem structure, function, and associated ecosystem services. Given the significant pressure of agriculture on global ecosystems, research has attempted to establish characterization factors (CFs) that reflect the impact of agricultural practices on ecosystem services. However, the current CFs lack precision and are unable to differentiate between the various types and intensities of agricultural management. This study aims to contribute to the evolving LCA field by introducing novel CFs that allow for the assessment of the impacts and benefits of growing wheat under different agricultural practices on three ecosystem services: water purification, soil erosion control, and carbon sequestration. Spatially explicit, nonlinear models (InVEST and RothC) were used, with the Galician region of northwestern Spain as the spatial setting. The quantified CFs indicated that wheat cultivated with conventional tillage, straw removal and without cover crop exhibited the least favorable outcomes in terms of ecosystem service supply, specifically water purification ($13.29 \text{ kg N}\cdot\text{ha}^{-1}\cdot\text{y}^{-1}$), soil erosion control ($11.71 \text{ t soil}\cdot\text{ha}^{-1}\cdot\text{y}^{-1}$), and carbon sequestration ($45.41 \text{ t C}\cdot\text{ha}^{-1}\cdot\text{y}^{-1}$). In contrast, the combination of conservation tillage, straw return and cover crop resulted in the highest ecosystem services gains ($-0.46 \text{ kg N}\cdot\text{ha}^{-1}\cdot\text{y}^{-1}$, $2.64 \text{ t soil}\cdot\text{ha}^{-1}\cdot\text{y}^{-1}$, $7.05 \text{ t C}\cdot\text{ha}^{-1}\cdot\text{y}^{-1}$, respectively). The geographical specificity of the CFs presented here, combined with the detailed classification of agricultural land use, offers essential insights into the potential gains and losses of ecosystem services resulting from various farming practices. This information can assist industry stakeholders and policymakers in making well-informed agricultural management decisions, and in developing strategies that prevent unintended environmental burden shifting.

1. Introduction

Agriculture is a vital sector for human survival and a key strategic activity on which political stability and economic development largely depend (Wells, 2015; United Nations, 2016; Ministry of Agriculture Livestock and Fisheries, 2019; Tsakok, 2020). This sector faces the significant challenge of providing food to a growing population with finite resources (United Nations Department of Economic and Social Affairs, 2023), while also addressing the effects of climate change on harvesting success (Rezaei et al., 2023). In addition, it plays a critical role in advancing several Sustainable Development Goals (SDGs) in the 2030 Agenda, including SDG 2 (zero hunger), SDG 5 (gender equality), SDG 6 (water), SDG 8 and 9 (economic growth), SDG 13 (climate) and SDG 15 (soil) (United Nations, 2016). In the environmental realm, the

achievement of a sustainable agriculture hinges on the implementation of effective crop management practices with the potential to markedly diminish the environmental impact of agriculture practices and enhance resource efficiency. Furthermore, in order for agriculture to be environmentally sustainable, it must also support natural ecosystem cycles and enhance ecosystem services (WWF, 2024).

The Life Cycle Assessment (LCA) is a standardized methodology used to evaluate the environmental performance of products, services, and organizations throughout their entire life cycle (ISO, 2006a, 2006b). The comprehensive coverage of this tool allows the assessment of impacts on a variety of environmental issues at each stage of the life cycle of the systems analyzed. This facilitates the identification of critical points and the examination of trade-offs between environmental concerns and life cycle stages (Sala et al., 2016).

^{*} Corresponding author.

E-mail address: saralago.oliveira@usc.es (S. Lago-Oliveira).

The ISO 14040 and 14044 standards (ISO, 2006a, 2006b) are the two core reference documents for LCA practitioners as they establish the LCA principles, framework, and methodological requirements. As detailed in the aforementioned standards, the LCA is comprised of four interrelated phases: (i) the definition of the goal and scope, (ii) the life cycle inventory (LCI), (iii) the life cycle impact assessment (LCIA), and (iv) the interpretation of the results (ISO, 2006a, 2006b). In the initial phase, the objective and intended use of the LCA study are explicitly stated. Furthermore, this phase involves detailing essential methodological elements, including the delineation of system boundaries, the specification of functional units, and the determination of the allocation procedures. In the LCI phase, data on inputs (e.g., energy and water consumption) and outputs (e.g., products, by-products, emissions to air, soil, and water) throughout the system life cycle are collected and quantified. In the LCIA, the inventory flows (i.e., stressors) are linked to environmental impact categories by means of characterization factors (CFs), which are derived from characterization models. This connection between stressors and environmental impacts is referred to as the cause-effect chain or impact pathway. Two distinct types of impact categories are identified depending on their position within the cause-effect chain. Midpoint impact categories provide an indication of the environmental impacts occurring at a level of the cause-effect chain situated between the stressors (LCI results) and before the endpoint level. In contrast, endpoint impact categories reflect environmental impacts at the end of the cause-effect chain. Endpoint categories can be aggregated into three primary areas of protection: human health, ecosystem quality, and resource availability. In the final phase of the LCA, the obtained results are interpreted in light of the objective and scope of the study.

In agriculture, LCA has been widely used to assess the environmental impact of different agricultural practices and crops production, with a focus on environmental areas such as climate change, water eutrophication, acidification, and toxicity (Raymond et al., 2020; Bishop et al., 2021; Costa et al., 2020; Mikosch et al., 2022). However, the impact of these practices on the structure and functioning of ecosystems and their associated ecosystem services has received little attention within the LCA field (Soulé et al., 2023; Taelman et al., 2024).

Ecosystem services are defined as “the contributions of ecosystems to the benefits that are used in economic and other human activity” (United Nations, 2021). Integrating ecosystem services into the LCA methodology represents a shift from traditional life cycle impact assessments, enabling the evaluation of both potential negative impacts of human interventions, and their potential benefits in protecting and restoring ecosystems (Liu et al., 2018a). For example, considering not only the impact of agricultural practices on climate change, but also their carbon sequestration potential; or assessing not only the level of water pollution, but also their potential to enhance the ecosystem’s mitigation capacity. In addition to providing a more holistic understanding of the environmental performance of agricultural practices, this approach can help identify practices operating within ecological limits (i.e., practices whose impacts are offset by ecosystem services), offering absolute environmental sustainability insights (Liu et al., 2018a; De Luca Peña et al., 2022).

The integration of ecosystem services into the LCA framework is an ongoing process, with preliminary research using a variety of methodological approaches. However, consensus on the most appropriate mechanisms has yet to be reached (Othoniel et al., 2019; Rugani et al., 2019).

At the level of inventory, Chaplin-Kramer et al. (2017) incorporated changes in ecosystem services supply due to land use changes as inventory flows, quantifying these changes at the agricultural stage to better capture impacts during the raw material sourcing. Similarly, Schaubroeck et al. (2013) integrated ecosystem services as internal system flows in the forestry sector. Boone et al. (2019) viewed ecosystem services as co-products of agricultural systems, allocating environmental impacts among these alongside primary crops. A similar approach was applied in an apicultural study, modelling pollination as a co-product

and conducting economic allocation between honey and the pollination service (Arzoumanidis et al., 2021).

From a mathematical standpoint, Liu et al. (2018a, 2018b) developed a computational structure for the Techno-Ecological Synergies (TES)-LCA framework, which incorporates ecosystem services into LCA assessments and captures the interactions between human activities and ecosystems. This framework expands the technological focus of LCA (i.e., how changes to the technological system may reduce impacts) to include the ecological perspective (i.e., how changes to the technological system may increase ecosystem services supply), thus reducing the risk of ecological overshoot (Liu et al., 2018a).

This perspective on environmental sustainability was echoed by Elliot et al. (2022a,b) in the context of urban areas, who developed ESTIMUM (Ecosystem Service Toolbox for Integrated Multi-scale modelling of Urban Metabolism), a dynamic framework for modelling ecosystem services changes driven by urban dynamics. Moreover, Almenar et al. (2023) proposed accounting for ecosystem service supply as positive impacts and aggregating these with the LCA midpoint impact categories through monetization to obtain a net value of nature-based solutions.

Another important stream of research focuses on integrating the impacts on ecosystem services at the midpoint and endpoint level of the impact pathway. The UNEP-SETAC Life Cycle Initiative framework (LULCIA) is particularly relevant, as it delineates the principles for developing CFs to assess land use impacts on ecosystem services (Koellner et al., 2013a). Several authors have developed CFs linking land-use interventions to impacts on various ecosystem services, such as carbon sequestration (Müller-Wenk and Brandão, 2010; Arbault et al., 2014; Othoniel et al., 2019; Alshehri et al., 2023; Blanco et al., 2018) biotic production (Brandão and Canals, 2013; Othoniel et al., 2019; Morais et al., 2019; Teixeira et al., 2018), nutrient cycling (Arbault et al., 2014; Alshehri et al., 2023), air filtration (Alshehri et al., 2023), pollination (Alejandro et al., 2022; Othoniel et al., 2019), water purification and erosion regulation (Saad et al., 2013; Alshehri et al., 2023).

Despite research efforts, most of these studies provide highly geographically aggregated CFs, using averaged values at the global, country, climatic, or ecoregion level, and covering broad land use classes (e.g., agriculture, forest, pasture and urban). Additionally, many CFs rely on statistical data or qualitative expert surveys, often failing to account for the spatial and temporal heterogeneity of ecosystem processes (Carpenter et al., 2009; Maia de Souza et al., 2018), thus limiting the ecological relevance of the results (Blanco et al., 2018). Notably, Alshehri et al. (2023) and Othoniel et al. (2019) developed CFs that consider this heterogeneity, with Othoniel et al. (2019) also incorporating feedback loops between ecosystems and human activities. However, their approach is limited to the municipal level and broad land use classes (e.g., “cropland”), while Alshehri et al. (2023) focuses solely on remediation technologies. As highlighted by Vidal Legaz et al. (2017), differentiating between management practices in agricultural systems is crucial for the assessment of practices and the delineation of appropriate sustainable strategies that take into account surrounding ecosystems.

In this context, the present study contributes to the ecosystem services-LCA integration research field by proposing a methodological framework for developing spatially explicit midpoint CFs to assess the impact and benefits of agronomic cultivated under diverse agricultural practices on the supply of three ecosystem services: water purification, soil erosion control, and carbon sequestration. Given the extensive time and resource requirements needed to calculate CFs for all crops and agricultural activities, it was deemed appropriate to narrow the scope of this study, with the intention of focusing on the wheat crop as a representative example. In this regard, midpoint CFs were developed for wheat cultivated under a combination of three agricultural practices: tillage intensity, stubble management, and cover cropping. Spatially explicit, non-linear models were used to derive these factors, capturing ecosystem dynamics and their time-spatial distribution, which were then translated into endpoint impacts using monetary methods. These

factors are tailored to the Galician region of north-west Spain and include a roadmap of the development process, providing the necessary material for future authors to replicate the process in other regions of the world, other agronomic crops and even consider other agricultural practices.

2. Methodology

2.1. Overall framework

The ecosystem service cascade model is a framework developed by Haines-Young and Potschin (2010) that conceptually depicts ecosystem services as relationships between nature and society through the interconnection of five key elements in a sequential manner. This begins with the biophysical structures and functions that give rise to ecosystem services and ends with the benefits and values that ecosystems provide to people (Potschin-Young et al., 2018) (Fig. 1).

In 2019, Rugani et al. proposed a revised version of the life cycle impact assessment (LCIA) cause-effect chain (stressor > midpoint effect > endpoint effect), using the lens of the ecosystem services cascade model (biophysical structure > ecological function > ecosystem service > benefit and value). This modification aimed to integrate ecological knowledge with the LCA framework to evaluate anthropogenic impacts on ecosystem service supply. In addition to the environmental impacts typically considered in conventional LCIA, this adaptation takes into account the potential benefits (supply of ecosystem services) that ecosystems can offer (Rugani et al., 2019).

The first component of Rugani's adapted LCIA cause-effect chain is the conventional life cycle inventory collection, encompassing all emissions, land, and resource flows associated with the studied system and which exert pressure on the biophysical structure of ecosystems. The second and third components reflect the impact on ecological processes and ecosystem services, respectively. In line with LCA perspective, these impacts are represented by midpoint indicators. The fourth element reflects the benefits and costs that changes in the supply of ecosystem services represent to end beneficiaries. In the context of LCA, these are accounted for as endpoint damage values.

The impact assessment pathway used in this study builds on the adapted LCIA cause-effect chain mentioned above, as illustrated in Fig. 1. This pathway serves as the conceptual foundation for evaluating

the impacts of agriculture on the supply of ecosystem services and understanding the connections between agricultural practices and their impact on ecosystem functioning.

A cause-effect chain starts with a stressor, which is any physical, chemical, or biological intervention resulting from an anthropogenic activity, such as use of resources, emissions to air, soil or water, or land use (European Commission, 2012). The studied impact pathway focuses on land use stressors, including both land occupation and transformation drivers that alter the biophysical structure of ecosystems and ultimately affect the ecological functions and the provision of ecosystem services. It is important to acknowledge that within the context of LCA, land occupation and transformation represent inventory elementary flows (Koellner et al., 2013a), meaning inputs from the environment into the system under study that have not undergone prior human alteration, as well as outputs from the studied system that have not been subjected to any human-induced transformation before reaching the natural environment (European Commission, 2012).

Following the LCIA cause-effect chain, the changes and impacts at the level of ecological functions and ecosystem services are presented by the midpoint indicators. Ultimately, the damage to areas that hold recognizable value to society, such as human health and well-being, is reflected by endpoint indicators (European Commission, 2012; Othoniel et al., 2019). From the perspective of the cascade model, endpoint indicators evaluate the gain or loss in goods and benefits delivered to people by assigning a damage value. To translate human interventions into impacts at the midpoint and endpoint levels, CFs derived from impact characterization models are required (ISO, 2006a).

In this study, we determine CFs that reflect the effects of various agricultural practices (stressors), in terms of land use intensity and transformation, on the delivery of three ecosystem services (midpoint indicators). Furthermore, the damage –either a gain or a loss– to the goods and benefits provided by each of the ecosystem services under study is quantified in monetary terms (endpoint values).

2.2. Stepwise approach to defining characterization factors

The following section presents a detailed, step-by-step description of the methodological framework proposed for the development of CFs to assess the impact of agricultural systems on the supply of ecosystem services and associated goods and benefits. These guidelines are

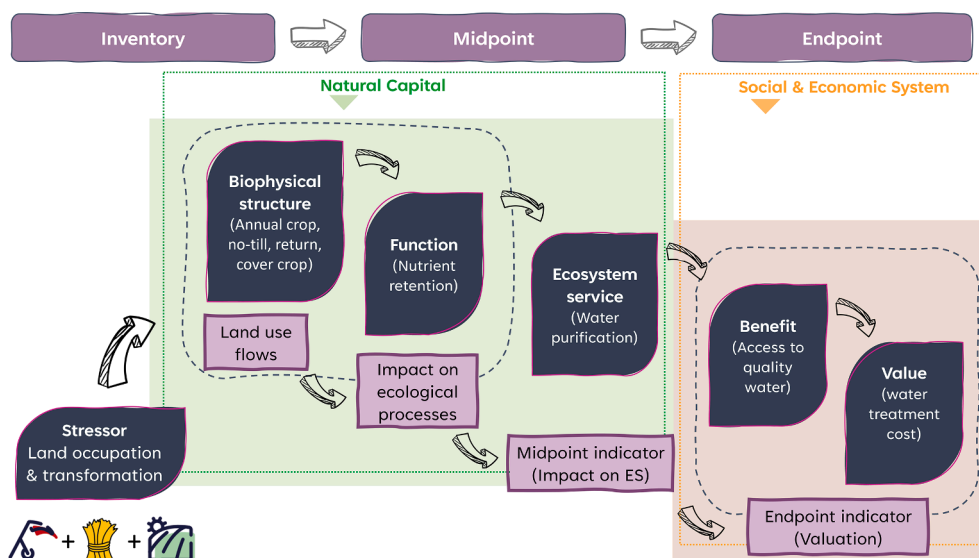


Fig. 1. Overview of the impact assessment pathway used in combination with the ecosystem service cascade model. Purple boxes at the top illustrate the position in the LCA cause-effect chain; dark boxes represent the different elements of the ecosystem services cascade model; and purple boxes at the bottom refer to sequence of impacts captured by the impact pathway. Acronyms: ES: ecosystem services. An example is provided in brackets. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

informed by the principles and recommendations set forth by Koellner et al. (2013b). It should be noted that wheat cultivation was selected for illustrative purposes; consequently, the CFs developed in this study are specific to this crop. Nevertheless, the objective of these guidelines is to provide a procedure that can be used to create CFs that are applicable to any agronomic crop, farming practice, and geographical region.

Step 1. Definition of the land use characterization model

The first step is to define the characterization framework that will be used to derive CFs, which involves specifying the cause-effect chain, geographic application, and reference state.

Environmental mechanism

The cause-effect chain studied here links land-use interventions with impacts at midpoint (ecosystem services supply) and endpoint level (valued gain or loss of goods or benefits). In particular, from the extensive list of ecosystem services defined by CICES v5.1 (including provisioning, regulation & maintenance and cultural ecosystem services) (CICES, 2018), this study focuses on three regulating services: water purification, control of soil erosion and carbon sequestration. These ecosystem services were selected because their provision is strongly influenced by the intensity and type of agricultural activities (Daryanto et al., 2017; European Commission, 2018; Xia et al., 2018; Jordon et al., 2022). Table 1 presents the specific impact pathway for each of the selected ecosystem services, with the proposed midpoint and endpoint impact categories.

Land use classes

New land-use interventions (land occupation and transformation inventory flows), representing different agricultural practices, were defined to account for the impact of these practices on ecosystem services. Specifically, eight land use classes (LULC) were proposed based on the combination of tillage practices, straw management and the use of cover crops (Fig. 2). Two options are possible for straw management and cover crops: returning or not returning straw to the field and using or not using cover crops. Moreover, three intensities of tillage were considered:

Conventional tillage: farming practice that involves the inversion of the soil profile by means of moldboard or a disc plough. This first operation is usually followed by a secondary tillage using a rotavating or disc harrow to flatten and level the surface (Blevins and Frye, 1993; Eurostat, 2023a).

Conservation tillage: low-intensity tillage that does not involve turning over the soil and leaves at least 30 % of the crop leftovers in the field (Eurostat, 2023a).

No-till or zero-tillage: farming approach in which no tillage is carried out and crop leftovers are left in the field (Eurostat, 2023a; Gellatly and Dennis, 2011).

By using a more exhaustive classification of agricultural land uses than that currently utilized in LCA methods (Chaudhary and Brooks, 2018; Wernet et al., 2016), this paper delves more profoundly into the environmental impacts of agricultural interventions, differentiating between various types and intensities of management practices. Note that there are no land uses that combine conservation or zero tillage without straw return, as these tillage practices include straw return to the soil by default. In addition, it is important to highlight that wheat was used as the default crop in the scenario modelling because of its relevant contribution to global food security and its productive importance in Spain (Kettlewell et al., 2023; Ministry of Agriculture, 2021).

Geographical resolution and scope

Specifying the geographical coverage of CFs is essential since the impacts associated with land use are spatially dependent, meaning that the same land use stressor in different regions may lead to different impacts (Koellner et al., 2013b). In this sense, in the present study, CFs were estimated at the regional level (Galicia, north-west Spain).

Reference state

In order to calculate the land-use related CFs, it is first necessary to select a baseline (reference state) for comparison with the evaluated scenario. This enables the magnitude of the impact to be determined, reflecting the difference between the ecosystem services provided in the evaluated land use and those potentially achievable in a scenario without anthropogenic interventions (Freer-Smith et al., 2022). The choice of the reference state among the several possible options will influence the obtained CFs (Koellner et al., 2013a; Alshehri et al., 2023). Following Milà i Canals et al.'s recommendation (2007), the (quasi-)natural land cover was adopted, which would allow to observe the different effects of land use among the different ecoregions.

Step 2. Quantification of ecosystem services

The delivery of ecosystem services varies depending on the geographical context, with factors such as climate, hydrology, soil and biota influencing the type and extent of ecosystem services provided. Additionally, the type of human management of the land also plays an essential role in their supply. Therefore, to quantify ecosystem services, it is essential to use spatially explicit models that take into account these location-specific factors. Three models, one for each ecosystem service, were used to determine the CFs for the different LULC classes studied for the Galician region. The models were run using the open source InVEST 3.14.1 Workbench from the Natural Capital Project (2024) and RStudio 2023.09.0 Build 463, with QGIS 3.28.10 used for spatial data management and processing. Below is a description of each model used to quantify ecosystem services, including its rationale, data requirements and intermediate processing and analysis.

Water purification

The Nutrient Delivery Ratio (NDR) from InVEST was considered to model the ecosystem service of water purification. This model maps nutrient loads at the watershed scale and their retention by the various ecosystems (purification services), that would otherwise end up in the stream. In particular, the nutrient nitrogen runoff was modeled as a proxy for this ecosystem service using a mass balance approach based on the nutrient inputs and retention efficiency per land use type.

The model requires a variety of data, which are presented in Table 2. The digital elevation model (DEM) from Copernicus Land Monitoring Service (2023) was used to take into account the topographic characteristics of the studied region. Based on this layer, the watershed and subwatersheds boundaries of the region were defined using the DelinateIt tool from InVEST 3.14.1 Workbench (Natural Capital Project, 2024). In addition, annual precipitation from TerraClimate (Abatzoglou et al., 2018) was used to estimate the nitrogen runoff potential

Table 1

Impact pathway for each ecosystem services and valuation mechanism of endpoint impact category (in brackets).

Inventory [Stressor]	Direct impact [Affected ecological structure & functions]	Midpoint impact category [Ecosystem service]	Endpoint impact category [Good or benefit]
Land occupation & land transformation	Changes in nutrient retention capacity	Water purification	Fertility maintenance (Fertilizers input costs)
Land occupation & land transformation	Changes in vegetation cover and soil erodibility	Soil erosion control	Productivity maintenance (Profit loss)
Land occupation & land transformation	Changes in soil organic matter content	Carbon sequestration	Productivity maintenance (Carbon credit revenues)

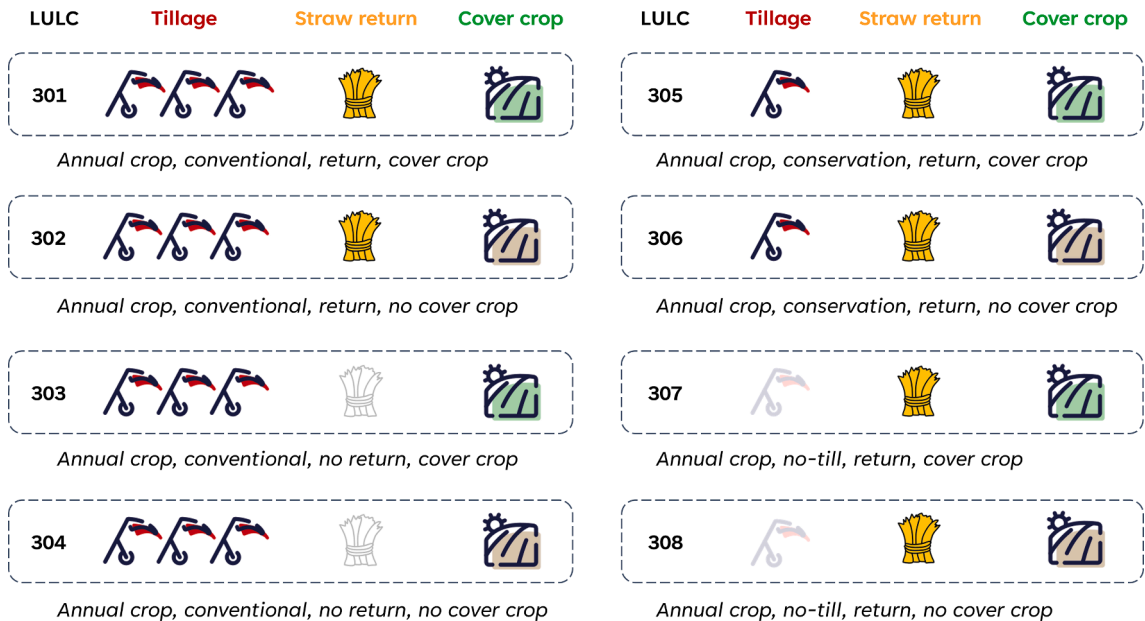


Fig. 2. Land use classes (LULCs).

downslope. Regarding land use, the LULC map of 2020 (Defourny et al., 2017) served as the basis for developing new LULC maps for the different scenarios studied (Fig. 2). Each new map was created by converting the entire land area to a specific agricultural LULC type, except for water bodies and barren areas, as well as natural areas in the reference LULC type, which remain unchanged.

The LULC map is an essential layer for quantifying the water purification ecosystem service because the parameters for nitrogen loads (e. g., amount of nitrogen exported), retention efficiency, and retention length depend on the specific type of LULC. Nitrogen load values, representing nitrogen that is not retained and therefore lost, were sourced from the InVEST database for the natural landscape (reference state scenario) in temperate climatic zone (2.12–11 kg·ha⁻¹) (Natural Capital Project, 2024). In the case of agricultural land uses, nitrogen loads were estimated based on the average nitrogen dose applied to wheat cultivation (52 kg·ha⁻¹) (Li et al., 2022), the nitrogen use efficiency (NUE), and nitrogen loss avoided of each agricultural practice (Equations (1) and (2)). It should be noted that, although the values of nitrogen load were selected to align as closely as possible with the Galician context (e. g., temperate region) in the absence of region-specific data, the chosen

values may not perfectly reflect the actual conditions in Galicia.

$$\text{Nitrogen uptake} = \text{NUE} \times \text{Nitrogen applied} \tag{1}$$

$$\text{Nitrogen load} = \text{Nitrogen applied} - \text{Nitrogen uptake} - \text{Nitrogen loss avoided} \tag{2}$$

The nutrient retention efficiency represents the proportion of nutrients retained in each LULC class. This parameter, also sourced from broader literature, was defined as 0.6 for the natural ecosystem according to the He et al. (2023), given the lack of region-specific data, and calculated using Equation (3) for each agricultural LULC. The retention length, or the distance that nitrogen must be transported to achieve maximum retention, was set at 25 m for all LULC scenarios, as recommended in the InVEST user manual. Table SM1 in Supplementary Material A summarized all data used to quantify nitrogen loads and retention efficiency parameters. Table SM2 presents the final inputs per LULC type used to model water purification.

Furthermore, two factors that are independent of land use were fine-tuned to improve the accuracy of the model simulation. The flow

Table 2
Summary of the data used for the quantification of ecosystem services.

Data	Format	Resolution	Model ¹	Reference
Land use/Land cover	Raster	300 m	1,2,3	(Defourny et al., 2017)
Digital elevation model	Raster	25 m	1,2	(Copernicus Land Monitoring Service, 2023)
Watersheds boundaries	Vector	–	1,2	Created with Delineatelt tool of InVEST (Natural Capital Project, 2024)
River network	Vector	–	1,2	(Autonomous Organization National Geographic Information Center, 2023)
Annual precipitation ²	Raster	4 km	1	TerraClimate (Abatzoglou et al., 2018)
Nitrogen loads	Numerical	–	1	Estimated (see main text)
Retention efficiency	Numerical	–	1	(He et al., 2023)
Retention length	Numerical	–	1	(Natural Capital Project, 2024)
Rainfall erosivity	Raster	1 km	2	European Soil Data Centre (ESDAC) (Panagos et al., 2022, 2017)
Soil erodibility	Raster	500 m	2	European Soil Data Centre (ESDAC) (Panagos et al., 2022, 2014)
Cover management factor	Raster	100 m	2	European Soil Data Centre (ESDAC) (Panagos et al., 2022, 2015a)
Practice factor	Raster	1 km	2	European Soil Data Centre (ESDAC) (Panagos et al., 2022, 2015b)
Climate data ³	Raster	4 km	3	TerraClimate (Abatzoglou et al., 2018)
Clay content in soil	Raster	500 m	3	European Soil Data Centre (ESDAC) (Ballabio et al., 2016)
Monthly vegetation cover	Raster	–	3	(NASA EOSDIS Land Processes Distributed Active Archive Center, 2015)
Fine particle content	Raster	1 km	3	European Soil Data Centre (ESDAC) (Hiederer, 2013)

¹ Model in which data were used. 1: Nutrient delivery model, 2: Sediment delivery model, 3: RothC model.

² Years: 2016–2021.

³ Montly temperature, precipitation and evapotranspiration (years: 1981–2020).

accumulation threshold, which represents the number of upstream pixels that must converge and flow into a single pixel for it to be considered part of a stream (Natural Capital Project, 2024), was set to 300 based on the region's river network (National Geographic Information Center, 2023), and the Borselli K parameter was adjusted to 0.5 after comparing model results with field observations reported by da Silva Días et al. (2019).

$$\text{Nutrient retention efficiency} = 1 - \frac{\text{Nitrogen load}}{\text{Nitrogen applied}} \quad (3)$$

The NDR InVEST model produces a map showing the amount of nitrogen that reaches the stream due to runoff, known as the nitrogen export map. This map was then converted to a nitrogen retention service map by subtracting the nitrogen export of the agricultural scenarios from that of the reference scenario.

Control of soil erosion

The InVEST Sediment Delivery Ratio (SDR) model was used to quantify soil erosion control, in particular the control of overland erosion, which is the process by which the top layer of soil is detached, transported, and redistributed across the land surface by the action of water flowing over the surface. Based on the Revised Universal Soil Loss formula (RUSLE, Renard et al. (1997)), the model quantifies the soil retention, which represents the ecosystem service of soil erosion control. Particularly, the model quantifies this ecosystem service by subtracting the soil erosion with landcover and management practices from the maximum soil erosion (e.g., in the absence of vegetation).

A number of factors influence the extent and severity of overland erosion, including rainfall intensity, topography, soil characteristics, and land use practices. Accordingly, DEM and watershed data were used to run the model, the sources of which are explained in section 2.1 *Water purification*. In addition, the model requires rainfall erosivity and soil erodibility data, the former referring to the intensity of precipitation and the latter to the susceptibility of soil particles to detachment and transport by water runoff. Both parameters were obtained from the European Soil Data Centre (ESDAC) portal of the Joint Research Centre as raster files (Panagos et al., 2022). Furthermore, the cover management factor (C-factor) and support practice factor (P-factor), both key elements to quantify the soil retention and linked to land use practices, were sourced from Panagos et al. (2015a, 2015b). Similar to the NDR model, LULC maps for the different scenarios were used, and each LULC class was assigned the average c-factor and p-factor specific to the Galician region. Table 2 provides a summary of the data used to run the model and its main characteristics. Additionally, Table SM3 in Supplementary Material A presents the specific values of the c-factor and p-factor used for each LULC class.

The flow accumulation threshold was set to 300 to more accurately represent the river network of the region (National Geographic Information Center, 2023) and to obtain better simulation results. Moreover, after calibrating the model using annual soil loss data from Panagos et al. (2015c) for the studied region, the maximum slope length parameter was set to 1, the Borselli IC0 and Borselli K parameters, to 0.5 and 2, respectively, and the maximum SDR value, which represents the portion of surface soil particles smaller than coarse sand (1000 µm), was set to 0.8.

Carbon sequestration

The carbon sequestration service was evaluated for each scenario using the RothC model (Coleman and Jenkinson, 1996). This process-oriented model estimates soil organic carbon (SOC) stocks and the changes over time based on the specific characteristics of the analyzed area. Following the quantification procedure developed by FAO (Peralta et al., 2022), the modelling of SOC stocks was carried out in two phases: i) initialization and ii) simulation phases.

During the initialization phase, the carbon inputs and shares of SOC among the five different compartments of the soil were determined, including decomposable plant material (DPM), resistant plant material

(RPM), microbial biomass (BIO), humified organic matter (HUM), and inert organic matter (IOM) compartments. The determination was based on the area's climatic, edaphic, and vegetation conditions, and assuming a decomposition rate of 1.44 for the conventional agricultural scenario (LULC 304, Fig. 2). Climate parameters, including monthly temperature, precipitation and evapotranspiration, were obtained from the TerraClimate database for the period 1980–2020 (Abatzoglou et al., 2018), clay content data was sourced from the ESDAC portal (Ballabio et al., 2016), and a vegetation cover map of Galicia, showing vegetated and bare areas, was obtained from NASA (2015).

In this phase, an initial layer of SOC was also required, which was calculated by first determining the maximum theoretical SOC capacity of the soil based on its mineralogical characteristics, and then, adjusting it to the actual SOC content achieved, taking into account the climate, vegetation, and management conditions (Georgiou et al., 2022). The maximum SOC capacity was calculated as a function of the amount of fine minerals (e.g., clay and silt) and their typology (minerals of high or low activity) (Equation (4) (Georgiou et al., 2022), where SOC_{min} is the maximum theoretical SOC capacity according to mineralogy, the factor m is associated with the mineral typology and represents the relationship between SOC_{min} and f , which is the fraction of fine mineral in the soil (%). The layer of fine mineral content across Galicia was obtained from ESDAC (Hiederer, 2013; Panagos et al., 2022), while m was derived from the model developed by Georgiou et al. (2022) assuming the occurrence of high activity minerals in the studied region (IPCC, 2019). Then, the actual SOC content achieved (SOC_{LULC}) was determined by multiplying SOC_{max} by the carbon saturation (C_{sat} , i.e., the carbon content at equilibrium) reported by Georgiou et al. (2022) for the natural and agricultural ecosystems (46 % and 31 %, respectively). The SOC map obtained for the natural land use was used as the reference state condition ($SOC_{LULC-nat}$) to calculate the CFs of carbon sequestration.

$$SOC_{min} = m \times f \quad (4)$$

$$SOC_{LULC} = SOC_{max} \times C_{sat} \quad (5)$$

In the simulation phase, RothC was run for a period of 20 years to model the SOC changes derived from changes in agricultural practices, starting from the conventional agriculture scenario as the basis. The 20-years running period was set based on the assumption that this is the time needed to reach a new equilibrium, as determined by the IPCC (Peralta et al., 2022). For this second phase, climate data from 2000 to 2020, clay content, and a land use map of the conventional agricultural scenario (LULC304, Fig. 2) were used. The other scenarios were modeled based on this scenario, assuming changes in carbon inputs and decomposition rates in response to their implementation. Decomposition rate factors associated with tillage practices were obtained from Jordon and Smith (2022), while carbon input factors were calculated based on each scenario's cover crop and stubble practices, taking into account the effects of tillage and cover crops on straw return rates in the calculation. Table SM4 in the Supplementary Material A summarizes the factors used to adjust carbon inputs and decomposition rate parameters for each agricultural scenario in RothC model. The data used for calculating the carbon input factors can be found in Table SM5 of the Supplementary Material A.

The amount and annual rate of SOC sequestration was calculated for each scenario by subtracting the baseline SOC stock (t_0 , 2020) from the stock after 20 years (t_{20} , 2040) (Equation (6)), and then dividing it by the simulated period (Δt , 20 years) (Equation (7)).

$$\text{SOC sequestered (t C-ha}^{-1}\text{)} = SOC_{t_{20}} - SOC_{t_0} \quad (6)$$

$$\text{Annual sequestration rate (t C-ha}^{-1}\text{.y}^{-1}\text{)} = \text{SOC sequestered} / \Delta t \quad (7)$$

Step 3. Calculation of midpoint characterization factors

In this step, the CFs for land occupation and transformation stressors

were quantified for each ecosystem service as the integral of the difference in the ecosystem's capability to deliver a service between the agricultural land use and the reference state over time (Equations (8) and (9), respectively) (Koellner et al., 2013b). CF_{occ} and CF_{trans} are the CFs for land occupation and land transformation stressors, respectively, Q_{ref} is the ecosystem service quantified for the reference state scenario, while Q_{LULC} represents the supply of ecosystem services estimated for one of the agricultural land uses. Since land transformation interventions are assumed to be reversible, it is necessary to account for the time it takes for the ecosystem to return to its natural state (t_{reg}). According to Brandão and Canals (2013), agricultural lands were assumed to return to their previous carbon sequestration levels 20 years after human intervention, while for water purification and soil erosion control, a regeneration time of 97 years was considered based on the estimates of Saad et al. (2013).

$$CF_{occ} = Q_{ref} - Q_{LULC} \quad (8)$$

$$CF_{trans} = (Q_{ref} - Q_{LULC}) \times 0.5 \times t_{reg} \quad (9)$$

It is important to note that the CFs for water purification were determined based on the decline in the ecosystem's ability to provide the service of water purification (nutrient export), in contrast to the approach used for CFs in soil erosion control and carbon sequestration, which focus on improvement (soil retention and SOC stocks, respectively). This led to an inverse interpretation, with positive CFs indicating benefits for water purification and detriments for the other two ecosystem services. As the LCA framework expresses environmental impacts in positive terms and environmental benefits as negative values (Bos et al., 2018), the CFs of water purification were multiplied by -1 to align with this logic. In this context, a negative value of CF indicates that the agricultural management practice contributes to reducing the impact on the supply of ecosystem services, as a larger amount of ecosystem services is generated than that provided in a natural state reference condition. Conversely, a positive CF implies an increased impact on the ecosystem services supply, as the ecosystem services generated by the agricultural management practice are less than those in a natural state reference condition.

Step 4. Midpoint impact quantification

To evaluate the effects of land-use interventions on ecosystem service supply, the interventions were multiplied by the corresponding CFs, as described in Eq. (10) and Eq. (11) for impacts resulting from land occupation and land transformation, respectively.

$$I_{occ} = CF_{occ} \times T_{occ} \times A \quad (10)$$

$$I_{trans} = CF_{trans} \times A \quad (11)$$

I_{occ} and I_{trans} refers to the impact resulting from occupation and transformation interventions, respectively, T_{occ} represents the occupation time (in years), and A denotes the occupied area (in hectares). The impact of land transformation should be allocated over a period of 20 years, in accordance with Koellner et al. (2013a), to avoid attributing the entire impact to the first year of intervention. These values (I_{occ} and I_{trans}) can be combined to obtain a single land use impact (I).

Step 5. Endpoint impact quantification

Endpoint indicators represent damage to the Areas of Protection: human wellbeing, ecosystem quality, and resource availability. Considering that the goods and benefits provided by ecosystem services are resources that society wishes to safeguard, they were quantified as endpoint damage indicators. In accordance with the rationale of ReCiPe (Huijbregts et al., 2017) and the Stepwise (Schmid and de Saxcé, 2016; Weidema, 2009) methods, in the context of the resource availability AoP

the endpoint damage indicators were defined in monetary units.

As the specific goods and benefits provided by ecosystem services may be subject to multiple interpretations and perceptions depending on the specific individuals and societal groups involved, it is first necessary to identify the target beneficiaries of these goods and benefits (Natural Capital Project, 2024; Olander et al., 2018; Wieland et al., 2016). In this study, farmers were selected as the target beneficiaries due to their central role in implementing sustainable agricultural practices (World Economic Forum, 2022).

There is a wide spectrum of monetary valuation methods, including market price, travel cost, budget constraints, among others (Pizzol et al., 2015). In this study, different monetary valuation methods were used depending on the ecosystem service analyzed.

In the case of the benefits derived from the water purification service, the valuation was based on the economic impact of nitrogen runoff, specifically the cost incurred by farmers to replenish lost nitrogen through additional fertilization, following the replacement cost method. The underlying rationale is that a higher supply of water purification service implies more nitrogen being retained in the soil, reducing the need for fertilizers. Conversely, a decline in this service implies that more nitrogen is being lost from the land, which farmers must compensate for by applying additional fertilizers. Nitrogen prices for the European market during the years 2021–2023 were sourced from the European Commission (2023).

In regard to soil erosion control, the provision of this ecosystem service confers benefits on farmers by maintaining soil fertility and, in the longer term, preventing a reduction in productivity. Accordingly, the production approach was selected, whereby the monetary value of the non-market benefits (such as soil fertility) is determined based on the direct economic impact on market goods (specifically, agronomic crops) when the supply of these benefits changes. The benefits from this ecosystem service were quantified on the assumption of an 8 % reduction in crop production for the areas where erosion rates exceeded $11 \text{ t} \cdot \text{ha}^{-1} \cdot \text{y}^{-1}$, in accordance with Panagos et al. (2018). FAO's database was used to obtain the average wheat yield ($3.19 \text{ t} \cdot \text{ha}^{-1} \cdot \text{y}^{-1}$), crop price for the period 2018 and 2023, along with the average exchange rate of $0.88 \text{ €} \cdot \text{USD}^{-1}$ for the same period (FAO, 2023).

Similarly to soil erosion control, carbon sequestration primarily benefits farmers by helping to maintain productivity. This is particularly important as climate change can significantly impact crop production by altering the frequency and timing of precipitation and temperature (Rezaei et al., 2023). Abramoff et al. (2023) estimated the reduction in yield associated with one-degree Celsius increase in temperature. However, the quantity of greenhouse gas emissions required to cause such a temperature rise is difficult to obtain. Due to the lack of data on this linking aspect, the price of carbon credits was used as a proxy indicator of productivity (Table 1). The price of carbon credits from the World Bank ($18.09 \text{ USD} \cdot \text{t CO}_2 \text{ eq}^{-1}$) for the period 2018–2023 were considered as the endpoint CF (The World Bank, 2023).

The Net Present Value was used to quantify all endpoint CFs by weighing the prices with a discounting factor (Hauschild et al., 2018), which, in this study, was considered as 3 % based on (Keeler et al., 2016). Endpoint CFs can be used to quantify impact at endpoint level ($I_{endpoint}$) by multiplying them with midpoint impact ($I_{midpoint}$) (Equation (12)).

$$I_{endpoint} = I_{midpoint} \times CF_{endpoint} \quad (12)$$

2.3. Uncertainty

To estimate uncertainties for each midpoint CF, the maximum and minimum simulated values of the ecosystem service were calculated, considering the maximum and minimum values of the data required by the models (Equation (13) and (14), where ES_{max} refers to the maximum accounted ecosystem service and ES_{min} to the minimum accounted ecosystem service). Equation (15) was used to calculate the uncertainty

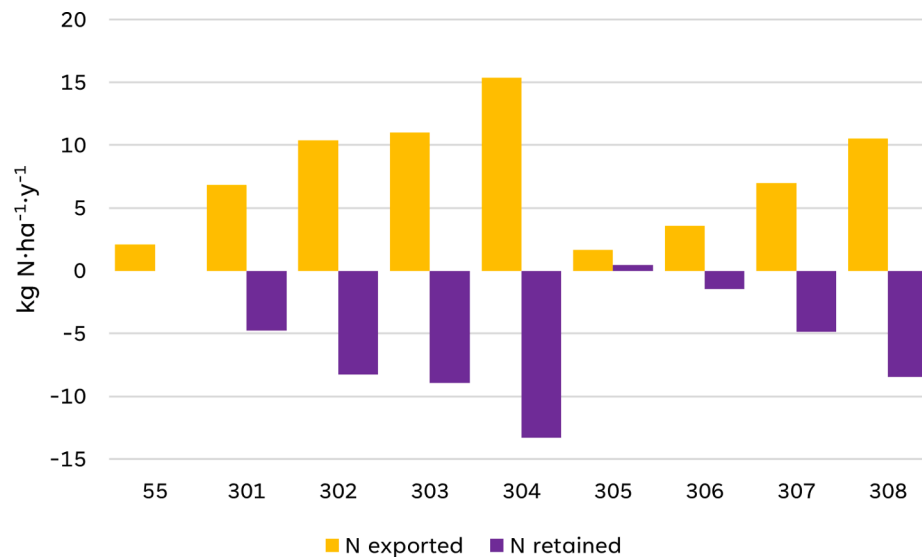


Fig. 3. Average nitrogen (N) export and retention rates per land use class.

(%) of each CF, taking into account the average CF, as well as the maximum and minimum CFs (CF_{max} and CF_{min} , respectively) obtained with ES_{max} and ES_{min} .

$$ES_{max} = Model(parameters_{max}) \quad (13)$$

$$ES_{min} = Model(parameters_{min}) \quad (14)$$

$$U(\%) = \frac{100 \times (CF_{max} - CF_{min})}{2 \times CF} \quad (15)$$

3. Results and discussion

3.1. Quantification of ecosystem services supply

3.1.1. Water purification

Fig. 3 presents the average nitrogen export and retention for each LULC scenario in the Galician region. Conventional tillage scenarios exhibit the highest nitrogen exports, particularly LULC 304 (15 N kg·ha⁻¹·y⁻¹), due to the absence of cover crops or straw return. No-

tillage scenarios exhibit levels of nitrogen export comparable to those of conventional tillage scenarios (e.g., 7 and 11 N kg·ha⁻¹·y⁻¹ for LULC 307 and 308, respectively). However, the scenario that included the cover crop practice (e.g., 307) results in reduced nitrogen runoff (34 % less than LULC 308). Conservation tillage leads to the lowest nitrogen export values, even slightly lower than the reference scenario in the case of LULC 305 (0.22 %), which also incorporates cover crops along with conservation tillage and returning of the straw. In examining prior studies on the decline in this ecosystem service, Sieber et al. (2021) estimated significantly higher N export for intensively managed agricultural lands, between 45 and 51 kg·ha⁻¹·y⁻¹, due to the fact that they are located on hilly slopes. Additionally, Rioux and Strong (2023) measured an average N loss of 7.8 kg·ha⁻¹·y⁻¹ for an agricultural area without differentiating between intensities.

According to Pärn et al. (2012), an analysis of peer-reviewed journal articles published between 1995–2011 on nitrogen transport dynamics in temperate climate zones revealed that lands under intensive agriculture experienced nitrogen loss ranging from 1.5 to 12 kg·ha⁻¹·y⁻¹, while extensive management had an average loss of 0.3 to 3 kg·ha⁻¹·y⁻¹.



Fig. 4. Average soil erosion and soil retention rate per land use class.

These results support the notion that more extensive agricultural land uses result in lower nitrogen loss rates, consistent with those obtained in the present study. However, the present study reports varying performance depending on the type of farming practice within the extensive practices, indicating nitrogen loss rates for non-till scenarios beyond the ranges previously described by Pärn et al. (2012) for extensive agriculture. The same increase in N loss in no-till practices was pointed out by Daryanto et al. (2017), who added that zero-tillage management should be complemented with additional farming practices, including cover crops and the optimization of N application, to observe an improvement in N export trends. This observation is in compliance with the results presented here, which report a 34 % reduction in N export when no-till is combined with cover crop practices (e.g., LULC 307 vs LULC 308, no-till scenarios combined with cover crops and alone, respectively).

Nitrogen retention (Fig. 3) represents the capacity of the ecosystem to retain N. Consequently, negative N retention values, as observed in the LULC 301, 302 and 303, among others, indicate a reduction in the capacity to retain N and thus a loss in the water purification ecosystem service. Conversely, positive N retention values represent an increase in capacity and thus a gain in the ecosystem service.

As illustrated in Fig. 3, nitrogen retention presents an inverse pattern to nitrogen export, with the LULC scenarios with the highest nitrogen export having the lowest nitrogen retention and vice versa. LULC 305 is the only land use class with positive nitrogen retention, suggesting that conversion from a (quasi)-natural state to LULC 305 could enhance the water purification service, by approximately 0.45 kg of N per hectare per annually. Conversely, for the other agricultural scenarios, the conversion would result in higher nitrogen losses than in the reference state, ranging from 1 to 13 N kg loss·ha⁻¹·y⁻¹. Table SM6 in the [Supplementary Material A](#) summarizes the nitrogen export and retention results for all LULC scenarios.

An examination of the spatial patterns of nutrient retention and export (Figure SM1 in the [Supplementary Material B](#)) reveals that these processes also follow opposite trends at geographical level, with the greatest nitrogen export occurring in areas near streams and at high elevations, and the greatest retention occurring in areas far from watercourses and on flatter terrain. As detailed by Terrado et al. (2014), who also observed a comparable spatial distribution of nitrogen retention in the Llobregat basin (northeast Spain), this distribution is explained by the lack of sufficient distance for vegetation to retain nutrients in areas closer to rivers and by the higher N loads from upper slopes ending in contiguous flatter areas. These regional differences suggest that relying on average regional retention values, rather than site-specific ones, may affect the accuracy of the environmental assessment. For instance, in certain areas of the region, the LULC 306 scenario reports positive retention rates, despite the average figure indicating a net nitrogen loss.

3.1.2. Control of soil erosion

Fig. 4 shows the average soil erosion rate for each scenario in the Galician region. The scenarios that use conventional tillage exhibit the highest erosion rates, while scenarios characterized by a lower intensity of tillage show significantly lower values (between 56 % and 82 % lower).

According to Eurostat's (2023b) classification of soil erosion intensity, which categorizes low erosion as below 5 t·ha⁻¹, moderate erosion as between 5 and 10 t·ha⁻¹, and severe erosion as more than 10 t·ha⁻¹, the LULC scenarios that apply conventional tillage exhibit severe (e.g., 302 and 304) and moderate levels (e.g., 301 and 303) of soil erosion, while the remaining scenarios do not exceed the 'low erosion' threshold. However, even scenarios classified as "low erosion" exceed the European soil formation rate (1.4 t·ha⁻¹·y⁻¹), as reported by Verheijen et al. (2009). Only the (quasi)-natural reference state (LULC_{nat}), which is the scenario with the lowest soil erosion (e.g., 0.32 t·ha⁻¹·y⁻¹), 97 % lower than the most erosive scenario (e.g., LULC 304: 12.03 t·ha⁻¹·y⁻¹), stays within the rate of soil formation. Sieber et al. (2021) documented moderate soil erosion values for agricultural lands in the Azores (Portugal), with an average of 5 t·ha⁻¹·y⁻¹ for irrigated crops and 7 t·ha⁻¹·y⁻¹ for rainfed crops. Terrado et al. (2014) estimated a significantly higher sediment export rate (22 t·ha⁻¹·y⁻¹), which could be explained by the higher erodible characteristics (k-factor) of the study area compared to Galicia (Panagos et al., 2014) and a drier climate (Masroor et al., 2022). In turn, Panagos et al. (2015c) quantified erosion rates across Europe and obtained moderate to severe soil erosion for agricultural lands in the Galician region.

The maps displaying the distribution of erosion intensity across the Galician region for the nine scenarios (Figures 6–10 of the [Supplementary Material B](#)) illustrate that the upper part of Galicia and two vertical strips, one on each side of the region, have the highest erosion rates regardless of the scenario considered, similar to the spatial pattern reported in the JRC's soil erosion map for Galicia (Panagos et al., 2015c). These areas with high erosion correspond to locations where soil particles are more susceptible to detachment and transport by water, such as the top and right strips. Moreover, the higher soil erosion on the left strip has been attributed to the higher rainfall intensity in the area, and in the case of the right strip, the higher topographic elevation has been also found to be a relevant factor. These findings are consistent with those of Sieber et al. (2021), who also identified topographic elevation as a contributing factor, and Kulsoontornrat and Ongsomwang (2021), who observed that rainfall was one of the most significant factors influencing sediment exports.

In line with results obtained for the soil erosion rate, the reference state scenario has the highest soil retention, followed by the low-intensity tillage scenarios. Conversely, LULC 304 has the lowest soil retention among the conventional tillage scenarios, exhibiting a 15 % reduction in soil retention compared to the (quasi)-natural scenario. The

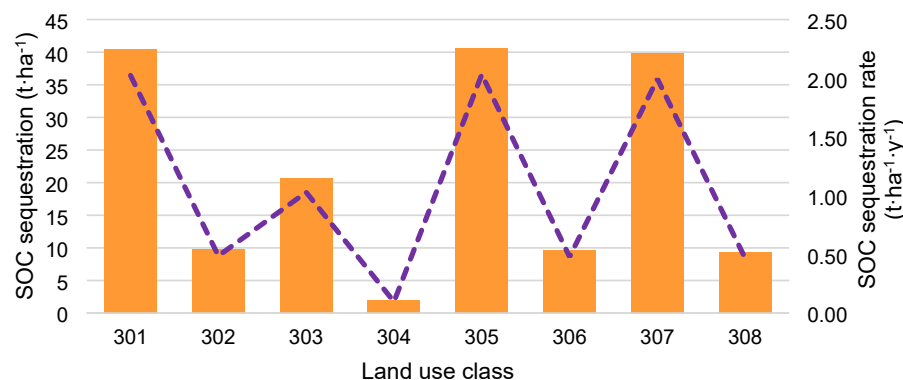


Fig. 5. Average soil organic carbon (SOC) sequestration capacity (orange) and SOC sequestration rate (purple) per land use class. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3Summary of midpoint characterization factors (CF) for land occupation stressors (CF_{occ}) and land transformation stressors (CF_{trans}) per land use class (LULC).

LULC code	LULC name	Midpoint CF _{occ}			Midpoint CF _{trans}		
		Water purification (kg N·ha ⁻¹ ·y ⁻¹)	Soil erosion control (t soil·ha ⁻¹ ·y ⁻¹)	Carbon sequestration (t C·ha ⁻¹)	Water purification (kg N·ha ⁻¹)	Soil erosion control (t soil·ha ⁻¹)	Carbon sequestration (t C·y·ha ⁻¹)
301	Annual crop, conventional, return, cover crop	4.74	8.14	7.22	229.67	395.22	72.20
302	Annual crop, conventional, return, no cover crop	8.27	10.26	37.67	401.04	497.89	376.70
303	Annual crop, conventional, no return, cover crop	8.91	9.30	26.94	432.10	451.23	269.35
304	Annual crop, conventional, no return, no cover crop	13.29	11.70	45.41	644.65	567.90	454.06
305	Annual crop, conservation, return, cover crop	−0.46	2.64	7.05	−22.19	128.28	70.46
306	Annual crop, conservation, return, no cover crop	1.46	3.38	37.83	70.64	164.22	378.30
307	Annual crop, no-till, return, cover crop	4.87	1.79	7.80	236.23	87.21	78.01
308	Annual crop, no-till, return, no cover crop	8.43	2.32	38.09	408.96	112.88	380.90

sediments retention rate per LULC is presented in Figure SM1 of [Supplementary Material A](#). Additionally, Table SM7 of the [Supplementary Material](#) provides soil erosion and sediment retention rates for each LULC.

3.1.3. Carbon sequestration

The analyzed region exhibits an average SOC sequestration ranging from 1.94 t SOC·ha⁻¹ to 40.65 t SOC·ha⁻¹, with a sequestration rate ranging from 0.10 to 2.03 t SOC·ha⁻¹·y⁻¹. The scenarios that implemented straw return and cover crop practices report the highest levels of carbon sequestration (39.88, 40.47 and 40.65 t SOC·ha⁻¹, 307, 301 and 305, respectively), demonstrating minimal variation contingent on the tillage practice implemented (between 0.4 % to 1.5 % variation) ([Fig. 5](#)). In contrast, the conventional agricultural land use (LULC 304: conventional tillage with no straw return and cover crop practices) reports the lowest level of carbon sequestration (1.94 t SOC·ha⁻¹). Under conventional tillage, the use of cover crops increases carbon sequestration more than returning straw to the field. This is evidenced by the notable discrepancy in carbon sequestration rates observed between LULC 302 (0.49 t SOC·ha⁻¹·y⁻¹) and 303 (1.93 t SOC·ha⁻¹·y⁻¹) ([Fig. 5](#)), where the former uses straw return and the latter uses cover crop.

In accordance with our findings, a report from the European Environment Agency (EEA) identified carbon sequestration rates varying from 0.2 to 1.6 t SOC·ha⁻¹·y⁻¹ depending on the farming intensity ([EEA, 2023](#)). Similarly, [Lal \(2018\)](#) reported carbon sequestration rates between 0.25 to 1 t SOC·ha⁻¹·y⁻¹ for arable lands. Furthermore, an analysis of studies on regenerative agriculture published between 2002 and 2020 revealed that regenerative agriculture can increase SOC by up to 3 t·ha⁻¹·y⁻¹ ([Rehberger et al., 2023](#)).

Moreover, in a previous study on carbon farming conducted by the European Parliament ([McDonald et al., 2021](#)), cover crops were already highlighted as one of the agricultural practices with the highest potential to increase SOC stocks, with SOC increments ranging from 0.21 to 0.56 t·ha⁻¹·y⁻¹ according to [Rehberger et al. \(2023\)](#). Nonetheless, returning straw to the field is also considered a relevant practice to increase SOC content (between 27 % to 75 % increase in words of [Chatterjee et al. \(2021\)](#)), which can vary depending on a series of variables, including the C:N ratio of crop residue, which affects the decomposition rates and ultimately, the SOC dynamics ([Chatterjee et al., 2021](#)). Regarding

different tillage intensities, a study comparing SOC sequestration rates between reduced tillage and conventional tillage (e.g., moldboard plow) in organic agricultural fields across several European countries (e.g., Netherlands, Switzerland, France, and Germany) found that reduced tillage increased SOC levels by 20.8 % in the upper part of soil ([Krauss et al., 2022](#)), compared to our 0.4 % to 1.5 % variation. This difference in results can be attributed to the fact that non-mineral fertilizers were used in the aforementioned study, which contribute to the lower mineralization rate and higher C inputs (associated with the substitution of synthetic fertilizers by organic amendments).

With regard to greenhouse gas emissions, the land use with the highest carbon sequestration avoids an average of 7.31 to 7.45 t of CO₂ per hectare per year, which exceeds Spanish per capita emissions (6.37 t CO₂eq·hab⁻¹ in 2022; [Instituto Nacional de Estadística, 2024](#)). Additionally, despite the low carbon sequestration rate of conventional agriculture (LULC 304, 20 times lower than that of 305), this land type avoids emitting 356 kg of CO₂ per hectare per year (equivalent to 6 % of Spanish per capita emissions). The results of the carbon sequestration service are presented in Table SM8 of [Supplementary Material A](#), accompanied by an explanation of the procedure followed to estimate the GHG emissions.

Upon examining the spatial distribution of carbon sequestration capacity (Figure SM3 in [Supplementary Material B](#)), a correlation between the distribution of fine minerals and carbon sequestration rates can be observed. Specifically, areas with higher carbon sequestration rates have higher shares of fine minerals, as illustrated in the fine minerals distribution map provided by [Hiederer \(2013\)](#). Furthermore, a region with higher carbon sequestration rates is observed on the right side of the region, which coincides with the highest altitude, a remarkable factor in the distribution of carbon stocks, as previously noted by [Luis Calvo et al. \(2015\)](#).

3.2. Midpoint & endpoint impacts

3.2.1. Midpoint characterization factors

The midpoint CFs for land use pressures have been calculated as the difference in ecosystem services supplied between the reference state scenario (LULC_{nat}) and each agricultural land use (e.g., LULC 301, 302, etc.) (Equation (8)). Specifically, CFs for water purification have been

determined by subtracting the difference in nutrient export, and for soil erosion control, by subtracting the difference in soil retention. Regarding the SOC sequestration service, CFs have been quantified as the difference between the attainable SOC in the (quasi-)natural state ($SOC_{LULCnat}$) and the SOC stocks of each agricultural land scenario. As detailed in the Methodology section, the CFs for water purification have been multiplied by -1 to align with the rationale used by the LCA framework, in which positive values are attributed to environmental impacts and negative values to environmental benefits. This adjustment

is consistent with established practices, as evidenced by the work of Saad et al. (2013) and Bos et al. (2018). Table 3 presents the average regional midpoint CFs for both land occupation and land transformation stressors. Furthermore, Figs. 6A and 6B display site-specific CFs that assess impacts when the activity's precise location is known.

In 2013, Saad et al. developed spatially differentiated CFs to assess the impact of land occupation on various ecosystem services at the regional level, using Holdridge life zones. For erosion regulation, they reported a global average of $31.13 \text{ t soil} \cdot \text{ha}^{-1}$ for "permanent and annual

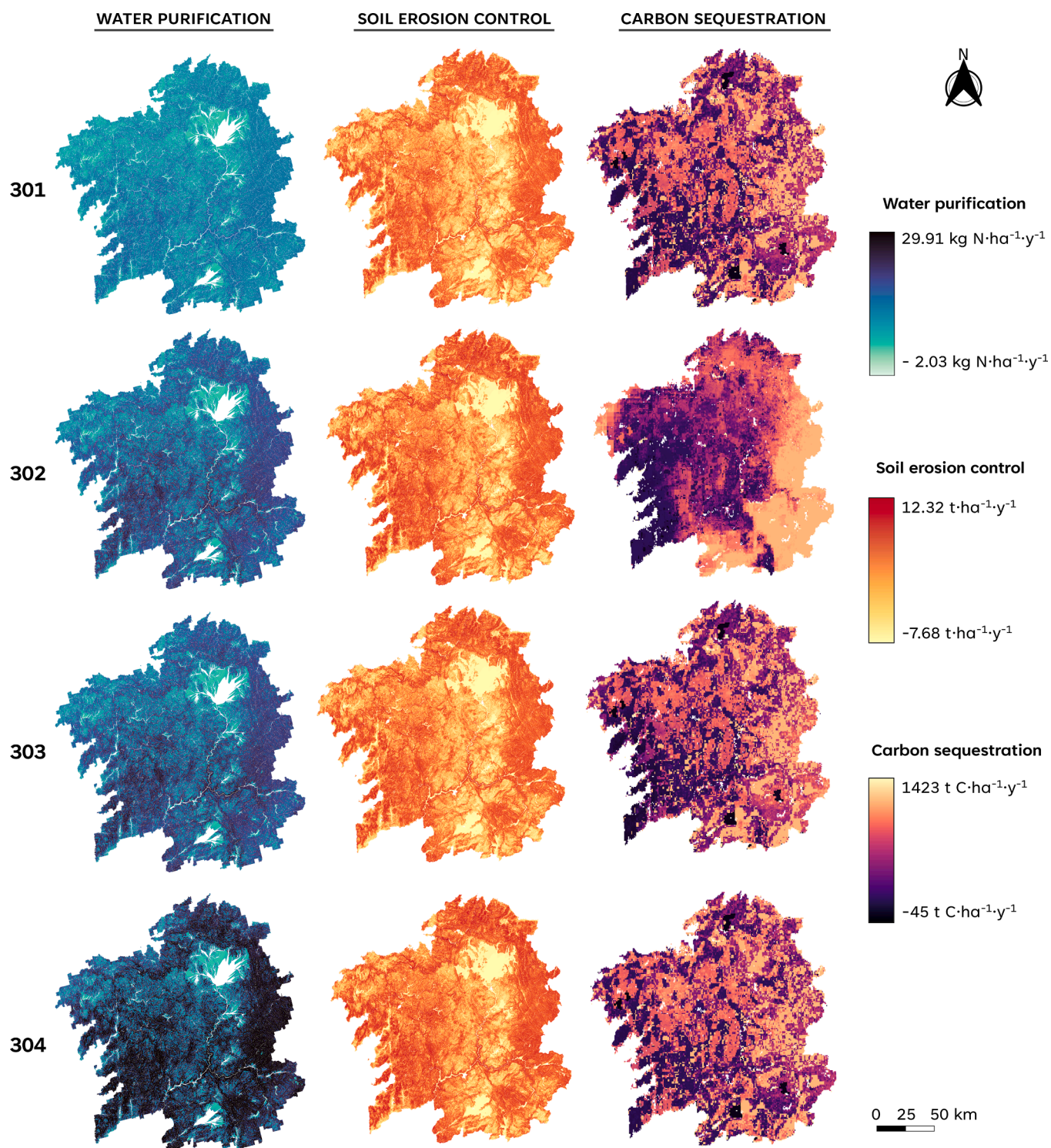


Fig. 6A. Spatial distribution of midpoint characterization factors for land occupation stressor for land use classes 301, 302, 303 and 304.

crops” and an average of $13.45 \text{ t soil}\cdot\text{ha}^{-1}$ for the Holdridge cool temperature region, which is in close alignment with our results, especially for the conventional agriculture class (LULC 304).

The occupation CFs of carbon sequestration services quantified in this study are also very much in line with those reported by Teixeira et al. (2018b) ($23.13 \text{ t C}\cdot\text{ha}^{-1}$) and Brandão and Canals (2013) ($23.47 \text{ t C}\cdot\text{ha}^{-1}$), although with certain variations depending on the land use class due to the agricultural diversity considered in this study compared to the general, aggregated agricultural class used in those studies. In

turn, Teixeira et al. (2021) presented an average occupation CF of $154.57 \text{ t C}\cdot\text{ha}^{-1}$ for agricultural lands, with a wide range of variation from 30 to $600 \text{ t C}\cdot\text{ha}^{-1}$. As argued by the authors, differences in data sources may explain this divergence, noting variations in the level of resolution and initial SOC values compared to other studies, which may cause significant variations in the results (Lal, 2018; Teixeira et al., 2021). Additionally, methodological assumptions, such as the reference state scenario chosen, may also contribute to this divergence (Koellner et al., 2013b). Regarding CFs representing the impact on the nutrient

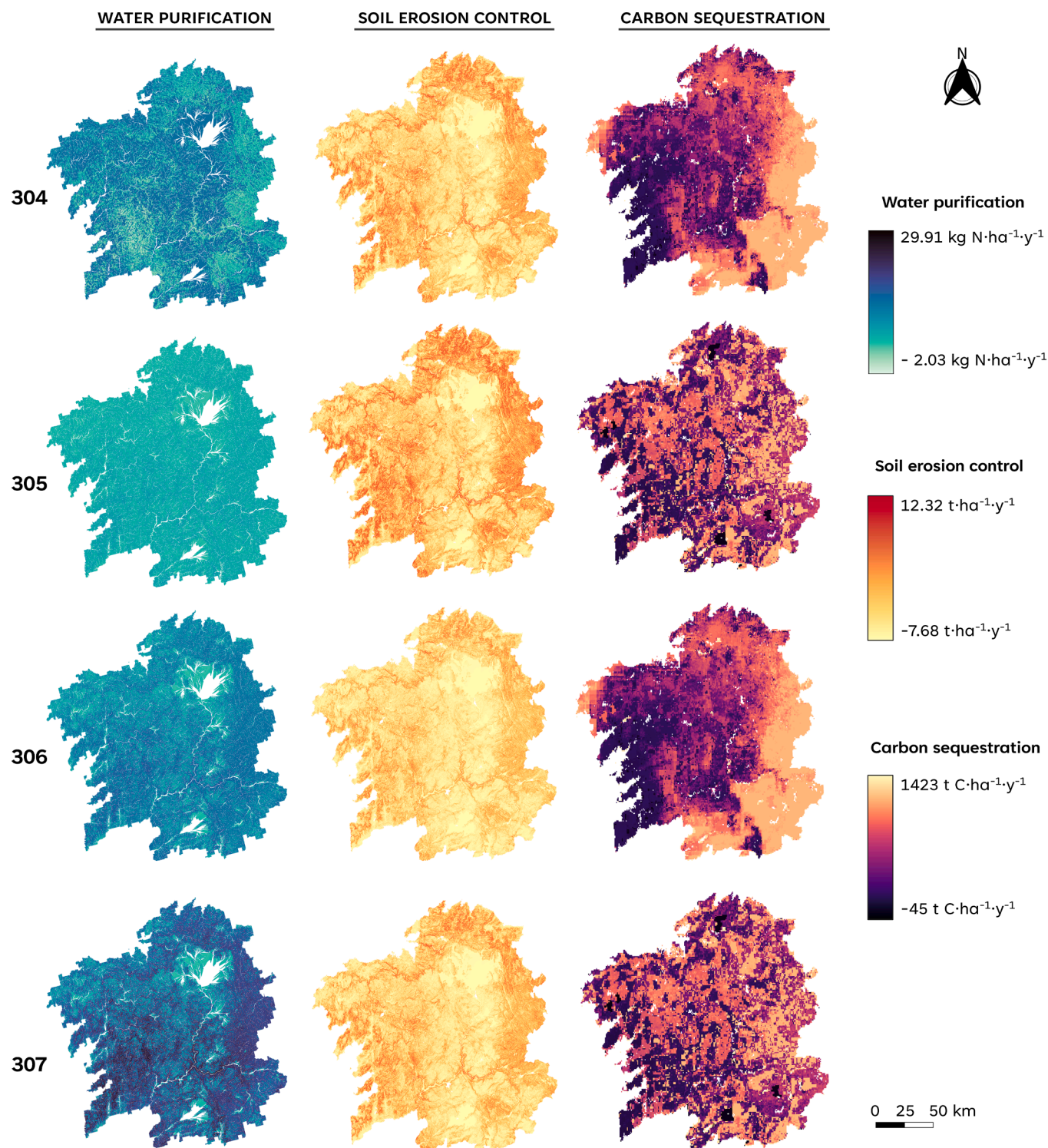


Fig. 6B. Spatial distribution of midpoint characterization factors for land occupation stressor for land use classes 305, 306, 307 and 308.

retention service, no comparison could be made due to the lack of alignment with available studies addressing this aspect in terms of impact characterization model.

Table SM9 in the [Supplementary Material A](#) presents the uncertainty values for each midpoint CF. According to FAO (2022), CFs show an acceptable degree of variability, with values ranging from 0.1 % to 20 % for soil erosion control and from 30 % to 72 % for carbon sequestration. The case of water purification is slightly different, with most land use classes falling within the acceptable threshold, but a few, namely LULC 305 and 306, showing important uncertainty levels. This could be attributed to the data used to model the different scenarios, highlighting the need to improve access to quality data for modelling ecosystem service supply.

3.2.2. Endpoint characterization factors

The monetization of impacts on ecosystem services and environmental impacts in general is still in its early stages, with ongoing initiatives contributing to its development, such as the Environmental Valuation Reference Inventory (EVRI) database ([Environment and Climate Change Canada, 2023](#)), and the Environmental Prices Handbook (CE Delf, 2023). The incorporation of economic valuation in terms of endpoint indicators allows for direct comparisons with economic profits or costs, thereby providing a tangible representation of aspects that are often considered abstract and diffuse and facilitating the decision-making processes. Three endpoint CFs have been developed for the purpose of assessing the impact on the benefits provided by each one of the ecosystem services under study. A value of $0.54 \text{ €} \cdot \text{t N loss}^{-1}$ was attributed to water purification, reflecting benefit of maintaining soil fertility. A value of $51 \text{ €} \cdot \text{t soil loss}^{-1}$ was attributed to control of soil erosion, and a value of $54 \text{ €} \cdot \text{t C loss}^{-1}$ (i.e., not sequestered) was attributed to carbon sequestration (considering for both the maintenance of productivity as the benefit).

3.2.3. Midpoint and endpoint impact on ecosystem services

With the obtained CFs, it is now possible to quantify the impacts of land occupation or transformation stressors on each one of the three characterized ecosystem services using Equations (10) and (11). [Supplementary Material C](#) provides an example of how to use the novel CFs to quantify the impacts of land occupation and transformation (mid- and endpoint) on each ecosystem service and associated goods and benefits.

3.3. Applicability & limitations of characterization factors

The midpoint CFs derived in the present study are intended to be both regional and site-specific, thereby representing the potential impact of land occupation and transformation stressors within a specific region or site. This is of particular importance given the high dependence of ecosystem service supply on related geographical characteristics, such as climate and soil typology ([Natural Capital Project, 2024](#)). Moreover, the formulated CFs are tailored to specific agricultural practices, thus enabling the differentiation between various farming techniques. This level of granularity facilitates the formulation of more informed agricultural strategies, and offers a valuable tool for decision-makers, agricultural practitioners, and other stakeholders involved in sustainable planning and resource management within the agricultural sector ([Valencia Torres et al., 2021](#)). Furthermore, the differentiation of management practices allows for the capture of core elements of organic farming in LCA, which might otherwise be overlooked under generic land use classes such as “arable land”, as observed in existing LCA studies ([van der Werf et al., 2020](#)). Nevertheless, further testing is required to evaluate the applicability of the presented CFs across different scenarios, such as conventional versus organic farming, in order to gain insights into their degree of flexibility and sensitivity to subtle changes in farming practices.

These elements collectively represent an important step forward in the ecosystem service-LCA integration stream of work. Previous studies

have frequently provided CFs with a spatial differentiation that is too coarse to accurately reflect the spatial variability of ecosystem service supply ([Blanco et al., 2018](#)). Furthermore, the land use classes included in these studies often lack sufficient detail to distinguish between different types of management practices. For instance, [Brandão and Canals \(2013\)](#), which is the recommended method by [UNEP-SETAC Life Cycle Initiative \(2019\)](#) to measure impacts on SOC depletion, provide CFs at the level of climate regions, and despite accounting for different intensities of tillage and fertilization practices (e.g., full, reduced, and no tillage; high, medium and low input), their characterization model is proxy-based and relies on statistical average data ([Teixeira et al., 2021](#)). Moreover, the LANCA method ([Bos et al., 2016; Saad et al., 2013](#)) provides CFs for various ecosystem services at the country level, with a distinction only between intensive and extensive land use classes. This broad differentiation lacks connectivity with specific management practices and their varying effects depending on the local context ([Teixeira et al., 2018a; van der Werf et al., 2020](#)).

The use of non-linear modelling is of particular significance when considering the intrinsic spatial and temporal variability of ecosystem services ([Maia de Souza et al., 2018](#)). Process-based models such as InVEST and RothC can assist in addressing this complexity ([Maia de Souza et al., 2018; Teixeira et al., 2021](#)). However, the tools utilized in this study are not designated to model ecosystem interactions with human activities, such as capturing feedback loops. To address this limitation, dynamic modelling frameworks such as MIMES (Multiscale Integrated Model of Ecosystem Services) ([Boumans et al., 2015](#)), as has been used by [Othoniel et al. \(2019\)](#), offer a promising avenue for capturing these interactions through the integration of different models within a system dynamics environment, including InVEST and RothC.

Another limitation that has been identified during the development of the CFs is the absence of geographically specific data for certain parameters. Consequently, more generic values have been used in such instances. While these more generic values have been selected with the intention of aligning as closely as possible with the Galician context, such as using those reported for temperate climates, they introduce an element of uncertainty into the results, as local environmental factors can exert a considerable influence on the estimated parameters. For instance, the nitrogen dose applied to wheat crops and the carbon saturation could vary considerably in Galicia, contingent on soil type and local climate. It is thus possible that these regional conditions are not adequately reflected by the average values utilized in this study. This simplification, while useful for this initial stage of application of these novel methods, highlights the necessity for further research that incorporates more local data in order to obtain accurate, geographically specific CFs.

3.3.1. Foreground and background systems

The high level of granularity of the CFs presented here renders them an optimal choice for implementation in foreground systems, where high-resolution primary data should be used ([Teixeira et al., 2021](#)). Nevertheless, generic, country-level CFs are also a valuable addition to the LCA framework, as LCA studies frequently rely on background data for their background processes, which lack the geographical and land use specificity to be coupled with the CFs proposed in this study ([Morais et al., 2016](#)). It is of particular importance that the background CFs are aligned with the land use classes found in widely used background inventory databases, such as ecoinvent, in order to ensure their operability.

3.3.2. Characterization factors coverage

The study analyzes the impact of several agricultural practices on the supply of three ecosystem services, with a particular focus on wheat cultivation. Nevertheless, there is a recognized need to expand the scope to encompass the multitude of other services provided by terrestrial ecosystems. This is an ongoing area of research, with new ecological models being developed or refined ([Turner et al., 2016](#)). Similarly, it is

important to note that the present study does not address a number of additional agricultural practices that have been demonstrated to exert a significant influence on ecosystem services. These include, but are not limited to, the intensity and type of fertilization, crop rotation practices, and agroforestry (Robertson et al., 2014; Xiao and Xiong, 2022; Tsai and Lee, 2023). The proposed framework, however, allows for the quantification of CFs applicable to other crops and management practices beyond wheat cultivation.

With regard to geographical coverage, the CFs developed are confined to the Galician region, which represents another relevant target for future research efforts aimed at formulating and comparing CFs across diverse geographical areas. An expansion of the geographical scope will not only enhance the representativeness of the CFs but also provide insights into the environmental impact of various agricultural practices on ecosystems based on their location. Such an approach will also facilitate the identification of regional disparities, the recognition of exemplary practices in each location, and the formulation of more universally applicable sustainability strategies.

3.3.3. Synergies and trade-offs

Ecosystem services frequently occur in bundles, resulting in synergies and trade-offs between the supply of services to different users (Turkelboom et al., 2016). For instance, practices that contribute to the maintenance and enhancement of SOC levels have also been demonstrated to improve water holding capacity and reduce the risk of soil compaction and erosion (McDonald et al., 2021; Yin et al., 2023). Consequently, when considering a single service at a time, CFs may not fully account for the intricate interconnections between ecosystem services (Othoniel et al., 2019), which is essential for achieving an accurate comprehension and precise assessment of the impact of farming management decisions on the supply of ecosystem services. In this study, the quantified midpoint CFs demonstrate consistent patterns across the three ecosystem services within different LULC classes. In particular, LULCs that exhibit higher CF values for one ecosystem service tend to exhibit similarly elevated values for the other services. In contrast, LULCs with lower CF values for one ecosystem service tend to exhibit lower values for the other ecosystem services. These synergies among the three ecosystem services are consistent with the well-established relationship between higher organic matter content in soils and improved soil structure (Corsi et al., 2012; Moinet et al., 2023), which enhances soil retention and nutrient availability. It should be noted, however, that an exception is observed in LULCs without cover crop management. In these instances, the CFs for carbon sequestration are markedly high, despite the relatively low values observed for the other two ecosystem services. This indicates that, based on the models used, the absence of cover crops may have a more pronounced impact on carbon sequestration than the other two ecosystem services, likely due to the lack of carbon inputs from cover crops in these LULCs.

3.3.4. InVEST model

InVEST is an open-source suite of software models that quantifies, maps and values various ecosystem services supplied by the terrestrial, freshwater and marine ecosystems (Posner et al., 2016). This ecosystem service toolbox is one of the most widespread since it is very well-documented, with dedicated software maintenance, and efforts are being put by their developers to improve models so that more of the available data can be used in the analysis (Hamel et al., 2021).

The models used by InVEST are scientifically sound, and compare to other existing tools, it offers a quantitative and spatially explicit approach to the quantification of ecosystem services (Bagstad et al., 2013), which are core characteristics of the objective of the present study. Among its weaknesses, it should be noted that it is a demanding tool, data- and time-intensive to apply, and requires experience with geographic information system (GIS) data treatment (Posner et al., 2016). Furthermore, this tool is inadequate for capturing the ecosystem dynamics, including the complex interdependencies and feedback loops

among ecosystems and the technosphere. Conversely, GUMBO (Boumans et al., 2002) and MIMES software are able to reflect these dynamic patterns, and even allow users to build custom ecosystem service models that integrate models from different disciplines (economics, demographics, etc.) (Othoniel et al., 2019). On its downside, these tools require highly advanced modelling expertise, and even more time and data in order to create tailored models for specific case studies.

There are also more specialized models for each discipline, such as SWAT (Soil & Water Assessment Tool), a model specialized in simulating hydrological processes (Arnold and Fohrer, 2005), which makes it particularly useful for studying water-related ecosystem services. The model simulates on a daily time step, compared to the annual time scale of InVEST, and therefore requires more detailed data (Vigerstol and Aukema, 2011). It also requires advanced technical expertise, which can be a limitation when pursuing a transdisciplinary approach. In addition, EPIC is a process-based model that models biophysical and biogeochemical changes due to soil management practices. Although it could be seen as a potential candidate, as it has been recognized as being particularly suitable for simulating carbon and nitrogen cycling under different management practices (Di Bene et al., 2022), it has a field-scale resolution that is too coarse for the purpose of this study, and it also makes it less practical for large-scale applications.

3.4. Economic valuation at the endpoint level assessment

The manner in which the final element of the ecosystem service cascade framework, namely the goods and benefits provided to humans, should be integrated within the LCA has been the subject of considerable debate (Blanco et al., 2018). Some authors, as is the case with the present study, advocate for quantifying the gains and losses of goods and benefits in monetary terms as a means of assessing damage to AoP resources. In this vein, Othoniel et al. (2019) applied monetary valuation methods as endpoint characterization models to derive endpoint indicators. For example, they used the market price of carbon as the endpoint CF for the climate regulation endpoint indicator. Furthermore, Teixeira et al. (2018b) applied a replacement cost method to derive an endpoint CF that reflected the future requirement of nutrients due to the SOC depletion. From a theoretical standpoint, Rugani et al. (2019) highlighted the potential use of damage scores in monetary units at the endpoint level. In contrast, Blanco et al. (2018) proposed the use of monetization as a means of weighting. Moreover, Babí Almenar et al. (2023) conducted an economic valuation of the ecosystem service supply in order to account for the positive environmental externalities.

Monetary terms are frequently an efficacious means of communicating the importance of caring for ecosystems through the implementation of more ecologically sustainable practices, and of “making nature’s value visible” (System Environmental Economic Accounting, 2019). Furthermore, conveying environmental concerns in monetary terms can reinforce the link with beneficiaries, as they can discern the direct impact on their financial resources.

In this study, the valuation focuses on farmers as the target beneficiaries because of their central role in achieving a more sustainable agricultural sector (World Economic Forum, 2022). By quantifying the monetary losses or gains that farmers experience due to changes in their practices, the study aims to enhance farmers’ awareness of the economic implications of their decisions. However, the impacts of farming extend beyond the farmer to other stakeholders who may also experience significant economic consequences due to changes in ecosystem services supply. Incorporating these additional stakeholders introduces a notable degree of complexity, as the valuation of ecosystem services for multiple beneficiaries requires the careful allocation of benefits among stakeholders when benefits are shared (Liu et al., 2020), and the prevention of double-counting through a clear delineation between final and intermediate ecosystem services (Rugani et al., 2019). Nevertheless, future research may benefit from incorporating all relevant stakeholders in the valuation process, thereby providing a more comprehensive assessment

of the trade-offs and synergies among beneficiaries.

A variety of approaches have been used as endpoint characterization models, with the specific method varying depending on the ecosystem service under consideration. In the case of WP and SEC, proxies have been used for the economic damage score due to the unavailability of direct quantitative measures. While this may limit the accuracy of the valuation results, and further research is needed to refine these monetization approaches, it can be argued that the attained accuracy is sufficient for the valuation purpose presented in this study (Liu et al., 2010), which is to enhance farmers' awareness. Furthermore, as previously indicated by Teixeira et al. (2018b), priority should be given to the midpoint impacts due to the simplification and value judgement of these endpoint values.

3.5. Uncertainty analysis

In the context of environmental modelling, the optimal approach to uncertainty analysis would be to consider all potential sources of uncertainty that could impact the precision of the resulting predictions (Peralta et al., 2022). These sources of uncertainty include, but are not limited to, those related to the model structure, model parameters, input data, and the choice of model (Baustert et al., 2018; Peralta et al., 2022). For example, the selection of a specific model introduces an intrinsic degree of uncertainty that cannot be fully quantified unless multiple models are used and compared. In addition, each model is constructed on a foundation of assumptions, simplifications, and approximations of the actual system, which may introduce structural uncertainties that could have a significant impact on the results. Moreover, uncertainty is inherent to the parameters of the model, which may be estimated on the basis of limited or uncertain data.

In the present study, the uncertainty associated with the input data has been quantified, but other sources of uncertainty have not been considered. Although this is a useful step in understanding the limitations of environmental modelling predictions, it does not offer a comprehensive representation of the total uncertainty involved. Therefore, further analyses aimed at incorporating additional sources of uncertainty in future stages of CFs development would be beneficial, which will enhance the accuracy and confidence of the environmental modelling efforts that underpin the developed CFs. In addition, conducting a sensitivity analysis and soliciting input from experts in diverse ecological disciplines regarding the findings could be essential in addressing uncertainties the uncertainties associated with data quality, data gaps, and the simplifications introduced by the ecological model (Maia de Souza et al., 2018).

3.6. Further challenges & suggestions for future research

Quantifying ecosystem services supply can be a demanding task, as it requires extensive data and usually technical skills beyond the traditional expertise of most LCA practitioners, such as handling spatial datasets and programming skills (Bagstad et al., 2021; Zulian et al., 2018). It is therefore essential that readily accessible CFs are made available in order to facilitate the inclusion of impacts on ecosystem service supply in LCA studies.

The authors suggest that future research efforts should focus on the development of such a set of spatially explicit CFs for integration into LCA software, with the aim of improving accessibility to a wider audience and sparing the need to undertake the process of quantifying ecosystem services. As previously mentioned, these CFs should provide worldwide coverage and encompass a greater range of ecosystem services and agricultural practices. As a next step, case studies are also recommended to test the reliability and effectiveness of the model in accurately classifying different agricultural practices in terms of their impact on ecosystem services, and to assess differences between geographical regions.

3.6.1. Potential future scenarios

Studying ecosystem services within foresight scenarios can also provide valuable insights into changes in the provision of ecosystem services by agriculture under different storylines, helping to adapt current agricultural practices to prospective future scenarios. For instance, quantifying ecosystem services on the various scenarios coordinated by the International Panel of Climate Change (IPCC) (e.g., AR 1990, SR 1994, and SRES 2000) may provide guidance on management changes needed to adapt to climate change at a spatially explicit scale and ensure future sustainability within ecological carrying capacity (Vesnic-Alujevic et al., 2023).

4. Conclusions

The present study develops novel CFs to assess the impacts of growing wheat under several agricultural practices on ecosystem services. Specifically, the effect of three tillage intensities, two straw management systems, and the inclusion of cover crop practices was analyzed on three ecosystem services: water purification, soil erosion control, and carbon sequestration, using spatially explicit, non-linear models (InVEST and RothC). Midpoint CFs for both land use occupation and land transformation pressures were quantified based on the supply of ecosystem services. Furthermore, endpoint factors were also derived for each ecosystem service benefit, with the objective of facilitating the communication of the impacts of agriculture on ecosystems and enhancing visibility and understanding among stakeholders. The granularity of the CFs developed in this study allows for more nuanced differentiations between farming regimes, which are often overlooked by using generic CFs, such as those assigned to "arable land". Furthermore, the high spatial differentiation offered by these CFs is crucial, given the strong dependence of ecosystem services on geographical factors such as climate and soil typology. Those engaged in policy-making, land management, and other aspects of land-use planning and resource management may find this level of detail beneficial, as it is crucial for the development of sustainable agricultural strategies that are tailored to local contexts. Moreover, it enables the formulation of well-informed decisions that prevent the unintended environmental burden shifting.

Although this study is limited in scope to a specific set of agricultural practices and a particular geographical area (Galicia, northwest Spain), it presents a stepwise procedure for deriving additional CFs to meet the specific requirements of practitioners. The authors argue that this work could be further enhanced by the quantification of country-level CFs, which would facilitate the assessment of the impacts on ecosystem services associated with the background system.

CRedit authorship contribution statement

Sara Lago-Oliveira: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Maria Teresa Moreira:** Writing – review & editing, Supervision. **Sara González-García:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ecoser.2024.101686>.

Data availability

Data will be made available on request.

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