One Ecosystem 11: e181068
doi: 10.3897/oneeco.11.e181068

OPEN ACCESS

Research Article

Condition Matters: Fine-Tuning Ecosystem Service Capacity with Ecosystem Condition

Philip K. Roche‡, C. Sylvie Campagne§

‡ Aix-Marseille Université, INRAE, UMR RECOVER, Aix-en-Provence, France
§ European Institute for Energy Research (ElfER), Karlsruhe, 76131, Germany

Corresponding author: Philip K. Roche (philip.roche@inrae.fr)

Academic editor: Benjamin Burkhard

Received: 02 Dec 2025 | Accepted: 08 Oct 2026 | Published: 21 Oct 2026

Citation: Roche PK, Campagne CS (2026) Condition Matters: Fine-Tuning Ecosystem Service Capacity with Ecosystem Condition. One Ecosystem 11: e181068. https://doi.org/10.3897/oneeco.11.e181068

Abstract

Ecosystem service (ES) capacity matrices are widely used for ES assessment and mapping due to their operational simplicity. However, capacity matrices assign uniform capacity scores to ecosystem types without accounting for local variations in ecosystem condition, leading to assessment errors arising from condition blindness. We present a methodological framework for integrating ecosystem condition into ES capacity matrices through ecosystem-specific condition thresholds. Ecosystem condition is characterised using two components: structural condition (e.g. vegetation cover, productivity, canopy height) and biological condition (e.g. biodiversity intactness, soil organic carbon, natural habitat proportion). We grouped ES into five functional groups according to their dependence on the two condition components. We then developed allocation tables linking condition levels to ES capacity within the capacity matrices. We applied our framework to a 430 km² study area in the Hauts-de-France region (France). After testing different ecosystem condition thresholds for this test case area, the 20th-80th percentiles of condition values appeared to be the most adequate to define condition classes. We also demonstrate that condition values have to be assessed separately for each ecosystem type (urban, agricultural, forest and aquatic). Condition adjustment modified capacity scores by 0.58-0.81 capacity score on average over the 0-5 ES scale (12-16% of the capacity range), with maximum local differences reaching 2.1 (42% of the range). Validation against six independent ES reference datasets shows statistically significant

© Roche P, Campagne C. This is an open access article distributed under the terms of the Creative Commons Attribution License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

improvements in correlation coefficients ranging from 0.036 to 0.130 (mean Δr = 0.078, p < 0.001 for all services) when incorporating condition adjustments. Our framework provides an operational method for implementing the SEEA-EA conceptual linkage between ecosystem condition and ecosystem service capacity, with potential applications in natural capital accounting, land-use planning, and environmental impact assessment.

Keywords

SEEA-EA, biotic integrity, percentile thresholds, condition-capacity linkage, biophysical indicators, remote sensing, expert-based valuation, Regional natural park Scarpe-Escaut, France

1. Introduction

Ecosystem services (ES), the benefits that humans derive from ecosystems, are fundamental to human well-being and economic development (Reid et al. 2005). Assessing these services meaningfully requires accounting for the state of the ecosystem that provides them, since a degraded ecosystem cannot be expected to sustain the same level of service provision as one in good condition. Yet, despite the wide range of methods now available to assess ES, most treat ecosystem condition only implicitly, if at all. Throughout this study we therefore rely on an explicit definition, following Czúcz et al. (2021), who define ecosystem condition as "the overall state of an ecosystem's biophysical characteristics that underpin its capacity to generate services sustainably".

One widely adopted method for ES assessment is the ES capacity matrix (Burkhard et al. 2009, Campagne and Roche 2018, Campagne et al. 2020). This approach involves assigning capacity scores to combinations of ecosystem types and services, typically on a scale from 0 to 5, representing the potential of an ecosystem to provide specific services. The matrix method's popularity stems from its flexibility, ease of implementation, and ability to integrate various data sources, including expert judgment, statistical data, and quantitative measurements (Campagne and Roche 2018, Burkhard and Maes 2017). Despite its widespread use, the ES capacity matrix approach has significant limitations. A critical shortcoming is its tendency to represent ecosystems as homogeneous entities, neglecting spatial variations in ecosystem condition, resulting in condition blindness of capacity matrices (Campagne and Roche 2018, Jacobs et al. 2015). Ecosystem condition is a dynamic attribute influenced by factors such as biodiversity, structural complexity, and ecological health (La Notte et al. 2022, Roche and Campagne 2017, Czúcz et al. 2021). Failing to incorporate these variations can lead to inaccurate assessments of ES capacities, particularly when matrices developed for one region are applied elsewhere without adjustment of the capacity values for local ecological and land use contexts (Burkhard et al. 2012, Maes et al. 2016). For instance, two forests classified within the same ecosystem type in the matrix may differ in their capacity to sequester carbon or support biodiversity due to differences in age structure, species composition, or disturbance history (Gamfeldt et al. 2013, Sieber et al. 2021). Similarly, grasslands with

varying levels of degradation will differ in their ability to prevent soil erosion or support pollinators (Power 2010). These examples highlight the necessity of integrating local ecosystem condition data into ES assessments to capture more accurately the variability in service provision.

The capacity matrix approach allows for integrating further data to refine capacity matrix assessments Burkhard et al. (2012). Weyland et al. (2017) showed that locally-parameterised capacity matrices yielded better results than a matrix covering large areas. Stoll et al. (2015) demonstrated that the ES capacity varies with context and location for the same land cover type. However, there remains a lack of standardised methods for systematically integrating ecosystem condition into ES capacity matrices. The challenge lies in identifying which aspects of ecosystem condition are most relevant for different ecosystem services in different ecosystem (or land cover) types and determining how to adjust capacity scores accordingly. Recent advancements in ecosystem accounting frameworks, such as the System of Environmental-Economic Accounting-Ecosystem Accounting (SEEA-EA), emphasise the importance of linking ecosystem condition to ecosystem service supply and use (SEEA-EA 2021, La Notte et al. 2022). These frameworks advocate for the use of condition indicators that reflect the key characteristics underpinning an ecosystem's ability to generate services. Recent methodological developments have proposed capacity indices to bridge condition and ecosystem services accounts within the SEEA-EA framework, demonstrating that ecosystem assets with identical condition profiles exhibit different capacities depending on the service being assessed (Martini et al. 2024, Bruzón et al. 2023). Studies have also highlighted the relationships between specific ecosystem attributes, such as net primary productivity, species diversity, and structural complexity and, the capacity to provide certain services (Harrison et al. 2014, Mace et al. 2012). Two distinct challenges must be addressed. First, a parsimonious set of condition variables must be identified that is relevant for the different ES across the different ecosystem (or land cover) types. Second, explicit rules are needed for adjusting capacity scores based on the selected condition variables.

The present study addresses the gap in existing ES assessment methods regarding the integration of ecosystem condition. We propose an operational framework to enhance ES capacity matrices through the incorporation of local ecosystem condition data.

2. Ecosystem Condition tuning of Ecosystem Services scores

In this section we will introduce the framework rationale that integrates ecosystem condition into ES capacity matrix assessments through three conceptual pillars (Fig. 1): (part 1) the characterisation of ecosystem condition through structural and biological components; (part 2) the ES assessment through the derivation of three parallel capacity matrices. The low and high capacity are derived from the 5th and 95th percentiles of the expert-score distribution, while the medium matrix is the mean of the expert scores; and (part 3) a functional grouping of ES based on their ecological dependencies and allocation rules linking condition states to adjusted capacity scores.

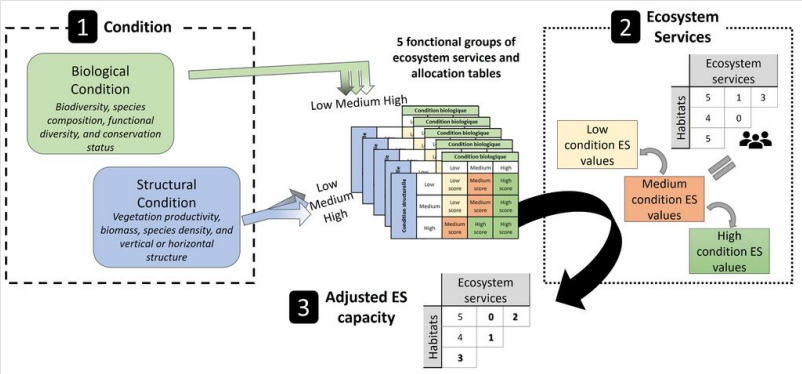


Figure 1.

Integration of biological and structural condition to adjust ecosystem service capacity matrix scores.

Part 1 (Ecosystem condition) shows the two condition components, each characterised from a set of biophysical indicators (biological condition: biodiversity intactness, species composition, functional diversity, conservation status; structural condition: vegetation productivity, biomass, canopy cover, vertical structure) and discretised into three classes (low, medium, high). Abiotic and landscape-level characteristics of the SEEA-EA condition typology are not included in this framework (see main text). **Part 2** (Ecosystem services) shows the derivation of three parallel capacity matrices from the 5th and 95th percentiles for the low and high scores and the mean of the expert-score distribution for the medium condition (Campagne et al. 2017), representing low, medium, and high condition ES capacity values. **Part 3** (Adjusted ES capacity) shows the output of combining Parts1 and 2: for each condition components, the appropriate capacity matrix is selected based on its structural and biological condition class pair via the ES group-specific allocation tables, producing the condition-adjusted capacity score.

2.1. Ecosystem condition assessment (Framework part 1)

Ecosystem condition is a critical concept linking the state of ecosystems to their capacity to sustainably provide services (Czúcz et al. 2021). This concept encompasses both the physical structure and biological components of ecosystems, including their responses to human pressures and disturbances. Roche and Campagne (2017) emphasised that ecosystem condition is multidimensional, involving aspects of ecosystem integrity, health, stability, and resilience. They identified ecosystem condition as an anthropocentric concept, focusing on the capacity of ecosystems to provide services expected by humans.

The cascade model proposed by Haines-Young and Potschin (2010) illustrates ecosystem condition as an intermediary between ecosystem structures and processes and the delivery of final ecosystem services. A key challenge in operationalising ecosystem condition for ES assessments is determining the minimum set of variables that effectively describe it and can be used to adjust ecosystem service capacity evaluations. This is critical for several reasons. A concise set of variables enhances practicality by making the assessment process manageable, especially across large or multiple

ecosystems. Standardised variables improve comparability across different studies and regions, while focusing key variables streamlines the assessment without sacrificing accuracy. Roche and Campagne (2017) suggested that indicators related to productivity, energy fluxes, nutrient cycling, biodiversity, and structural complexity are particularly important. However, the specific set of indicators may vary depending on the ecosystem type and the services being assessed.

Empirical research consistently demonstrates that ES do not respond uniformly to changes in ecosystem condition. Braat and ten Brinks (2008) showed that ES categories exhibit distinct response curves. Harrison et al. (2014), in a systematic review of 530 studies, identified service-specific dependencies on biotic attributes: timber production is strongly associated with community or habitat area, while pest regulation depends more on species richness and diversity. Gamfeldt et al. (2013) provided further evidence from boreal and temperate forests, showing that different ES are maximised by different forest stand types. Cardinale et al. (2012) demonstrated that while some services (e.g. timber provision) are influenced by functional composition, others (e.g. pollination) depend more on species diversity. These findings indicate that a uniform adjustment of ES capacity based on a single condition index, or based on the Common International Classification of Ecosystem Services (CICES) sections, would be ecologically inappropriate. The relationship between condition and ES capacity must be differentiated according to the ecological drivers of each service.

Accordingly, we propose to split ecosystem condition into two main components: structural condition and biological condition. This dual categorisation is based on the view that a good ecosystem condition needs both high ecological integrity and well-functioning vegetation and soils, acknowledging its multidimensional nature and facilitating its integration into ecosystem service assessments. By considering both structural and biological aspects, we can more accurately assess how variations in ecosystem condition influence the capacity to provide services. Structural condition relates to the physical and biophysical structure of ecosystems, including factors such as vegetation productivity, biomass, species density, and vertical or horizontal structure. Biological condition encompasses biodiversity, species composition, functional diversity, and conservation status, capturing the living components and interactions within ecosystems. We provide here some key definitions Table 1

Table 1.

Key definitions

Ecosystem condition: The overall state of an ecosystem asset in terms of its biophysical characteristics that underpins its capacity to generate ecosystem services sustainably (adapted from SEEA-EA; Czúcz et al. 2021).
Structural condition: The physical and biophysical attributes of ecosystems, including vegetation productivity, biomass, canopy cover, and vertical structure. Corresponds to abiotic and structural state characteristics in the SEEA Ecosystem Condition Typology (principally category B2, with productivity-related elements of B3; Czúcz et al. 2021).
Biological condition: The living components and ecological interactions within ecosystems, including biodiversity intactness, species composition, functional diversity, and conservation status. Corresponds to compositional and functional state characteristics in the SEEA framework (categories B1 and the remaining elements of B3; Czúcz et al. 2021).
Ecosystem service capacity score: The potential of an ecosystem to provide a specific service, typically scored on a 0-5 scale in matrix-based assessments, where 0 indicates no capacity and 5 indicates maximum capacity. Capacity scores represent potential supply under specified conditions, not realised flows or actual use (Burkhard et al. 2012, Campagne and Roche 2018).
Capacity matrix: a lookup table assigning capacity scores to combinations of ecosystem types and ecosystem services, typically derived from expert elicitation (Burkhard et al. 2012, Campagne and Roche 2018).
Condition-adjusted capacity score: The ecosystem service capacity score modified according to local ecosystem condition.

2.1.1 Structural and Biological Components

The SEEA Ecosystem Condition Typology (Czúcz et al. 2021) distinguishes abiotic (A), biotic (B), and landscape-level (C) characteristics, with the biotic dimension further divided into B1 compositional state, B2 structural state, and B3 functional state. Building on the SEEA Typology, our framework focuses on the biotic dimension and aggregates these sub-categories into two operational components (see Table 1 for definitions). Structural condition draws primarily on B2, with productivity elements from B3. Biological condition integrates elements from B1 (taxonomic and functional composition) and from the remaining elements of B3. Considering a two-dimensional framework yields manageable 3×3 allocation tables.

Within the biotic dimension, the structural and the biological distinction captures the primary axis differentiating ES responses: some services scale with biomass quantity regardless of composition, while others depend fundamentally on species identity and diversity. Additional biotic dimensions would increase complexity without proportionate gains in explanatory power for the condition–capacity relationship.

Scope and deliberate exclusions

Our framework deliberately omits the abiotic dimension (A) and the landscape-level dimension (C) of the SEEA Ecosystem Condition Typology. This is not because they are unimportant: soil properties, hydrology, topography, and landscape configuration and connectivity can drive substantial within-type variation in ES supply, and LULC-based capacity matrices only capture what is implicit in the ecosystem type itself, not this finer-grained variation. This is a genuine limitation, and the framework holds best where abiotic conditions and landscape context are relatively homogeneous within an ecosystem type; where they vary strongly, for example across steep topographic or hydrological gradients within a single LULC class, within-type capacity estimates should be interpreted with more caution. Landscape configuration in particular affects several

services largely independently of ecosystem extent (pollination, erosion control, recreation, habitat provision). This allows landscape effects to be addressed at the ecosystem-mapping stage mainly applies to range and area, rather than configuration or connectivity. Therefore, the latter remain outside the scope of the present framework. Integrating spatially explicit abiotic and landscape modifiers would shift the approach toward process-based modelling (e.g. InVEST, ARIES), which is not the objective of the present study. The framework's scope is therefore the refinement of expert-based capacity matrices through biotic condition variation, applied with most confidence where abiotic and landscape context are comparatively stable within ecosystem types; elsewhere, complementary spatially explicit approaches are needed.

Relationship between the structural and biological components

Those two components are often correlated in ecological systems: ecosystem degradation frequently manifests as simultaneous declines in both biomass and biodiversity, driven by shared pressures such as land-use intensification or pollution. Partial independence between the dimensions nevertheless occurs in specific contexts, particularly in human-modified landscapes: plantation forests may exhibit high structural condition (substantial biomass, closed canopy) while maintaining low biological condition (monospecific stands, reduced functional diversity). Ecosystems undergoing restoration may show recovering biodiversity while biomass remains limited. Semi-natural grasslands managed through extensive grazing can support high floristic diversity despite relatively low standing biomass. This illustrates that structural and biological conditions, while often coupled, can respond differentially to management regimes and disturbance histories.

2.2. Ecosystem services assessment (Framework Part 2)

The ES matrix can be filled by different sources of data but is generally filled using expert elicitation, where the score ranges from 0 to 5 based on the capacity assessment of ecosystems (Burkhard et al. 2014, Campagne et al. 2020). Expert elicitation is a valuable approach that overcomes data scarcity, incompatible indicator data, and limited accessibility to field work, among other limitations often encountered in indicator- or model-based quantification methods (Wangai et al. 2018,Sohel et al. 2015). Furthermore, expert elicitation provides rapid, integrative, and readily-appropriable ES assessments (Burkhard et al. 2012, Jacobs et al. 2015), and is more readily adopted by managers and decision-makers than precise ES measurements (Grêt-Regamey et al. 2008).

The capacity matrix typically represents ecosystem capacity under medium condition within the study area. A dedicated elicitation protocol where the experts are requested to propose estimates of the ES values under low, medium and high condition is the best approach but require a long elicitation protocol and a high level of expertise. To derive ES scores for low and high conditions, when dedicated estimates of low and high ES capacities are not possible to define or available, we propose to use the distribution of expert scores to determine values corresponding to the lower 5th percentile (representing low condition) and the upper 95th percentile (representing high condition).

This approach will capture the range of expert assessments and reflect potential variations in ES capacities due to ecosystem condition changes. Using the 5th and 95th percentiles of the distribution of individual scores allowed us to account for extremes of expert opinion while avoiding reliance on outliers, ensuring that both low and high condition matrices remained grounded in credible expert assessments. Low condition scores represent scenarios where ecosystems are significantly degraded, resulting in reduced service capacities. High condition scores reflect optimal ecosystem states with enhanced capacities for service provision. We acknowledge that this approach is not the most adequate since it expresses the variation of average values as estimated by the expert panel.

2.3. Adjusted ES capacity with the ecosystem condition (Framework part 3)

2.3.1 Functional grouping of Ecosystem Services

Some studies have highlighted limitations in the standard classification's ability to reflect the diverse ecological drivers of ES. For instance, de Groot RS et al. (2010) and Kremen (2005) emphasise that broad categories can obscure the complex ecological interactions underlying service delivery. Services within the same category (i.e. provisioning, regulation and cultural categories) may respond differently to changes in ecosystem condition due to varying ecological dependencies. Harrison et al. (2014) observed that timber production was strongly associated with community or habitat area, while pest regulation depended more on species richness and diversity. This suggests that even within traditional categories, such as regulating services category, services can have fundamentally different ecological drivers. Similarly, Gamfeldt et al. (2013) demonstrated that different ecosystem services are maximised by different forest stand types in boreal and temperate forests, underscoring the importance of considering both structural and compositional aspects of ecosystems. Cardinale et al. (2012) further showed that while some services, such as primary production, are influenced by functional composition, others like pollination depend more on species diversity. This variability in the relationship between biodiversity and ecosystem services supports the need for a more nuanced classification system.

We emphasise that the grouping proposed here is not an alternative to the classic classifications (i.e. provisioning, regulation and cultural categories) such as CICES, but an internal methodological device specific to our framework. Its sole purpose is to operationalise differential condition-capacity relationships for matrix adjustment. ES may be reassigned across groups based on local ecological knowledge or as new evidence accumulates; the grouping should be treated as a working hypothesis to be refined empirically.

Traditional ES classifications, such as CICES, categorise services according to the type of benefit provided to society: provisioning, regulating, and cultural services. This demand-side perspective is appropriate for economic valuation and policy applications,

but is less adequate for linking ecosystem condition to service capacity. The fundamental issue is that services within the same CICES section may respond differently to changes in ecosystem condition because they depend on different ecological attributes. Carbon sequestration and pollination are both regulating services, but the former depends primarily on biomass accumulation while the latter requires specific pollinator assemblages and floral resources. Conversely, services in different CICES sections may share similar ecological dependencies: timber production (provisioning) and carbon sequestration (regulating) are both primarily driven by standing biomass.

A uniform condition adjustment to the current three ES categories might oversimplify ecological relationships and risk obscuring important service-specific responses. The alternative (treating each ES individually) would require calibrating relationships for dozens of services across multiple ecosystem types, resulting in a framework that is difficult to generalise and operationally impractical. We therefore defined five functional groups of ES based on the relative importance of structural and biological condition for the ES capacity provision (Table 2). This functioning grouping complements rather than replaces CICES: it provides an ecologically grounded basis for adjusting capacity scores according to local condition, while CICES remains appropriate for categorising the benefits received by society.

Table 2.

Dependence of ecosystem services groups on structural and biological conditions. The + signs indicate the importance of the condition for the services of the group. A '0' indicates a very weak to negligible importance.

Group number	Functional ES group name	Structural Condition	Biological Condition	Example of Ecosystem Services
1	ES dependent on ecosystem biomass	+++	+	Carbon sequestration (Climate Regulation)
2	ES dependent on both ecosystem structure and specific composition	++	++	Pollination and seed dispersal
3	ES dependent on biomass plant cover, and functional diversity	++	+	Food production
4	ES dependent on specific and functional composition	+	++	Provision of habitat, refuge, and nursery, Recreation
5	ES dependent on conservation status and biodiversity	+	+++	Pest regulation, Soil quality maintenance

In the following paragraphs, each group is described concisely, with examples and supporting references drawn from the ES-biodiversity literature.

Group 1: Ecosystem services primarily dependent on ecosystem biomass and productivity. These services are driven by the physical structure and productivity of ecosystems, with less reliance on species composition or biodiversity. The lead example

is climate regulation through carbon sequestration, where capacity is largely determined by standing biomass (Brockerhoff et al. 2017, Weyland et al. 2017). Erosion control, storm protection, and the limitation of visual, olfactory and noise nuisances are additional examples; for these, plant cover and root-system density are critical alongside overall biomass (Riis et al. 2020), and species composition is of secondary importance relative to the overall physical structure of the ecosystem.

Group 2: Ecosystem services dependent on both ecosystem structure and specific composition. These services require not only a robust physical structure but also the presence of specific species. Wild food resources, pollination, and seed dispersal are examples. The availability of wild edible plants is influenced by overall ecosystem productivity, but the presence of specific plant species is crucial for providing these resources (Carrick and Forsythe 2020, Pinto et al. 2014). Pollination and seed dispersal rely both on the structural presence of flowering plants and nesting sites and on the availability of specific pollinator species (Balvanera et al. 2006).

Group 3: Ecosystem services primarily dependent on biomass, plant cover, and functional diversity. The quantity and functional type of vegetation play a dominant role, with less emphasis on species-specific traits but with substantial influence from management inputs (cropping systems, silvicultural regimes, fertilisation). Timber production is directly related to tree biomass and stand structural attributes (Harrison et al. 2014). Flood regulation is primarily determined by vegetation biomass and forest extent, with species composition of secondary importance (Vári et al. 2022). Agricultural production similarly responds more to structural soil-plant conditions and management inputs than to wild species identity or conservation status (Power 2010, Pinto et al. 2014).

Group 4: Ecosystem services primarily dependent on specific and functional composition. These services are highly sensitive to changes in biodiversity and species composition. Recreation, Aesthetic, and Habitat and nursery services belong to this group. The relationship between cultural and aesthetic values and biodiversity is empirically variable; for some cultural services the link is direct (ecotourism, wildlife observation), while for others (spiritual, heritage) the dependence is mediated by cultural context as much as by ecological attributes (Daniel et al. 2012, Zhao et al. 2024). Recreation and ecotourism service is often directly related to the biodiversity and conservation status, as biodiverse ecosystems attract visitors seeking diverse wildlife and natural landscapes (Balmford et al. 2015). Habitat provision depends on the presence of a wide range of species and ecological niches; diverse ecosystems support a variety of niches that sustain different species (Cardinale et al. 2012, Harrison et al. 2014).

Group 5: Ecosystem services primarily dependent on conservation status and biodiversity. These services are closely linked to overall ecosystem health and biodiversity. Pest regulation, disease regulation, and soil fertility maintenance belong to this group. Pest regulation depends critically on the diversity and composition of natural enemy communities: Bianchi et al. (2006), in a review of biological pest regulation across agricultural landscapes, showed that natural enemy species diversity and composition are the primary determinants of pest suppression, and Greenop et al. (2018) confirmed,

in a meta-analysis of 51 studies that functional diversity of predator communities outperforms species richness alone as a predictor of prey suppression. Soil fertility maintenance is similarly governed by soil community composition: Wagg et al. 2014 demonstrated that soil community composition, rather than structural biomass, determines the simultaneous delivery of multiple soil-mediated functions including nutrient cycling and fertility maintenance. Díaz et al. (2007) further emphasise the importance of functional diversity for soil processes.

2.3.2 Linking Condition to Adjusted Capacity via Allocation Tables

As shown in Fig. 2, the interactions between the two condition components (structural and biological) result in different capacity scores for each ES functional group.

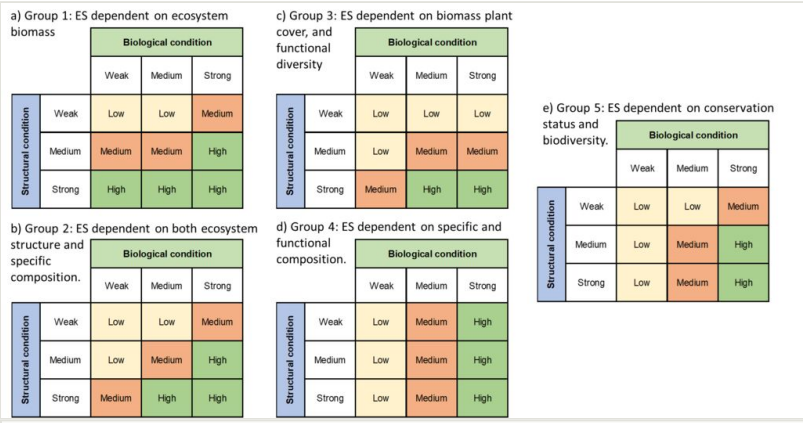


Figure 2.

Allocation tables for ecosystem services (ES) grouped by their dependence on structural and biological conditions. The tables a,b,c,d and e respectively present the ES functioning groups 1 to 5, each representing ES with varying dependencies on biological and structural conditions. The interactions between structural and biological conditions are evaluated, and corresponding ES capacity scores within the three capacity matrices (low, medium, high) are assigned based on the local ecosystem condition.

The allocation tables operationalise the functional grouping by providing explicit rules for determining which capacity matrix (low, medium, or high) should be applied to a given ecosystem unit based on its structural and biological condition indices (Fig. 2).

The framework assumes that (i) both condition components have been discretised into three ordinal classes (low, medium, high) based on the procedure described in the Methods, and (ii) three parallel capacity matrices have been derived from the distribution of expert scores. The underlying logic is straightforward: for each functional group, the condition dimension(s) identified as primary drivers in Table 1 exert the dominant influence on capacity allocation. This creates a direct, traceable link between the ecological rationale for each group and the operational adjustment of capacity scores.

For Group 1 (biomass-dependent services), structural condition is the primary determinant. When structural condition is high, capacity is high regardless of biological condition, because the services depend on biomass quantity rather than species composition. When structural condition is low, capacity is constrained to low, except when biological condition is high.

For Groups 2, 3, and 4, both dimensions contribute to capacity determination, with the balance reflecting the relative dependencies specified in Table 1. Group 2 services require both structural resources (flowering plants, nesting sites) and appropriate species assemblages, so capacity is maximised only when both conditions are favourable. Group 3 weights structural condition more heavily but incorporates functional-diversity considerations. Group 4 weights biological condition more heavily while requiring a minimum structural baseline.

For Group 5 (biodiversity-dependent services), the inverse logic applies. Biological condition dominates the allocation: high biodiversity yields high capacity for habitat provision regardless of biomass levels. Low biodiversity constrains capacity even in structurally intact ecosystems, because species-poor systems cannot support the ecological niches or wildlife experiences that define these services.

2.3.3. Defining the adjusted ES capacity scores

For each ecosystem unit and each ecosystem service, the adjusted capacity score is obtained in three steps. First, the service is assigned to one of the five functional groups (Table 1), which selects the corresponding allocation table (Fig. 2a-e). Second, the structural and biological condition classes of the unit are used as entries in that table, whose cell returns the condition level to apply (Low, Medium or High). Third, this level selects one of the three capacity matrices, from which the capacity score for the relevant ecosystem type and service is read. The Low, Medium and High levels correspond respectively to the low, medium and high capacity matrices. The resulting condition-adjusted score retains the 0-5 scale of the original matrix but reflects the local structural and biological condition of the ecosystem unit.

3. Application of the framework to a case study site

3.1. Study Area

We applied the framework to the Regional Natural Park (RNP) Scarpe-Escaut in the Hauts-de-France region of northern France thanks to the availability of an ES capacity matrix developped by the authors in 2017 and a good knowledge of the area (Campagne et al. 2017). Located at the Belgian border, the park extends over 430 km² encompassing 55 municipalities crossed by the Scarpe and Escaut rivers. As France's oldest RNP and part of the larger transboundary Hainaut Nature Park (together with Belgium's Plaines de l'Escaut Natural Park), it provides an ideal test case for condition-adjusted capacity

assessment. The landscape is characterised by extensive wetlands and lowland plains along the river systems, creating a complex mosaic of agricultural lands (crops and grasslands), semi-natural ecosystems (woodlands, marshes, ponds), and urbanized areas. As a peri-urban region, the park experiences significant urban pressure while maintaining diverse ecological functions through centuries of water management for agriculture, navigation, and land drainage.

3.2. Case study site methods

3.2.1. Ecosystem condition assessment

The indices of structural and biological condition were defined through two layers integrating variables from local data described as follows. The layers were derived for a 430km² study area covering the Scarpe-Escaut RNP, and surrounding areas, in France for the year 2020 using multi-source remote sensing data accessed through Google Earth Engine (GEE) and processed in QGIS 3.32.3. All datasets were resampled to 100-metre spatial resolution and aligned to a common reference grid. Each component variable was independently normalised to a 0-1 scale before integration. Then the layers were clipped according to the limits of the Scarpe-Escaut RNP. The following three steps were done:

1. Computation of the Structural Condition Index (SCI) and Biological Condition Index (BCI) at 100-m resolution from remote-sensing variables.
2. Stratification of the study area into four ecosystem types (AQUA, AGRO, FORE, URBA) using the Dynamic World land cover classification.
3. Calculation of ecosystem-specific 20th and 80th percentiles of SCI and BCI within each stratum, defining low / medium/ high condition classes.

3.2.2. Indicator aggregation and weighting

We combined the component variables of each index using min-max normalisation followed by an unweighted arithmetic mean. In the absence of empirical evidence supporting differential weights for our component variables, equal weighting represents a parsimonious, transparent and reproducible default. This practice is well established in composite-index construction (Greco et al. 2018, Nardo et al. 2008, OECD 2008) and is the recommended baseline when expert-derived or empirically-calibrated weights are not available. Min-max normalisation followed by arithmetic mean is likewise a standard procedure for combining indicators measured on different units and scales. We acknowledge that the component variables of each index integrate processes operating at different temporal scales: BII (Biodiversity Intactness Index) reflects multi-year biodiversity dynamics, SOC (Soil Organic Carbon) reflects multi-decadal biogeochemical accumulation, and the proportion of natural habitat can change over months. Tree canopy cover, EVI and GEDI canopy height likewise differ in their temporal signatures. For the purpose of a static cross-sectional condition assessment in a given year, this aggregation is acceptable, but it limits the framework's sensitivity to short-term condition

changes. Future applications may replace equal weighting with empirically-derived weights through expert elicitation, multi-criteria decision analysis, or principal-component-based weighting, when such evidence becomes available.

3.2.3. Structural Condition Index

The structural condition layer integrated three key biophysical variables representing vegetation cover, productivity, and vertical structure:

Vegetation Cover was derived from the Global 30m Landsat Tree Canopy Cover Version 4 (TCC v4) dataset (Sexton et al. 2013, Hansen et al. 2023) at 30-metre resolution. We extracted the 2020 annual tree canopy cover layer from the TCC v4 Science product suite (years 2008-2021), which provides continuous estimates of tree canopy coverage per pixel ranging from 0% to 100%. The TCC product was generated through Landsat-based rescaling of MODIS Vegetation Continuous Fields with lidar-based error estimates, integrating Landsat and Sentinel-2 imagery. Tree canopy cover represents the vertically projected area of tree crowns as a percentage of ground area, serving as a direct measure of woody vegetation structural density. The 30-metre native resolution layer was resampled to 100 metres using bilinear interpolation, preserving the percentage values.

Maximum Annual Enhanced Vegetation Index (EVI) was calculated from Landsat 8 OLI surface reflectance data (USGS Landsat 8 Collection 2 Level-2; USGS, 2021) at 30-metre native resolution. We compiled all cloud-free scenes (cloud cover <20%) over the study area for 2020, applying the CFMask quality assessment band (pixel_qa) to exclude cloud, cloud shadow, and snow pixels. EVI was calculated from surface reflectance bands following Huete et al. (2002):

$$EVI = 2.5 * \frac{NIR - RED}{(NIR + 6 * RED - 7.5 * BLUE) + 1}$$

where NIR is Band 5 (0.85-0.88 μm), RED is Band 4 (0.64-0.67 μm), and BLUE is Band 3 (0.53-0.59 μm). For each pixel, we extracted the 95th percentile of EVI values across all clear observations in 2020, representing peak photosynthetic activity and vegetation vigor during the growing season. EVI was selected over NDVI due to its superior performance in high-biomass vegetation and reduced sensitivity to atmospheric effects and soil background (Huete et al. 2002).

Canopy Height was derived from the GEDI L2A Canopy Top Height product (LARSE/GEDI/GEDI02_A_002_MONTHLY; Dubayah et al. 2021) at 25-metre resolution. We aggregated monthly rasters from January to December 2020, extracting the 98th percentile relative height (rh98) as the standard metric for canopy top height. Only high-quality waveforms were retained based on quality flags (quality_flag = 1, degrade_flag = 0, sensitivity ≥ 0.95). Where multiple GEDI observations intersected a 100-metre pixel during the year, we computed the mean rh98 value. GEDI coverage within the study area was assessed to be 68% complete, with gaps primarily in agricultural areas where low vegetation provides insufficient waveform returns. Missing canopy height values were assigned zero for non-vegetated land cover classes (water, built area, bare ground)

based on Dynamic World classification and spatially interpolated using inverse distance weighting for vegetated areas without GEDI coverage.

Each structural variable was resampled to 100-metre resolution using bilinear interpolation in QGIS 3.32.3 and independently normalised to a 0-1 scale using min-max normalisation:

$$Xnorm = \frac{X - Xmin}{Xmax - Xmin}$$

where X_{min} and X_{max} represent the minimum and maximum values observed across the entire study area for each variable.

The preliminary structural condition index (SCI_{prelim}) was computed as the unweighted arithmetic mean of the three normalised variables:

$$SCIprelim = \frac{(Cover + EVI + CanopyHeight)}{3}$$

The preliminary index was then rescaled to a final 0-1 range using min-max normalisation across the study area to produce the final structural condition layer (SCI).

This two-step normalisation ensures that the final structural condition values span the full 0-1 range while maintaining the relative weighting of component variables.

3.2.4. Biological condition Index

The biological condition layer integrated three datasets representing biodiversity intactness, soil quality, and landscape-scale habitat availability:

Biodiversity Intactness Index (BII) was obtained from the IO BioIntact dataset (Impact Observatory 2021) at 100-metre resolution for 2020. BII quantifies the remaining average abundance of naturally present species relative to reference conditions based on statistical models calibrated with the PREDICTS database of 32,000+ biodiversity survey sites (Newbold et al. 2016). BII values range from 0 (complete loss of species abundance) to 1 (intact biodiversity assemblage). The 2020 layer was directly incorporated without additional resampling.

Soil Organic Carbon (SOC) concentration was extracted from the SoilGrids 2.0 global dataset (Poggio et al. 2021) at 250-metre resolution. We utilised the 0-30 cm depth-weighted average soil organic carbon content (g/kg) as an indicator of soil biological quality and ecosystem functioning. Higher SOC values indicate greater soil fertility, microbial biomass and activity, carbon storage capacity, nutrient cycling rates, and overall soil health, which support plant productivity, below-ground biodiversity, and ecosystem services (Lal 2016). The SOC layer represents predictions based on machine learning models trained on approximately 240,000 soil profile observations from the World Soil Information Service database, with estimates representing long-term averaged conditions. We treated this as a static baseline for 2020.

Proportion of Natural Habitat was calculated as the percentage of semi-natural and natural land cover within a 500-metre radius moving window around each pixel. We used the 2020 Dynamic World land cover classification (Brown et al. 2022) at 10-metre resolution. Natural habitat classes included trees, shrubs, grass (excluding intensively managed pastures), and flooded vegetation. Anthropogenic classes (crops, built area) and non-habitat classes (water, bare ground, snow/ice) were excluded. For each 100-meter pixel, we calculated the proportion of natural habitat within a circular buffer of 500-meter radius using focal statistics in QGIS 3.32.3. This metric captures landscape-scale habitat availability, spatial configuration, and potential connectivity, which strongly influence species persistence, movement, and meta-population dynamics (Fahrig 2003, Hanski 1998). The 500-metre radius was selected based on the median dispersal distances of terrestrial fauna in temperate European ecosystems (Baguette et al. 2013).

Each biological variable was resampled to 100-metre resolution using bilinear interpolation (for BII and SOC) or was calculated directly at 100-metre resolution (for natural habitat proportion). All three variables were independently normalised to a 0-1 scale using min-max normalisation.The preliminary biological condition index (BCI_{prelim}) was computed as the unweighted arithmetic mean of the three normalised variables:

$$BCIprelim = \frac{(BII + SOC + \%NatArea)}{3}$$

The preliminary index was then rescaled to a final 0-1 range using min-max normalisation across the study area to produce the final biological condition layer (BCI).

As with the structural condition layer, this two-step normalisation ensures full utilisation of the 0-1 value range while preserving the equal weighting of component variables.

The six component variables map to the SEEA-EA categories as follows: Tree canopy cover and GEDI canopy height correspond to category B2 (structural state). Maximum annual EVI corresponds to productivity-related elements of B3 (functional state) and is treated within our structural condition index as a productivity proxy for the structural dimension. The Biodiversity Intactness Index corresponds to B1 (compositional state). Soil organic carbon and the proportion of natural habitat within a 500 m buffer correspond to the remaining elements of B3 (functional state) at the within-pixel and landscape scales, respectively. This mapping is consistent with SEEA-EA's recommendation that condition assessments integrate multiple state characteristics to provide a holistic picture of ecosystem integrity.

The three structural variables (tree canopy cover, maximum annual EVI, and GEDI canopy height) are most informative for woody vegetation. For grasslands and agricultural systems, tree canopy cover takes low or zero values and EVI provides the principal structural signal reflecting primary productivity. GEDI canopy height is informative only where vegetation is present, and is set to zero for non-vegetated land covers (see paragraph on GEDI below). For aquatic systems, the structural index reflects primarily the riparian and surrounding land cover. These differences in the sensitivity of the structural index across ecosystem types reinforce the need for ecosystem-specific

condition thresholds (see section "Ecosystem-specific thresholds") and are discussed further under the Limitations section.

3.3. Ecosystem-specific thresholds

Recognising that absolute condition values vary systematically among ecosystem types, we adopted an ecosystem-specific approach to threshold condition classes rather than applying global thresholds. This methodological choice was necessitated by fundamental differences in structural and biological characteristics across ecosystem types.

To achieve this, we first stratified the different ecosystem types into four major ones. We then calculated ecosystem-specific percentile distributions to define low, medium, and high condition classes. Finally, to identify optimal condition classification thresholds, we implemented a comprehensive validation protocol examining multiple percentile combinations for both structural and biological condition boundaries.

3.3.1 Ecosystem Stratification

The study area was stratified into four major ecosystem types using the Dynamic World land cover classification (Brown et al. 2022) at 10-metre resolution, aggregated to 100-metre resolution using mode statistics:

1. **AQUA** - aquatic and wetland systems (water and flooded vegetation classes),
2. **AGRO** - agricultural systems (crops and grass classes),
3. **FORE** - forest and semi-natural systems (trees and shrubs classes), and
4. **URBA** - urban and peri-urban systems (built area class).

Pixels classified as bare ground or snow/ice represented <1% of the study area and were excluded from threshold analysis.

3.3.2. Percentile-Based Threshold Calculation

The workflow uses percentile statistics in two distinct places that must not be confused.

- First, the 5th and 95th percentiles of the expert-score distribution are used to derive the low and high capacity matrices. This is a property of the existing expert-elicitation data and is not part of the condition adjustment protocol. Details are presented in section 3.4.
- Second, the 20th and 80th percentiles of the SCI and BCI values are used to discretise the condition indices into low/moderate/high classes within each ecosystem stratum. This choice was empirically optimised against six independent reference datasets, as reported below. The two uses operate on unrelated data (expert scores vs. pixel-level condition values) and reflect distinct methodological choices.

For each ecosystem type separately, we extracted all structural condition index (SCI) and biological condition index (BCI) values at 100-metre resolution. We then calculated ecosystem-specific percentile distributions to define low, medium, and high condition classes.

3.3.3. Threshold Validation Protocol

To identify optimal condition classification thresholds, we implemented a comprehensive threshold validation protocol examining multiple percentile combinations for both structural and biological condition thresholds. The validation approach assessed how well different threshold schemes improved the relationship between condition-adjusted ecosystem service capacity estimates and independent reference datasets.

We systematically evaluated threshold scenarios using combinations of lower and upper percentiles: 5th-95th, 5th-90th, 5th-80th, 5th-70th, 10th-90th, 10th-80th, 10th-70th, 20th-80th, 20th-70th, and 30th-70th percentiles. Each threshold combination was applied to both structural and biological condition components (e.g. s20-80_b20-80 indicates 20th and 80th percentiles for both structural and biological conditions). These combinations define the thresholds between low, medium, and high condition classes differently, thereby affecting the spatial distribution of condition classifications and subsequent ecosystem service capacity assignments through the allocation tables (a-e).

For each threshold combination, we computed ecosystem-specific percentile values separately for aquatic (AQUA), agricultural (AGRO), forest (FORE), and urban (URBA) ecosystems.

To evaluate threshold performance, we utilised quantitative reference datasets for six ecosystem services available across the study area, 4 of which were previously used in Roche and Campagne (2019) to compare ES capacity scores and quantitative proxies as reference datasets. These services represent diverse ES groups as defined in our classification framework.

- Wild plant resource (Group 2: Structure and composition dependent)
- Wood material and fibres (Group 3: Biomass and plant cover dependent)
- Nature-based recreation (Group 4: Composition and function dependent)
- Climate regulation (carbon sequestration) (Group 1: Biomass dependent)
- Pest regulation (Group 5: Conservation and biodiversity dependent)
- Pollination (Group 2: Structure and composition dependent)

For each threshold combination, we applied the three-step adjustment procedure described in the methodological framework (Section 2.3.3. "Defining the adjusted ES capacity scores") to every 100 m pixel: each pixel was first assigned to a low, medium or high condition class from the ecosystem-specific percentiles, and the procedure then returned its condition-adjusted capacity score for the relevant ecosystem type and service, yielding one adjusted capacity map per service and per threshold combination.

Then, we quantified threshold performance by calculating Pearson correlation coefficients (r) between the condition adjusted capacity scores and the corresponding ES reference dataset values across all pixels. This analysis was performed separately for each of the six ES. The improvement in correlation was calculated as: $\Delta r = r_{adjusted} - r_{unadjusted}$

where $r_{adjusted}$ is the correlation coefficient using the condition-adjusted capacity scores and $r_{unadjusted}$ is the baseline correlation using the unadjusted capacity matrix.

3.4. Ecosystem Services

3.4.1. Ecosystem Service Capacity Matrix

We used the regional capacity matrix for the Hauts-de-France region (Campagne et al. 2017) as the ES mean capacity for the case study site. This matrix provides expert-elicited capacity scores (0-5 ordinal scale) for combinations of ecosystem types and ES.

We acknowledge that expert scoring distributions reflect multiple sources of variability beyond ecosystem condition alone, including expert background, regional experience, and interpretation differences (Campagne et al. 2017). Our use of the 5th and 95th percentiles to derive the low- and high-condition matrices does not assume that experts explicitly scored against condition gradients. Rather, we treated the spread of expert scores as an envelope bracketing the plausible capacity range for each ecosystem type: the lower percentile represents the degraded states that experts considered plausible for that ecosystem type, and the upper percentile represents the optimal states. The measured condition components then determine, for each ecosystem type and each service group, the appropriate ES capacity via the allocation tables. This is a working assumption, not an empirically validated equivalence between expert-score variability and condition variability. Direct condition-stratified expert elicitation, in which experts are asked to score capacity separately under low, medium, and high condition scenarios for each ecosystem type, would be methodologically superior but considerably more resource-intensive. This is a perspective for future research.

The medium (average condition) matrix is interpreted as representing typical capacity within the area for which it was elicited. Heavily modified land-cover types (e.g. intensive cropland, built areas) are typically scored low for many regulating services already in the medium matrix; the condition adjustment then captures within-class variation around this typical value, rather than shifting the overall capacity level for the ecosystem type.

Each ES in the existing regional capacity matrix was assigned to one of the five functional groups defined in the methodological framework (Table 1). This assignment determines which allocation table governs the condition-capacity linkage for that service.

3.4.2. Quantitative reference datasets of six ecosystem services

We considered six ES for which it was possible to obtain or derive independent quantitative values at the same scale as the land cover map in the case study site.

Climate Regulation (Carbon Sequestration): We used the Forest above ground carbon stock and soil carbon content. Data were obtained from the French National Forest Inventory (2006-2016), which provides annual geolocated sampling plots following a systematic sampling grid of 10 km, with each successive year shifted by 1 km. Forest carbon stock was computed for each sampling point using allometric equations per species, average wood densities per species, and a wood-to-carbon conversion factor of 0.5 t carbon per 1 t of dry wood. Point estimates were interpolated using Bayesian kriging in ArcGIS 10.3 and filtered using the Copernicus forest cover layer (100 m² resolution) to remove areas with less than 10% forest cover. This layer was then combined with topsoil organic carbon content data obtained from the European Soil Data Centre (ESDAC) Lucas database for EU25 regions. Forest and soil carbon stocks were combined to produce a total carbon stock layer expressed in $t \cdot ha^{-1}$.

Pest Regulation: Pest regulation index developed by Rega et al. 2018 was used. This spatially explicit model quantifies landscape potential to support natural pest regulation services based on habitat suitability for natural enemies and their dispersal capacity. The index ranges from 0 to 100 (unitless) at 100m resolution.

Pollination: The relative pollination index from the JRC MAES framework was used (Zulian et al. 2013). This model-based indicator considers pollinator habitat suitability and foraging distances to estimate pollination service provision to croplands. The index ranges from 0 to 1 (unitless) and was obtained at 100 m resolution for 2016.

Nature-based Recreation: Recreation use was quantified using recreation track density data from Strava Labs Inc. (2017). This indicator represents actual use of landscapes for outdoor sport activities, specifically running and biking tracks. The data were decorrelated for road density to focus on nature-based recreational use. Track density was calculated as number of tracks per hectare ($nb\ tracks \cdot ha^{-1}$).

Wild Plant Food Resources: For wild plant food resources, there is no available published layer for the area. We designed a model. Wild Plant Resources are evaluated through a multiplicative potential capacity model expressed as

$$P = B \times C^{0.35} \times S^{0.35} \times V^{0.30},$$

where P is the potential annual production (kg dry matter/ha/year). The land cover layer determines habitat suitability coefficients (H) for each resource type, which are then combined with reference production values based on European non-wood forest product studies (Lovrić et al. 2020, Schulp et al. 2014) to calculate base production $B = 0.55 \cdot (H_{plants} \cdot R_{plants}) + 0.40 \cdot (H_{fungi} \cdot R_{fungi}) + 0.05 \cdot (H_{algae} \cdot R_{algae})$, where reference values are: wild plants (berries 12.0, herbs 4.0, leafy vegetables 3.0, nuts 8.0

kg/ha/year), fungi (mushrooms 15.0, truffles 2.0 kg/ha/year; Egli et al. 2006), and algae (freshwater 1.0, seaweed 5.0). Climate suitability C is calculated from temperature (using a Gaussian response curve with 12°C optimum and 8°C tolerance) and rainfall (using a Michaelis-Menten saturation curve with 600 mm half-saturation value). Soil quality S combines soil organic carbon (half-saturation at 25 g/kg), cation exchange capacity (half-saturation at 12 cmol/kg), and pH (Gaussian response with 6.0 optimum and 1.5 tolerance) with weights 0.4, 0.3, and 0.3 respectively. Vegetation productivity V is scaled from the Enhanced Vegetation Index (EVI). The fractional exponents (0.35, 0.35, 0.30) reflect multiplicative limiting factors.

Material and fibres: We used the same source as the climate regulation service for estimating wood biomass. Data were obtained from the French National Forest Inventory (2006-2016), which provides annual geolocated sampling plots following a systematic sampling grid of 10 km, with each successive year shifting by 1 km. Standing wood volume was computed for each sampling point using allometric equations per species to derive m3/ha data. Point estimates were interpolated using Bayesian kriging in ArcGIS 10.3 and filtered using the Copernicus forest cover layer (100 m² resolution) to remove areas with less than 10% forest cover.

3.5 Results

3.5.1. Ecosystem-Specific Thresholds for condition indices

Analysis of condition components distributions revealed substantial systematic variation among ecosystem types (Fig. 3). For structural condition, the 20th percentile ranged from 0.16 (URBA) to 0.27 (FORE), while the 80th percentile ranged from 0.43 (URBA) to 0.90 (FORE), representing more than a twofold difference in threshold values between urban and forest ecosystems. For biological condition, the 20th percentile ranged from 0.13 (URBA) to 0.31 (AQUA), and the 80th percentile ranged from 0.60 (URBA) to 0.87 (FORE). The necessity of ecosystem-specific thresholds becomes evident when comparing them to generic thresholds that are common to all land cover categories. A global 20th percentile calculated across all ecosystem types would approximate 0.25 for structural condition. Applying this single threshold would classify only 5% of urban pixels as low condition (since most urban pixels have values below 0.25), while misclassifying 35% of forest pixels as low condition, despite the forest pixels being in relatively good condition for their ecosystem type. Conversely, a global 80th percentile of approximately 0.70 would classify 95% of forest pixels as high condition while classifying only 5% of urban pixels as high condition, regardless of their actual quality relative to comparable ecosystems of the same type. The divergence between ecosystem types becomes more pronounced at higher condition values, as evidenced by the increasing separation of percentile curves from the 50th to 95th percentiles (Fig. 3). This pattern indicates that "poor condition" manifests similarly across ecosystem types (convergent low values for tree cover, EVI, canopy height, and biodiversity), whereas "excellent condition" is highly ecosystem-specific. For instance, an urban ecosystem at the 95th percentile may achieve

40-50% tree canopy cover, maximum EVI of 0.5, mean canopy height of 8 m, and 45% natural habitat within 500 m, whereas a forest at the 95th percentile exhibits 85-95% tree canopy cover, maximum EVI of 0.75, mean canopy height of 25 m, and 80% natural habitat within 500 m. Both represent optimal functioning within their contexts and should receive high-capacity scores for ecosystem services appropriate to their type.

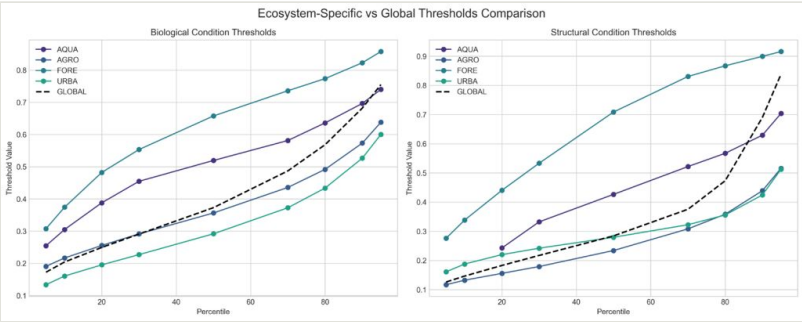


Figure 3.

Comparison of ecosystem-specific and global threshold values for structural and biological condition components across percentile distributions. Percentile distributions of (left) biological condition and (right) structural condition across four ecosystem types: AQUA (aquatic/ wetlands, blue), AGRO (agriculture, purple), FORE (forests, teal), and URBA (urban, green). Dashed black line shows hypothetical global thresholds.

3.5.2. Ecosystem Service Capacity Adjustment

For the unadjusted capacity matrix, correlations ranged from r = 0.324 (pest Regulation) to r = 0.672 (Climate regulation) (Table 3). Among the six services evaluated, none exhibited lower correlations with condition adjustment compared to the unadjusted matrix; correlations either increased or remained stable across all tested threshold combinations (Tables 3, 4). With the selected 20th-80th percentile thresholds (s20-80_b20-80), correlations improved respectively to r = 0.454 for pest Regulation and r =0.708 for Climate Regulation (Table 3). Most critically, all correlations remained statistically significant at $p < 0.001$, establishing robust relationships between condition-adjusted estimates and ES reference layers.

Table 3.

Correlation coefficients between the ecosystem service capacity unadjusted matrix scores and condition adjusted matrix scores with the reference datasets. Pearson correlation coefficient for six ecosystem services under different structural (s) and biological (b) condition percentile threshold combinations. "Best Combination" represents the optimal threshold configuration identified through exhaustive search across all tested percentile values. Values indicate the improvement gained by incorporating condition-based capacity adjustments compared to unadjusted matrices. In Bold the highest values. All correlations are significant at p<0.001.

Percentile Combinations	Material and fibres	Wild Plant Resources	Nature-based Recreation	Climate regulation	Pollination	Pest regulation
Unadjusted Matrix	0.587	0.436	0.504	0.672	0.531	0.324
Best Combination	0.648	0.573	0.566	0.711	0.616	0.459
s5-95_b5-95	0.636	0.494	0.578	0.698	0.600	0.394
s10-90_b10-90	**0.648**	0.511	**0.600**	0.708	**0.606**	0.433
s20-80_b20-80	0.647	0.539	0.591	**0.708**	0.588	**0.454**
s30-70_b30-70	0.618	**0.568**	0.561	0.708	0.564	0.444

Table 4.

Improvement in correlation coefficients between ecosystem service capacity estimates and reference datasets across threshold combinations. Pearson correlation coefficient improvements ($\Delta r = r_{adjusted} - r_{unadjusted}$) for six ecosystem services under different structural (s) and biological (b) condition percentile threshold combinations. "Best Combination" represents the optimal threshold configuration identified through exhaustive search across all tested percentile values. Values indicate the improvement gained by incorporating condition-based capacity adjustments compared to unadjusted matrices. In Bold the highest values. All correlation improvements are significant at $p<0.001$.

Percentile Combinations	Material and fibres	Wild Plant Resources	Nature-based Recreation	Climate regulation	Pollination	Pest regulation	Mean
Best Combination	0.061	0.137	0.062	0.039	0.085	0.136	0.093
s5-95_b5-95	0.049	0.058	0.074	0.026	0.069	0.070	0.058
s10-90_b10-90	**0.061**	0.075	**0.096**	0.035	**0.075**	0.110	0.075
s20-80_b20-80	0.060	0.103	0.087	**0.036**	0.057	**0.130**	**0.078**
s30-70_b30-70	0.031	**0.132**	0.057	0.036	0.033	0.121	0.068

3.5.3. Mapping Ecosystem services

Unadjusted capacity patterns (Fig. 4, top row) derived from the medium regional capacity matrix showed relatively homogeneous distributions within land cover types, with high-capacity values concentrated in forested areas for Climate regulation, Recreation, and Material and fibres. These patterns reflect the baseline capacity scores assigned to each ecosystem type without accounting for local condition variation.

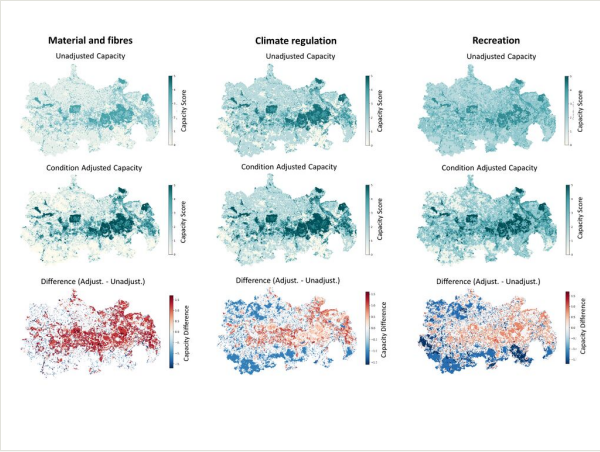


Figure 4.

Spatial distribution of ecosystem service capacity before and after condition-based adjustment for three example services.

Columns: Material and fibres (left); Climate regulation through carbon sequestration (centre); Aesthetic and recreational values (right). Rows: Unadjusted capacity (top) from the medium regional matrix; Adjusted capacity (middle) after applying ecosystem-specific condition thresholds (20th-80th percentiles); Difference (bottom) = Adjusted - Unadjusted. Capacity scores in the upper and middle rows are 0-5 ordinal values from the capacity matrix. The difference panel (bottom row) displays the arithmetical difference between adjusted and unadjusted scores, expressed in capacity-score units on the same 0-5 scale; values range from -2.5 to +2.5. Blue colours indicate decreases in capacity associated with lower than average local condition for the ecosystem type; red colours indicate increases associated with higher than average local condition; white indicates marginal change (±0.1). Study area: RNP Scarpe-Escaut, Hauts-de-France, France; 100-m resolution, year 2020; ETRS89-LAEA (EPSG:3035).

Adjusted capacity patterns (Fig. 4, middle row) incorporating ecosystem-specific structural and biological condition thresholds (20th-80th percentiles) revealed substantially higherspatial heterogeneity within land cover types. High-capacity pixels became more spatially clustered in areas with higher ecosystem condition, while capacity values decreased in degraded pixels of the same ecosystem type. This fine-scale variation was particularly pronounced for Climate Regulation, where adjusted capacity values ranged from 0.2 to 5.0 within forest ecosystems, compared to 3.5-4.2 in the unadjusted matrix.

Capacity differences (Fig. 4, bottom row) between adjusted and unadjusted matrices revealed systematic spatial patterns and service-specific responses. For Material and fibres, adjustments were predominantly positive (red colours) across forested pixels. This indicates that the medium matrix underestimated material and fibres capacity in areas with above-average structural and biological condition. Conversely, 18% of agricultural pixels showed negative adjustments (blue colours) averaging -0.8 capacity score in low-condition areas, indicating lower capacity than estimated with the medium matrix.

For climate regulation, the spatial pattern of adjustments was more balanced, with 45% of pixels showing capacity decreases (blue) and 41% showing increases (red), while 14% remained unchanged. Positive adjustments (mean +0.7) concentrated in forest stands with high canopy cover (>80%) and tall canopy height (>20 m). Negative adjustments (mean -0.9) occurred in fragmented forest patches, and urban green areas with reduced structural complexity and low biomass. This service exhibited the most visible spatial condition adjustment, reflecting its strong dependence on both biomass (structural condition), consistent with its Group 1 classification in our allocation framework (Fig. 2). The low average increase of the ES for the whole area is due to compensation effects between increasing and decreasing areas.

For recreational values, adjustments showed intermediate heterogeneity, with 52% of pixels experiencing capacity decreases with the adjustment (mean -0.6) and 38% experiencing increases (mean +0.5). Positive adjustments were concentrated in high-quality forest ecosystems, wetlands with intact vegetation, and well-vegetated urban parks characterised by high tree canopy cover, diverse vegetation structure, and low human modification in surrounding landscapes. Negative adjustments occurred predominantly in degraded semi-natural habitats, intensively managed grasslands, and urban areas with limited green space connectivity.

The mean absolute difference between adjusted and unadjusted capacity scores was 0.73 for Material and fibres, 0.81 for Climate Regulation, and 0.58 for Recreation on a scale 0-5, representing 12-16% of the full capacity range. However, maximum local differences reached 2.1 (42% of range) for Climate Regulation.

Ecosystem-specific thresholds successfully prevented systematic bias in capacity adjustments. Urban ecosystems, which exhibited lower absolute condition values than forests (Fig. 4), received proportional adjustments relative to other urban areas rather than being uniformly downgraded when compared to forests. For example, a well-managed urban park in the 85th percentile of urban structural condition (tree canopy cover 45%, canopy height 8 m, maximum EVI 0.52) received a high-capacity classification despite having lower absolute values than a degraded forest in the 25th percentile of forest structural condition (tree canopy cover 55%, canopy height 12 m, maximum EVI 0.58).

The spatial concordance of adjustments across the three ES was moderate (Spearman's $\rho = 0.51$-0.63 for pairwise comparisons), indicating that while high-condition ecosystems generally support elevated capacity across multiple services, the magnitude and the direction of adjustments are service-specific. This reflects the differential dependencies of ESs on structural versus biological condition components, as formalised in our five-group classification and allocation tables (Table 2 and Fig. 2a-e). Services primarily dependent on biomass and structure (Groups 1 and 3) showed stronger spatial correlation with structural condition patterns, while services dependent on species composition and conservation status (Groups 4 and 5) correlated more strongly with biological condition patterns.

4. Discussion

4.1. Tuning Ecosystem Services scores through Condition Integration

The general positive direction of correlations for the evaluated ES demonstrates that condition integration in ES scores improves the capacity matrices rather than introducing arbitrary adjustments. As shown in the results, no evaluated ES exhibited degraded performance following condition adjustment. Correlations either increased or remained stable. This pattern is consistent with Gamfeldt et al. (2013), whose meta-analysis showed that ecosystem multifunctionality (provision of multiple services simultaneously) increases predictably with forest structural attributes including species diversity and biomass.

The analysis revealed consistent and statistically significant improvements in ES capacity estimates when incorporating ecosystem-specific condition thresholds. With the selected 20th-80th percentile thresholds (s20-80_b20-80), mean correlation improvements across the six services were $\Delta r = 0.078$ (Table 3), with all six correlation improvements statistically significant ($p < 0.001$). Expressed as changes in explained variance ($\Delta R^2 = r^2_{adjusted} - r^2_{unadjusted}$), the corresponding mean gain was approximately 0.08 in R^2, with the largest improvement observed for pest regulation and wild plant resources. Expressed as a relative change over the unadjusted baseline correlation ($r \approx 0.32$-0.67 across services), the improvements represent a 3.5% to 13% relative gain in correlation coefficient.

The systematic improvement in correlations across all evaluated services supports the broader recognition that ecosystem condition underpins service generation in service-specific ways (La Notte et al. 2022, Martini et al. 2024). Harrison et al. (2014), in their systematic review of 530 studies examining ES-biodiversity linkages, identified mean correlations between biodiversity metrics and ES provision ranging from $r = 0.35$ to $r = 0.62$, comparable to baseline correlations observed in our study. Our improvements from $r = 0.55$ to $r = 0.64$ represent performance enhancements within the documented range of ES assessment accuracy, achieved through systematic incorporation of locally observed condition variation. The maximum improvement for wild plant resources ($\Delta r = 0.103$) reflects these services' well-documented sensitivity to site-specific conditions. Schulp et al. (2014) analysing wild food provision across European ecosystems, found that wild edible plant availability varied up to fivefold to eightfold within regions of identical land cover classification, driven primarily by microhabitat conditions, soil fertility, and species composition. The non-linear nature of condition-capacity relationships presents a recognised challenge for ecosystem accounting applications (Martini et al. 2024).

The absolute magnitude of the correlation improvement may appear moderate, but is highly statistically significant for every service considered. Formal statistical robustness was not tested explicitly in the present study. Evaluating robustness would require

replicating the analysis across different case studies, and we encourage the application of our framework in other contexts so that its robustness can be properly assessed.

4.2. Allocation Tables

Our allocation table approach shares conceptual foundations with recent capacity index methodologies proposed for SEEA-EA implementation. Martini et al. (2024) developed a quartile-based scoring procedure linking condition variables to service-specific capacity and demonstrated that condition scores differ systematically across services. Our results confirm this service-specificity at landscape scale: the differential magnitude of correlation improvements across groups (Δr ranging from 0.036 for climate regulation to 0.130 for pest regulation under the selected 20th-80th percentile thresholds) mirrors the differential condition sensitivities reported by Martini et al. (2024) at site level, and extends their findings to spatially explicit raster-based assessment across heterogeneous ecosystem mosaics.

The largest improvements were obtained for pest regulation (Δr = 0.130) and wild plant resources (Δr = 0.103), the two services in our sample that depend most strongly on biological condition (Groups 5 and 2, respectively). This pattern is consistent with the ecological rationale underlying our functional grouping: services governed by species composition and diversity, rather than by biomass alone, are expected to be the most sensitive to variation in ecosystem condition Balvanera et al. (2006).

Climate regulation showed the smallest improvement (Δr = 0.036). Above-ground carbon stocks are largely a function of tree size and stand basal area, which are already captured by the ecosystem-type classification of the medium matrix, leaving a narrower margin for condition-based refinement.

Across the remaining services, the pattern of improvement aligns with Harrison et al. (2014), who found in a systematic review of 530 studies that services dependent on species richness and diversity were more responsive to biotic attributes than biomass-dominated services. The absence of any service showing degraded performance after condition adjustment, across all tested threshold combinations, reinforces the conclusion of La Notte et al. (2022) that condition and capacity accounts are complementary rather than redundant, and that integrating condition systematically improves rather than distorts capacity estimates.

4.3. Ecosystem Condition Thresholds

The tension between standardisation and context-specificity has long challenged ES mapping efforts (Crossman et al. 2013). Burkhard et al. (2009) conceptualised ES capacity scores as representing ecosystems under "average conditions." Our approach operationalises this concept by adjusting only when condition deviates substantially from the typical range. Our percentile-based approach balances these competing needs by applying a standardised methodology (percentile calculation) while enabling ecosystem-specific thresholds that reflect local condition distributions. This methodological choice

aligns with recent critiques emphasising that "assessments based only on LULC proxies are not suitable for local quantitative assessment" (Perennes et al. 2020) and that capacity matrices must move beyond uniform land cover classifications to capture within-class heterogeneity (Jacobs et al. 2015).

The selection of 20th and 80th percentiles as condition class boundaries represents a methodological choice with substantial implications for assessment accuracy. The ecosystem-specific threshold approach resolves a fundamental challenge in condition assessment: ecosystem types exhibit inherently different biophysical characteristics regardless of management or degradation status. Forests naturally exhibit greater tree canopy cover (typically 60-95%) compared to grasslands (typically 10-40%) or urban systems (typically 5-20%), even when all are in "good condition." As a consequence, applying global thresholds would systematically misclassify ecosystems based on inherent characteristics rather than actual condition. As illustrated in Fig. 3, a global 20th percentile of 0.25 (structural condition) would classify only 5% of urban pixels as low condition despite urban areas genuinely containing many degraded examples, while simultaneously misclassifying 35% of forest pixels as degraded despite being in relatively good condition for their type.

Hein et al. (2020), analysing SEEA-EA framework implementation across diverse landscapes, emphasised that ecosystem condition assessment is a key element that should consider ecosystem-type-specific baselines to avoid conflating management effects with inherent ecosystem characteristics. Weyland et al. (2017) implemented percentile-based ecosystem condition approaches in four ecoregions of southern South America (Valdivian Forests, Campos, Chaco and Pampas) and concluded that percentile thresholds produced more stable classifications across temporal data snapshots than absolute-value thresholds. Ecosystem-specific thresholds prevent the systematic bias that global thresholds would introduce. In this study, the 20th percentile for structural condition ranged from 0.16 (urban) to 0.27 (forest), representing a greater than 1.7-fold difference and reflecting genuine ecosystem type characteristics. Similarly, the 80th percentile ranged from 0.43 (urban) to 0.90 (forest). These differences are not arbitrary but reflect documented structural characteristics: forests can accumulate tall vegetation and dense canopy cover due to tree growth potential; urban areas face inherent constraints from building density and fragmented green space.

Applying single global thresholds would systematically undervalue urban ecosystems condition relative to forests. Applying ecosystem-specific ones will evaluate each ecosystem type against its own distribution of condition index. A well-managed urban park achieving the 85th percentile of urban condition thus receives high-capacity classification despite lower absolute structural values than a degraded forest, appropriately recognising that both are evaluated within their respective contexts. The percentile thresholds defined and used in the test case study are not proposed as a one-size-fits-all solution but correspond to the local condition. Further studies should be conducted in different contexts to confirm or refute those thresholds.

The practical implications extend to ES accounting frameworks. The SEEA-EA standard explicitly requires linking ecosystem condition to service capacity (SEEA-EA 2021), yet operational methods for this linkage have remained underdeveloped. Our findings demonstrate that incorporating condition indices would substantially alter national accounts of ecosystem ES capacity. Using our approach, we observed typical differences of 12-16% (up to 42% maximum) between adjusted and unadjusted capacity scores, suggesting that ES accounts require condition integration to meet accuracy standards appropriate for policy use. Our study provides an operational framework for the conceptual relationship established by ecosystem accounting standards. The SEEA-EA framework defines ecosystem capacity as "the capability of an ecosystem to deliver a specific ecosystem service in a sustainable way given its current condition" (SEEA-EA 2021, Chapter 6), explicitly linking condition to service provision potential. However, translating this conceptual linkage into quantitative assessment protocols has remained challenging. As La Notte et al. (2022), page 1, observed, "Without a concrete linkage, the two sets of accounts run in parallel," with ecosystem extent and condition accounts disconnected from ecosystem service accounts. Our adjustment mechanism provides this concrete linkage through a transparent, reproducible protocol. As Weyland et al. (2017) also concluded, the consideration of local ecological condition provides a more reliable source of spatially explicit information on ES supply for decision makers than a general matrix.

Alternative approaches to improving ES assessments exist along a complexity-accuracy continuum. This was clearly identified as a tension byBagstad et al. (2013), page 27: "*To enter widespread use, ecosystem service assessments need to be quantifiable, replicable, credible, flexible, and affordable*.". Process-based models such as InVEST provide mechanistically explicit predictions but require substantial technical capacity and data inputs (Bagstad et al. 2013). Empirical validation studies demonstrate that such models can achieve high accuracy when properly calibrated. For example, the InVEST water yield model improved from R^2=0.963 to R^2=0.990 when using national scale versus global input data (Redhead et al. 2016), but the resource intensity of such models limits widespread adoption. At the opposite extreme, purely land-cover-based classifications remain too coarse, with studies showing massive within-region variation that simple land use proxies cannot capture: crop production ranging 0-16.42 t/ha, water supply 197-1173 mm, and soil retention 0-82.54 t/ha within single regions (Liu et al. 2017). Model results derived from land cover proxies are themselves strongly dependent on the LULC classification used, and substantial biases can be introduced by the choice of classification scheme (Liu et al. 2017; Sieber et al. 2021). Our framework occupies a methodological middle ground. Similarly to continuous field mapping approaches that relate local conditions to ecosystem service provision through regression (Palomo et al. 2014), our method integrates spatially explicit condition data to refine capacity estimates. However, rather than requiring site-specific calibration of regression models, we apply a generalisable statistical framework that can be implemented across diverse contexts with moderate data requirements. A methodological parallel is the confidence-weighting scheme developed by Keele et al. (2019) for river ES assessments. Confidence weighting is a procedure that assigns to each service-feature linkage a score based on

the number and quality of supporting studies (e.g. 1-2 papers → score 1; 3-4 → score 2; more than 5 → score 3), providing objective criteria for distinguishing well-established from speculative linkages. In our framework, condition-based adjustment is applied only when the observed condition deviates substantially from the within-type reference range. Both our approach and that of Keele et al. (2019) seek to enhance expert-based methods with statistical rigour while preserving operational tractability.

4.4. Limitations

Several limitations of our framework need to be considered. First, the selection of 20th and 80th percentiles as condition thresholds, while defensible as a means of separating the central tendency from distributional tails, remains empirical and was defined based on the specific condition of our test study case. Repeating this framework in different situations will allow us to evaluate those thresholds as robust values. Accordingly, we recommend testing several thresholds before the application of our approach. Second, structural and biological condition are treated as separable axes combined through deterministic rule-based allocation tables. In reality, the two dimensions are often strongly correlated, and their effects on capacity may be non-additive. For instance, high structural complexity may only translate to high capacity if species composition is also favourable, suggesting multiplicative or threshold-dependent relationships. Studies demonstrating that functional diversity affects ecosystem multifunctionality more strongly than taxonomic diversity (Huang et al. 2019) indicate that interaction effects should be investigated.

Third, the condition indicators used in the two components operate at different temporal scales: BII reflects multi-year biodiversity dynamics, SOC reflects multi-decadal biogeochemical accumulation, the proportion of natural habitat can change over months, and vegetation indices (EVI, tree canopy cover) respond to sub-annual to inter-annual timescales. Combining these variables through equal weighting provides a usable cross-sectional snapshot for a single reference year but limits the framework's sensitivity to short-term condition changes.

4.5. Future Research Directions

The framework proposed here provides a structured, transparent and reproducible way to link condition components to Ecosystem Services capacity estimates. The priorities below are natural extensions that would further strengthen this approach. The most immediate priority is independent validation. Comparing the prediction accuracy of static capacity scores, condition adjusted scores, and process based models against empirical service measurements would quantify the improvement that condition adjustment delivers, building on validation protocols already well established in the field (Redhead et al. 2016 , Willcock et al. 2019).

A second priority is refining the allocation tables through empirical calibration. The rule-based relationships used here, already grounded in expert elicited capacity ranges, can be progressively complemented by empirically derived condition capacity response

curves, particularly through targeted studies focusing on single services across condition gradients. A full calibration across all ecosystem type and service combinations would constitute a major research programme in its own right, but service by service progress offers a tractable and high value near term path building directly on the framework established in this study.

Thirdly, the framework currently considers only biotic condition. Incorporating abiotic indicators (soil properties, water chemistry, local climate) through coupling with process-based models would extend its applicability to services where abiotic factors are the dominant capacity drivers.

Fourthly, testing is required to establish transferability across biogeographic regions and management contexts. Multi-region applications would reveal whether the percentile thresholds adopted here transfer across contexts or require local recalibration.

Finally, conducting a cost-benefit analysis of condition data collection would help to define tiered assessment strategies and identify which services would benefit from condition integration. This would also establish whether basic (land cover), intermediate (structural indicators), or advanced (biological indicators) data would justify the additional collection effort.

5. Conclusions

This study contributes (i) a conceptual framework integrating ecosystem condition into capacity-matrix assessments, (ii) a functional grouping of ES based on their differential dependencies on structural and biological condition, (iii) an operational protocol for constructing spatially explicit condition indices from remote-sensing data, and (iv) a procedure for combining these elements through allocation tables to produce condition-adjusted capacity maps. The integration of these four components into a single reproducible workflow, validated against six independent reference datasets in the RNP Scarpe-Escaut, is the main contribution of the paper. By providing transparent, reproducible protocols for translating condition-monitoring data into capacity adjustments, the method operationalises the SEEA-EA conceptual linkage between ecosystem condition and capacity, with immediate applications in natural capital accounting, conservation prioritisation, payment-for-ecosystem-services design, and environmental impact assessment. Application in the RNP Scarpe-Escaut demonstrates that condition adjustment modifies capacity scores by 0.58-0.81 capacity score on average (12-16% of the 0-5 scale), with local maxima of 2.1 (42% of the scale), and yields statistically significant correlation improvements (mean $\Delta r = 0.078$, $p < 0.001$ for all services).

Acknowledgements

Part of this work was funded by the DREAL French Regional Directorate For The Environment, Development And Housing (Direction Régionale Environnement Aménagement Logement) Haut de France, under the project "Guide pour la prise en compte des services écosystémiques dans les évaluations des incidences sur l'environnement" 2019-2021.

Author contributions

The two authors contributed equally to the study and the redaction of this paper.

Conflicts of interest

The authors have declared that no competing interests exist.

References

- Bagstad KJ, Semmens DJ, Waage S, Winthrop R (2013) A comparative assessment of decision-support tools for ecosystem services quantification and valuation. Ecosystem Services 5: 27-39. https://doi.org/10.1016/j.ecoser.2013.07.004
- Baguette M, Blanchet S, Legrand D, Stevens VM, Turlure C (2013) Individual dispersal, landscape connectivity and ecological networks. Biological Reviews 88 (2): 310-326.
- Balmford A, Green JM, Anderson M, Beresford J, Huang C, Naidoo R, Walpole M, Manica A (2015) Walk on the Wild Side: Estimating the Global Magnitude of Visits to Protected Areas. PLoS Biology 13 (2): 1002074. https://doi.org/10.1371/journal.pbio.1002074
- Balvanera P, Pfisterer AB, Buchmann N, He JS, Nakashizuka T, Raffaelli D, Schmid B (2006) Quantifying the evidence for biodiversity effects on ecosystem functioning and services. Ecology Letters 9 (10): 1146-1156. https://doi.org/10.1111/j.1461-0248.2006.00963.x
- Bianchi CA, Booij CJ, Tscharntke T (2006) Sustainable pest regulation in agricultural landscapes: a review on landscape composition, biodiversity and natural pest control. Proceedings of the Royal Society B 273: 1715-1727.
- Braat L, ten Brinks P (Eds) (2008) The Cost of Policy Inaction: The case of not meeting the 2010 biodiversity target. Alterra Wageningen/Brussels . URL: https://www.researchgate.net/publication/265269550
- Brockerhoff E, Barbaro L, Castagneyrol B, Forrester D, Gardiner B, González-Olabarria JR, Lyver P, Meurisse N, Oxbrough A, Taki H, Thompson I, van der Plas F, Jactel H (2017) Forest biodiversity, ecosystem functioning and the provision of ecosystem services. Biodiversity and Conservation 26 (13): 3005-3035. https://doi.org/10.1007/s10531-017-1453-2
- Brown C, Brumby S, Guzder-Williams B, Birch T, Hyde SB, Mazzariello J, Czerwinski W, Pasquarella V, Haertel R, Ilyushchenko S, Schwehr K, Weisse M, Stolle F, Hanson C,

Guinan O, Moore R, Tait A (2022) Dynamic World, Near real-time global 10 m land use land cover mapping. Scientific Data 9 (1). https://doi.org/10.1038/s41597-022-01307-4

- Bruzón AG, Arrogante-Funes P, Santos-Martín F (2023) Modelling and testing forest ecosystems condition account. Journal of Environmental Management 345: 118676.
- Burkhard B, Kroll F, Müller F, Windhorst W (2009) Landscapes' capacities to provide ecosystem services - A concept for land-cover based assessments. Landscape Online 15: 1-22. https://doi.org/10.3097/lo.200915
- Burkhard B, Kroll F, Nedkov S, Müller F (2012) Mapping ecosystem service supply, demand and budgets. Ecological Indicators 21: 17-29. https://doi.org/10.1016/j.ecolind.2011.06.019
- Burkhard B, Kandziora M, Hou Y, Müller F (2014) Ecosystem service potentials, flows and demands-concepts for spatial localisation, indication and quantification. Landscape Online 34: 1-32. https://doi.org/10.3097/lo.201434
- Burkhard B, Maes J (Eds) (2017) Mapping Ecosystem Services. Pensoft Publishers
- Campagne CS, Roche P, Gosselin F, Tschanz L, Tatoni T (2017) Expert-based ecosystem services capacity matrices: Dealing with scoring variability. Ecological Indicators 79: 63-72. https://doi.org/10.1016/j.ecolind.2017.03.043
- Campagne CS, Roche P (2018) May the matrix be with you! Guidelines for the application of expert-based matrix approach for ecosystem services assessment and mapping. One Ecosystem 3 https://doi.org/10.3897/oneeco.3.e24134
- Campagne CS, Roche P, Müller F, Burkhard B (2020) Ten years of ecosystem services matrix: Review of a (r)evolution. One Ecosystem 5 https://doi.org/10.3897/oneeco.5.e51103
- Cardinale B, Duffy JE, Gonzalez A, Hooper D, Perrings C, Venail P, Narwani A, Mace G, Tilman D, Wardle D, Kinzig A, Daily G, Loreau M, Grace J, Larigauderie A, Srivastava D, Naeem S (2012) Biodiversity loss and its impact on humanity. Nature 486 (7401): 59-67. https://doi.org/10.1038/nature11148
- Carrick P, Forsythe K (2020) The species composition—ecosystem function relationship: A global meta-analysis using data from intact and recovering ecosystems. PLOS ONE 15 (7). https://doi.org/10.1371/journal.pone.0236550
- Crossman N, Burkhard B, Nedkov S, Willemen L, Petz K, Palomo I, Drakou E, Martín-Lopez B, McPhearson T, Boyanova K, Alkemade R, Egoh B, Dunbar M, Maes J (2013) A blueprint for mapping and modelling ecosystem services. Ecosystem Services 4: 4-14. https://doi.org/10.1016/j.ecoser.2013.02.001
- Czúcz B, Keit H, Maes J, Drive A, Jackson B, Nicholson E, Kiss M, Obst C (2021) Selection criteria for ecosystem condition indicators. Ecological Indicators 133: 108376.
- Daniel T, Muhar A, Arnberger A, Aznar O, Boyd J, Chan KA, Costanza R, Elmqvist T, Flint C, Gobster P, Grêt-Regamey A, Lave R, Muhar S, Penker M, Ribe R, Schauppenlehner T, Sikor T, Soloviy I, Spierenburg M, Taczanowska K, Tam J, von der Dunk A (2012) Contributions of cultural services to the ecosystem services agenda. Proceedings of the National Academy of Sciences 109 (23): 8812-8819. https://doi.org/10.1073/pnas.1114773109
- de Groot RS, Fisher B, Christie M, Aronson J, Braat L, Haines-Young R, Gowdy J, Maltby E, Neuville A, Polasky S, Portela R, Ring I (2010) Integrating the ecological and economic dimensions in biodiversity and ecosystem service valuation The Economics of Ecosystems and Biodiversity (TEEB): Ecological and Economic Foundations. In: Kumar

P (Ed.) The Economics of Ecosystems and Biodiversity (TEEB): Ecological and Economic Foundations . Earthscan, London and Washington, 9-40 pp.

- Díaz S, Lavorel S, de Bello F, Quétier F, Grigulis K, Robson TM (2007) Incorporating plant functional diversity effects in ecosystem service assessments. Proceedings of the National Academy of Sciences 104 (52): 20684-20689. https://doi.org/10.1073/pnas.0704716104
- Dubayah R, Armston J, Kellner J, Kroeger W, LaPoint E, Luthcke S, Simard M, Slay C, Tang H, Thomas N, Neuenschwander A (2021) GEDI L2A Elevation and Height Metrics Data Global Footprint Level V002. NASA EOSDIS Land Processes DAAC.. https://doi.org/10.5067/GEDI/GEDI02_A.002
- Egli S, Peter M, Buser C, Stahel W, Ayer F (2006) Mushroom picking does not impair future harvests-results of a long-term study in Switzerland. Biological Conservation 129 (2): 271-276.
- Fahrig L (2003) Effects of habitat fragmentation on biodiversity. Annual Review of Ecology, Evolution, and Systematics 34 (1): 487-515.
- Gamfeldt L, Snäll T, Bagchi R, Jonsson M, Gustafsson L, Kjellander P, Ruiz-Jaen M, Fröberg M, Stendahl J, Philipson C, Mikusiński G, Andersson E, Westerlund B, Andrén H, Moberg F, Moen J, Bengtsson J (2013) Higher levels of multiple ecosystem services are found in forests with more tree species. Nature Communications 4 (1). https://doi.org/10.1038/ncomms2328
- Greco S, Ishizaka A, Tasiou M, Torrisi G (2018) On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation, and Robustness. Social Indicators Research 141 (1): 61-94. https://doi.org/10.1007/s11205-017-1832-9
- Greenop A, Woodcock BA, Wilby A, Cook SM, Pywell RF (2018) Functional diversity positively affects prey suppression by invertebrate predators: a meta-analysis. Ecology 99: 1771-1782.
- Grêt-Regamey A, Bebi P, Bishop I, Schmid W (2008) Linking GIS-based models to value ecosystem services in an Alpine region. Journal of Environmental Management 89 (3): 197-208. https://doi.org/10.1016/j.jenvman.2007.05.019
- Haines-Young R, Potschin M (2010) The links between biodiversity, ecosystem services and human well-being. In: Raffaelli D, Frid C (Eds) Ecosystem Ecology: A New Synthesis. Cambridge University Press, Cambridge, 110-139 pp.
- Hansen M, Potapov P, Moore R, Hancher M, Turubanova S, Tyukavina A, Thau D, Stehman S, Gorelick S, Kommareddy A, Vermote E, Loboda T, Pittman K (2023) Global 30m Landsat Tree Canopy Cover. Version 4 (2008-2021).. University of Maryland. Available through Google Earth Engine Community Catalog..
- Hanski I (1998) Metapopulation dynamics. Nature 396 (6706): 41-49. https://doi.org/10.1038/23876
- Harrison PA, Berry PM, Simpson G, Haslett JR, Blicharska M, Bucur M, Dunford R, Egoh B, Garcia-Llorente M, Geamănă N, Geertsema W, Lommelen E, Meiresonne L, Turkelboom F (2014) Linkages between biodiversity attributes and ecosystem services: A systematic review. Ecosystem Services 9: 191-203. https://doi.org/10.1016/j.ecoser.2014.05.006
- Hein L, Bagstad K, Obst C, Edens B, Schenau S, Castillo G, Soulard F, Brown C, Driver A, Bordt M, Steurer A, Harris R, Caparrós A (2020) Progress in natural capital accounting for ecosystems. Science 367 (6477): 514-515. https://doi.org/10.1126/science.aaz8901

- Huang X, Su J, Li S, Liu W, Lang X (2019) Functional diversity drives ecosystem multifunctionality in a Pinus yunnanensis natural secondary forest. Scientific Reports 9 (1). https://doi.org/10.1038/s41598-019-43475-1
- Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG (2002) Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment 83: 195-213. https://doi.org/10.1016/s0034-4257(02)00096-2
- Impact Observatory (2021) IO Biodiversity Intactness. Available through Google Earth Engine Community Catalog..
- Jacobs S, Burkhard B, Van Daele T, Staes J, Schneiders A (2015) 'The Matrix Reloaded': A review of expert knowledge use for mapping ecosystem services. Ecological Modelling 295: 21-30. https://doi.org/10.1016/j.ecolmodel.2014.08.024
- Keele V, Gilvear D, Large A, Tree A, Boon P (2019) A new method for assessing river ecosystem services and its application to rivers in Scotland with and without nature conservation designations. River Research and Applications 35 (8): 1338-1358. https://doi.org/10.1002/rra.3533
- Kremen C (2005) Managing ecosystem services: what do we need to know about their ecology? Ecology Letters 8 (5): 468-479. https://doi.org/10.1111/j.1461-0248.2005.00751.x
- Lal R (2016) Soil health and carbon management. Food and Energy Security 5 (4): 212-222. https://doi.org/10.1002/fes3.96
- La Notte A, Czúcz B, Vallecillo S, Polce C, Maes J (2022) Ecosystem condition underpins the generation of ecosystem services: an accounting perspective. One Ecosystem 7 https://doi.org/10.3897/oneeco.7.e81487
- Liu Y, Bi J, Lv J, Ma Z, Wang C (2017) Spatial multi-scale relationships of ecosystem services: A case study using a geostatistical methodology. Scientific Reports 7 (1). https://doi.org/10.1038/s41598-017-09863-1
- Lovrić M, Da Re R, Vidale E, Prokofieva I, Wong J, Pettenella D, Verkerk PJ, Mavsar R (2020) Non-wood forest products in Europe – A quantitative overview. Forest Policy and Economics 116 https://doi.org/10.1016/j.forpol.2020.102175
- Mace G, Norris K, Fitter A (2012) Biodiversity and ecosystem services: a multilayered relationship. Trends in Ecology & Evolution 27 (1): 19-26. https://doi.org/10.1016/j.tree.2011.08.006
- Maes J, Liquete C, Teller A, Erhard M, Paracchini ML, Barredo J, Grizzetti B, Cardoso A, Somma F, Petersen J, Meiner A, Gelabert ER, Zal N, Kristensen P, Bastrup-Birk A, Biala K, Piroddi C, Egoh B, Degeorges P, Fiorina C, Santos-Martín F, Naruševičius V, Verboven J, Pereira H, Bengtsson J, Gocheva K, Marta-Pedroso C, Snäll T, Estreguil C, San-Miguel-Ayanz J, Pérez-Soba M, Grêt-Regamey A, Lillebø A, Malak DA, Condé S, Moen J, Czúcz B, Drakou E, Zulian G, Lavalle C (2016) An indicator framework for assessing ecosystem services in support of the EU Biodiversity Strategy to 2020. Ecosystem Services 17: 14-23. https://doi.org/10.1016/j.ecoser.2015.10.023
- Martini F, Conroy K, King E, Farrell C, Kelly-Quinn M, Obst C, Buckley Y, Stout J (2024) A capacity index to connect ecosystem condition to ecosystem services accounts. Ecological Indicators 167 https://doi.org/10.1016/j.ecolind.2024.112731
- Nardo M, Saisana M, Saltelli A, Tarantola S (2008) Handbook on constructing composite indicators: methodology and user guide. OECD / EC-JRC report..
- Newbold T, Hudson L, Arnell A, Contu S, De Palma A, Ferrier S, Hill SL, Hoskins A, Lysenko I, Phillips HP, Burton V, Chng CT, Emerson S, Gao D, Pask-Hale G, Hutton J, Jung M, Sanchez-Ortiz K, Simmons B, Whitmee S, Zhang H, Scharlemann JW, Purvis A

(2016) Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. Science 353 (6296): 288-291. https://doi.org/10.1126/science.aaf2201

- OECD (2008) Handbook on Constructing Composite Indicators: Methodology and User Guide. OECD Publishing, Paris. https://doi.org/10.1787/9789264043466-en
- Palomo I, Montes C, Martín-López B, González J, García-Llorente M, Alcorlo P, Mora MRG (2014) Incorporating the Social–Ecological Approach in Protected Areas in the Anthropocene. BioScience 64 (3): 181-191. https://doi.org/10.1093/biosci/bit033
- Perennes M, Campagne CS, Müller F, Roche P, Burkhard B (2020) Refining the Tiered Approach for Mapping and Assessing Ecosystem Services at the Local Scale: A Case Study in a Rural Landscape in Northern Germany. Land 9 (10). https://doi.org/10.3390/land9100348
- Pinto R, de Jonge V, Marques JC (2014) Linking biodiversity indicators, ecosystem functioning, provision of services and human well-being in estuarine systems: Application of a conceptual framework. Ecological Indicators 36: 644-655. https://doi.org/10.1016/j.ecolind.2013.09.015
- Poggio L, de Sousa L, Batjes N, Heuvelink GM, Kempen B, Ribeiro E, Rossiter D (2021) SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty. SOIL 7 (1): 217-240. https://doi.org/10.5194/soil-7-217-2021
- Power A (2010) Ecosystem services and agriculture: tradeoffs and synergies. Philosophical Transactions of the Royal Society B: Biological Sciences 365 (1554): 2959-2971. https://doi.org/10.1098/rstb.2010.0143
- Redhead JW, Stratford C, Sharps K, Jones L, Ziv G, Clarke D, Oliver TH, Bullock JM (2016) Empirical validation of the InVEST water yield ecosystem service model at a national scale. Science of The Total Environment1418-1426. https://doi.org/10.1016/j.scitotenv.2016.06.227
- Rega C, Bartual A, Bocci G, Sutter L, Albrecht M, Moonen A, Jeanneret P, van der Werf W, Pfister S, Holland J, Paracchini ML (2018) A pan-European model of landscape potential to support natural pest control services. Ecological Indicators 90: 653-664. https://doi.org/10.1016/j.ecolind.2018.03.075
- Reid WV, Mooney HA, Cropper A, Capistrano D, Carpenter SR, Chopra K, Dasgupta P, Dietz T, Duraiappah AK, Hassan R, Kasperson R, Leemans R, May RM, McMichael AJ, Pingali P, Samper C, Scholes R, Watson RT, Zakri AH, Zurek MB (2005) Ecosystems and human well-being - Synthesis: A Report of the Millennium Ecosystem Assessment. Island Press, Washington DC. URL: https://edepot.wur.nl/45159
- Riis T, Kelly-Quinn M, Aguiar FC, Manolaki P, Bruno D, Bejarano MD, Clerici N, Fernandes MR, Franco JC, Pettit N, Portela AP, Tammeorg O, Tammeorg P, Rodríguez-González PM, Dufour S (2020) Global Overview of Ecosystem Services Provided by Riparian Vegetation. BioScience 70 (6): 501-514. https://doi.org/10.1093/biosci/biaa041
- Roche P, Campagne CS (2019) Are expert-based ecosystem services scores related to biophysical quantitative estimates? Ecological Indicators 106 https://doi.org/10.1016/j.ecolind.2019.05.052
- Roche PK, Campagne CS (2017) From ecosystem integrity to ecosystem condition: a continuity of concepts supporting different aspects of ecosystem sustainability. Current Opinion in Environmental Sustainability 29: 63-68. https://doi.org/10.1016/j.cosust.2017.12.009

- Schulp CJ, Thuiller W, Verburg PH (2014) Wild food in Europe: A synthesis of knowledge and data of terrestrial wild food as an ecosystem service. Ecological Economics 105: 292-305. https://doi.org/10.1016/j.ecolecon.2014.06.018
- SEEA-EA (2021) System of Environmental-Economic Accounting-Ecosystem Accounting (SEEA-EA). White cover publication, pre-edited text subject to official editing.. URL: https://seea.un.org/ecosystem-accounting
- Sexton J, Song X, Feng M, Noojipady P, Anand A, Huang C, Kim D, Collins K, Channan S, DiMiceli C, Townshend J (2013) Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS vegetation continuous fields with lidar-based estimates of error. International Journal of Digital Earth 6 (5): 427-448. https://doi.org/10.1080/17538947.2013.786146
- Sieber I, Hinsch M, Vergílio M, Gil A, Burkhard B (2021) Assessing the effects of different land-use/land-cover input datasets on modelling and mapping terrestrial ecosystem services - Case study Terceira Island (Azores, Portugal). One Ecosystem 6 https://doi.org/10.3897/oneeco.6.e69119
- Sieber IM, Campagne CS, Villien C, Burkhard B (2021) Mapping and assessing ecosystems and their services: a comparative approach to ecosystem service supply in Suriname and French Guiana. Ecosystems and People 17 (1): 148-164.
- Sohel MSI, Ahmed Mukul S, Burkhard B (2015) Landscape's capacities to supply ecosystem services in Bangladesh: A mapping assessment for Lawachara National Park. Ecosystem Services 12: 128-135. https://doi.org/10.1016/j.ecoser.2014.11.015
- Stoll S, Frenzel M, Burkhard B, Adamescu M, Augustaitis A, Baeßler C, Bonet F, Carranza ML, Cazacu C, Cosor G, Díaz-Delgado R, Grandin U, Haase P, Hämäläinen H, Loke R, Müller J, Stanisci A, Staszewski T, Müller F (2015) Assessment of ecosystem integrity and service gradients across Europe using the LTER Europe network. Ecological Modelling 295: 75-87. https://doi.org/10.1016/j.ecolmodel.2014.06.019
- Vári Á, Kozma Z, Pataki B, Jolánkai Z, Kardos M, Decsi B, Pinke Z, Jolánkai G, Pásztor L, Condé S, Sonderegger G, Czúcz B (2022) Disentangling the ecosystem service 'flood regulation': Mechanisms and relevant ecosystem condition characteristics. Ambio 51 (8): 1855-1870. https://doi.org/10.1007/s13280-022-01708-0
- Wagg C, Bender SF, Widmer F, van der Heijden MA (2014) Soil biodiversity and soil community composition determine ecosystem multifunctionality. Proceedings of the National Academy of Sciences 111 (14): 5266-5270. https://doi.org/10.1073/pnas.1320054111
- Wangai PW, Burkhard B, Müller F (2018) Quantifying and mapping land use changes and regulating ecosystem service potentials in a data-scarce peri-urban region in Kenya. Ecosystems and People 15 (1): 11-32. https://doi.org/10.1080/21513732.2018.1529708
- Weyland F, Barral MP, Laterra P (2017) Assessing the relationship between ecosystem functions and services: Importance of local ecological conditions. Ecological Indicators 81: 201-213. https://doi.org/10.1016/j.ecolind.2017.05.062
- Willcock S, Hooftman DP, Balbi S, Blanchard R, Dawson T, O'Farrell P, Hickler T, Hudson M, Lindeskog M, Martinez-Lopez J, Mulligan M, Reyers B, Shackleton C, Sitas N, Villa F, Watts S, Eigenbrod F, Bullock J (2019) A Continental-Scale Validation of Ecosystem Service Models. Ecosystems 22 (8): 1902-1917. https://doi.org/10.1007/s10021-019-00380-y

- Zhao Y, Han Z, Zhang C, Wang Y, Zhong J, Gao M (2024) Coastal Cultural Ecosystem Services: A Bridge between the Natural Ecosystem and Social Ecosystem for Sustainable Development. Land 13 (9). https://doi.org/10.3390/land13091352
- Zulian G, Maes J, Paracchini M (2013) Linking Land Cover Data and Crop Yields for Mapping and Assessment of Pollination Services in Europe. Land 2 (3): 472-492. https://doi.org/10.3390/land2030472