On the spatial aggregation of ecosystem condition indicators

Anders Lorentzen Kolstad[a,*], Hanno Sandvik[a], Bálint Czúcz[a], Chloé R. Nater[a]

[a]*Norwegian Institute for Nature Research, Department of Terrestrial Ecology, Pb 5685 Torgarden, Trondheim, 7485*

Abstract

In face of the ongoing nature crisis, the international community is setting targets and deciding on actions to combat the current biodiversity crises. For this to be effective they need tools to accurately describe the current situation and to monitor trends in ecosystems over time. Ecosystem condition accounts (ECA) is one such tools that use variables and indicators to describe key ecosystem characteristics, reflecting their condition and deviations from a reference condition. Because the purpose is to inform decisions at relatively high political levels, these metrics are often spatially aggregated to represent larger areas, such as countries. However, spatial aggregation of information has the potential to alter the descriptive and normative interpretations one can make from these metrics. For example, aggregation displacement causes the information held in variables and indicators to diverge when these are aggregated spatially. This process is influenced also by the order of steps involved in normalising and aggregating variables, i.e. the aggregation pathway. Although aggregation displacement and the type of aggregation pathway chosen for the indicator clearly impact both the indicator values and their interpretation, there are no clear guidelines or deliberation on these topics in the SEEA EA standard for ecosystem accounting. This paper outlines the consequences of different aggregation pathways, emphasising their impact on the credibility of ECAs, and how these are interpreted by users. We introduce a standardised terminology for aggregation pathways specific to ecosystem condition indicators following the SEEA EA standard and provide recommendations for selecting appropriate pathways in various contexts. Our discussion of this topic is aimed at raising the general awareness of spatial aggregation issues and to guide indicator developers in choosing and reporting spatial aggregation methods.

Keywords: SEEA EA, ecosystem condition, ecosystem accounting, indicators, aggregation bias, aggregation error, aggregation displacement, upscaling

1. Introduction

The world is facing a nature crisis of a magnitude that requires urgent political decision making and international coordination (IPBES, 2019). Ecosystem accounting has been fronted as a framework for providing a knowledge base for this. EAs are environmental assessments aimed at communicating on the status and trends in the extent and condition of ecosystems at a scale and in a format that is relevant for decision makers (Edens et al., 2022, Comte et al. (2022)). For ecosystem condition accounting (ECA) and assessments, this often requires that **metrics** (terms in bold are explained in Table 1) used to describe the condition of ecosystems are **aggregated spatially** to produce a single value for a larger area. This represents a type of knowledge synthesis, aimed at condensing the complexity of the real world into something that is relevant to decision makers and potentially actionable at a political level (King et al., 2024). However, the

*Corresponding author

Email addresses: anders.kolstad@nina.no (Anders Lorentzen Kolstad), hanno.sandvik@nina.no (Hanno Sandvik), balint.czucz@nina.no (Bálint Czúcz), chloe.nater@nina.no (Chloé R. Nater)

way spatial aggregation is done affects how a metric should be interpreted, and the descriptive properties and normative claims one can make based on it (Allain et al., 2018). Without an understanding of the pitfalls during spatial aggregation of information, one risks introducing unintended and undetected systematic bias into the decision making process.

Although much attention has been devoted to the **vertical aggregation** of environmental indicators into composite **indices** (e.g. Langhans et al., 2014; Maes et al., 2020; Union/EC-JRC, 2008), as well as to the spatial aggregation of relatively unmodified or raw **variables** (e.g. Allain et al., 2018), there is a lack of explicit deliberation on the special case of spatially aggregating highly modified **indicators** used for ecosystem condition accounting (but see van Beurden and Douven, 1999). This paper therefore focuses on explaining and providing guidelines for the spatial aggregation of ecosystem indicators in the context of the System of Environmental Economic Accounting - Ecosystem Accounting (SEEA EA) (United Nations, 2024) - the most used ecosystem accounting framework in the world (Comte et al., 2022). There is is a jungle of terms for the topics of indicators and aggregation, which are used inconsistently across scientific fields and different frameworks for ecosystem assessments, and there is a clear need for a standardised terminology, at least with the SEEA EA field of practice. This study goes some way towards this by including a list of terms and their definitions in Table 1 and by suggesting a new reporting terminology for the different steps in spatial aggregation, i.e. the **aggregation pathway**.

SEEA EA includes principles for compiling accounts for ecosystem extent, ecosystem condition, and ecosystem services (United Nations, 2024; 2022). We will focus on the SEEA EA condition accounts in this paper, although spatial aggregation is also a relevant topic for the other parts of the account, and for other types of indicator-based ecosystem assessments. In 2026, EU and EEA countries will be required to report ecosystem condition accounts to Eurostat and the European Commission (European Council and Parliament, 2024), and these accounts will have to be spatially aggregated to national levels. This underlines the importance of having a robust methodological framework for the spatial aggregation of data and information.

This paper is aimed primarily at indicator developers to provide them with recommendations for how to choose the best aggregation pathway for variables and indicators, and how to report these choices in an accessible and transparent way. Indicator developer subjectivity affects indicator interpretation (Allain et al., 2018) and thus ultimately the conclusion from ECAs. Still, the process of designing indicators and estimating indicator values is often left entirely to them, with little real involvement from indicator users, such as regional and local land managers and policy makers. It is therefore important to be aware of the role that indicator developers play in shaping the type of information and the narratives that are presented to decision makers. We use four real-world examples to illustrate some of the effects arising from choosing different aggregation pathways (Table 2).

Table 1: Key terms and concepts as they are used in this paper.

Term or concept	Definition and deliberation
Variables, indicators and metrics	We use the SEEA EA definitions of the terms variables, indicators (normalised variables) and metrics (referring to either a variable or an indicator) (United Nations 2024). Variables are typically either in percentages or fractions, or as raw biophysical units, such as biomass or density. Indicators, on the other hand, are always on a unitless scale between 0 and 1, where 0 represents very poor (or the worst possible) condition, and 1 represents very good (or the best possible) condition. Sometimes indicators are calculated directly (e.g. Åström and Kolstad 2025), but usually indicators are made by normalising variables based on two or more reference levels (United Nations 2024, sec. 5.60).

Term or concept	Definition and deliberation
Reference condition (RC)	Reference condition is the state or condition of the ecosystem that we want to compare the current state against. It can be a purely theoretical construct or a real historical state. It does not need to be defined with any real data.
Reference levels (RL)	Reference levels (also called reference values) are variable values that act as anchoring points to specific values on the indicator scale, and are used to convert variables into indicators. This definition is different from that in SEEA EA, but at least conceptually it is the same. There can be from two to many RLs per indicator and they are distinguished with a special nomeclature X_n where *n* is the corresponding indicator value times 100. For example, X_0 and X_{100} refer to variable values coded as 0 or 1 on the indicator scale, respectively (sometimes called the lower and upper RLs). The X_{60} can hold a special meaning if, like in the WFD and in some applications of SEEA EA, the value 0.6 on the indicator scale represents the boundary or threshold between good and reduced condition. Defining X_{60}, or any RL other than X_0 and X_{100}, is one way to quantitatively describe a non-linear relationship between the variable and ecosystem condition (referred to as *Transformation*).
Normalisation	This is the mathematical process of turning a condition variable into an indicator *sensu* SEEA EA. It consists of three distinct steps: scaling, truncation, and transformation (see also (**fig-term?**)). **Scaling** a variable means to recode a variable to a unitless unbound scale based on two reference levels, a lower (X_0) and an upper (X_{100}), that define the variable values to be coded as zero and one on the indicator scale, respectively. **Truncation** means to recode scaled variable above 1 to become 1, and values below 0 to become 0.**Transformation** means to adjust the indicator scale to reflect potentially nonlinear relationships between the variable and ecosystem condition. This is commonly done by anchoring specific variable values to predefined class boundaries (sensu WFD) which we call reference levels (Czúcz et al. in prep; Jakobsson et al. 2020), but may also be done without explicit reference levels, for example by using a sigmoid or exponential transformation (Mienna and Venter 2024). Normalisation is frequently referred to as **rescaling** in the SEEA EA literature, but we avoid this terms because of the need to provide better differentiation between the three steps of the normalisation process, where scaling is one of them. Also, in a parallel terminology, normalisation can be considered modeling, and spatial aggregation before and after normalisation can be referred to as pre or post processing, respectively (Beurden and Douven 1999).
Categorisation	Means to divide the indicator scale into discrete fractions, either based on reference levels, or some other rule (e.g. equal range for each class).

Term or concept	Definition and deliberation
Aggregation displacement	Referring to the systematic shift that occurs to the relative values of variables and their corresponding indicators when they are spatially aggregated. When we take the average of two variables, each of which have attribute values (i.e. indicator values) associated with them via some non-linear function (e.g. truncation or transformation), then the attribute of the average variable value differs from the average of the attributes of the original variable. Rastetter et al. (1992) referred to this as aggregation error and used it to describe some of the dangers associated with upscaling in the sense of using precise fine-scale information to explain or predict large scale phenomena. However, in ECAs, the difference between variables and indicators is an intentional one, and we therefore choose to refer to what is essentially the same mathematical phenomenon with the less derogatory term aggregation displacement.
Spatial aggregation	Spatial (sometimes called horizontal) aggregation is the process of summarising data from different sub-areas and taking this new value as the value for all constituent sub-areas. In means going from fine-resolution data to less fine or coarse resolution data. In related fields of study this operation may be described as *increasing the support* or *reducing the grain* (Bierkens, Finke, and Willigen 2002). Aggregation can be partial, resulting in two or more spatial areas with unique values, or total, if it results in just a single number summarising all the data. Different summary functions can be used, including the area-weighted arithmetic mean, which is required under when aggregation indicator values in SEEA EA. The term *upscaling* is sometimes used synonymously to our definition of spatial aggregation, but it also has a wider definition tied to the ambiguous use of the terms scale to mean either grain or extent. It's common to lump spatial aggregation together with some types of extra- or interpolation operation, such as averaging point data and attributing this value to entire polygons (Gruijter and Braak 1990), or spatial estimation methods (e.g. geostatistics) and subsequent spatial sampling (D. J. Brus and Gruijter 1997). However, for the detailed deliberation in this study it is important to note the distinction between these.
Temporal aggregation	Refers to operations involved in combining data from different time points or periods to represent a single temporal period (e.g. an accounting period or a growing season).
Thematic aggregation	Also called vertical aggregation. In the case of ECA, this refers to an aggregation of two or more indicators into a composite index (*plural*: indices).

Term or concept	Definition and deliberation
Spatial prediction	It refers to any estimation of the value of a variable at an unobserved location, and therefore include both inter- and extraolation. **Interpolation** means to *fill in the gaps*, or to increase the density of the data. **Extrapolation** means to expand the spatial extent of the data or beyond the current data range. There is often no clear boundary between these two operations when applied in ECA as an area may for example be within the geographical range of the current data, but outside the environmental range. Many different methods are employed for spatial predictions within ECAs, such as statistical models (e.g. regression models) or geostatistical models (e.g. kriging). These methods are more or less sophisticaled ways to essentially *spread* or learn from the available data to give values to areas where there is no data. This is distinct from the process and purpose of spatial aggregation, which seeks to simplify data.
Design-based and model based prediction	These are two fundamentally different ways of doing and thinking about spatialand statistical prediction. Design-based approaches relies on classical sampling theory and uses what is know about the sampling design to make spatial inferences. It is generally applied in more simple ways, such as with look-up tables, but model-assisted estimation using statistical models is also possible. Design-based approaches produce things like the sample mean and sample variance and assumes the sampled values are correct (fixed), and uncertainty arises due to where we chose to sample (the locations are random). Model-based prediction uses geostatistical models, such as kriging and produces estimates such as the model mean or model variance. In this framework, the locations are considered fixed and the uncertainty arises due in the statistical model. Readers are referred to Dick J. Brus (2021) for more details.
Ecosystem assets and ecosystem accounting areas	Ecosystem assets in SEEA EA are the smallest spatial units for which information is shought, made up of contiguous spaces of a specific ecosystem type. The ecosystem accounting area is the *'geographical territory for which an ecosystem account is compiled'* (United Nations 2024)
The ecological fallacy	The ecological fallacy (Robinson 2009) is the error of assuming that relationships or patterns observed for groups (at the aggregate level) must also hold true for the individuals within those groups. In EA, aggregated data will mask differences within regions and lead some people to interpret this as regions being more homogenous then they really are.
The Modifiable Area Unit Problem (MAUP)	MAUP describes the sensitivity of spatially aggregated information to the choice of spatial units used for data collection or aggregation Wong (2009). These units can be arbitrary (*modifiable*), and different sizes and configuration of units can have large effects on the outcome of aggregation.
Spatial compensation	In this context, spatial compensation refers specifically to the ability of variable values above X_{100} in some areas to compensate for values below X_{100} elsewhere (assuming here that $X_0 < X_{100}$). Whether or not to allow spatial compensation in spatial aggregation has a large impact on the value and interprettaion of indicator values.

Term or concept	Definition and deliberation
Post-stratfication	A statistical technique used to correct for a biased sample by forcing the sample to match the main population in some key characteristcis. In ECAs it is common to have data that lack a clear probability based sampling design, and therefore end up with more samples from certain strata (e.g. some geographic region or within some shared environmental condition). Post-stratification seeks to remove this unevenness in the *post*-processing, e.g. by doing a step-wise spatial aggregation via the same strata.

2. Reasons for normalising variables

Normalisation of ecosystem condition indicators serves at least three purposes. Firstly, it gives a normative interpretation of a variable, defining a good and a bad state, and simultaneously a directionality to say when something is getting better or worse over time (Czúcz et al., 2021). Although some variables may have normative properties (due to decisions about how they are chosen, defined, aggregated or presented (Allain et al., 2018)), the **normalisation** of variables into indicators makes them explicitly normative by introducing a clear directional interpretation, where increasing values always refer to an increase in condition in the direction of a **reference condition**. The mathematical part of this normalisation contains several steps (Figure 1). Two or more **reference levels** are needed to convert variables into indicators.

Secondly, normalisation sets a limit to how much a high variable value in one place can **compensate** for a low value somewhere else, and vice versa (Pedersen et al., 2016). This is because **truncation** effectively means that when spatially aggregating an indicator, one is always aggregating the negative deviations from the upper reference level X_{100}, and ignoring any positive deviations which would otherwise compensate for the negative ones (see **Example 2**). **Transformation** with asymptotes have the same effect as truncation, e.g. sigmoid transformations. It is important to note that this is by design, i.e. that X_{100} is set (or should be set) so that values above this limit (assuming $X_{100} > X_0$) do not represent any further increase in ecosystem condition (for an exception, see **Example 3**). Therefore, aggregation of truncated indicators summarises the estimated ecosystem condition over an area, and not the variable itself. The flip-side of this is that spatially aggregating the original variable values does not directly summarise information about ecosystem condition for that area.

Thirdly, we normalise in order to standardise the indicator on the same unitless scale, making them comparable, so that we can perform thematic (i.e. vertical) aggregation (Jakobsson et al., 2021; United Nations, 2024, §5.81). This is commonly referred to as *the* reason for normalising variables, not least because it is perhaps the least confusing one for many; nonetheless, as we have shown, it is not the only reason.

3. Spatial aggregation of data in ecosystem condition accounting

Spatial aggregation of data refers to the conversion of fine-resolution data into coarser-resolution data and, depending on both the purpose and the nature of the metric, there can be several reasons for both performing and refraining from spatial aggregation. Readers are referred to Allain et al. (2018) for a more comprehensive review of different reasons for spatially aggregating variables. As we will illustrate below, there are several requirements in the SEEA EA that make spatial aggregation necessary.

Generally, spatial aggregation increases the clarity and accessibility of a metric because it simplifies or compresses the information, sometimes into just a single number (**total aggregation**). This may be necessary in some cases of ecosystem accounting when information is required at a relatively high administrative level

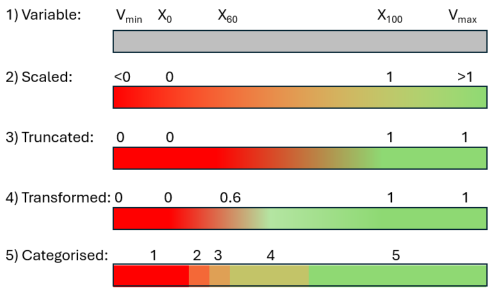

Figure 1: Examples of how important terms are used in this manuscript. Note that the meaning of the terms may differ from how they are used in other fields, such as mathematics. The variable (1), in original units, has a minimum (V_{min}) and a maximum value (V_{max}), as well as points anchoring it to the indicator scale (reference levels; X_n). Scaled variables (2) are scaled based on X_0 and X_{100}. Truncation (3) implies assigning the value of 0 to values below X_0, and the value 1 to value above X_{100}. Transformation (4) refers to the non-linear transformation of values within the 0-1 range, as in this piecewise-linear example by mapping X_{60} to 0.6 on the indicator scale. Transformations without anchoring points are also included in this term, such as exponential or sigmoid transformation. Categorisation (5) refers to the creation of discrete bins (here five) where incremental change in uncategorised indicator values within a set of class boundaries is ignored. Although truncation, scaling and categorisation can be seen as types of transformations, we exclude these methods from the definition here. Examples 2-5 are normative (hence the gradient colour scale from red to green) because we assume it has been declared that one end of the scale represents a good state and the other a poor state. All variables that are treated so that they conform to the definition of indicators in the SEEA EA are said to be normalised. For example, if a truncated variable is assumed to have a linear relationship with the indicator scale, then this variable has been normalised even though it has not been transformed. The term rescale is a synonym to normalise, but we only use the latter to avoid confusion with the specific operation of scaling.

(e.g. nations) and when variables and indicators need to be presented in standardised tables which don't allow for describing a lot of spatial variation.

Sometimes aggregation of a metric is required for it to actually fit its purpose and become relevant to what it is designed to describe. For example, a hypothetical variable "*proportion of total land area above critical nitrogen load",* informed from a spatial map of nitrogen loads, would only make sense if data was aggregated across some defined area. The reason and need for aggregation may therefore originate in the original idea for the metric.

Data may also be only **party aggregated**, or the same metric may be presented at different levels of aggregation (Allain et al., 2018). A minimum level of aggregation may be decided based on uncertainties in the data: high spatially resolute data may be imprecise at fine scales, leading to false sense of certainty and potential misinterpretation (Lyytimäki et al., 2013), but these same data seen over a larger area may be assumed to converge on some true value, making spatially aggregated data better suited for communication to users. Other common arguments for performing spatial aggregation are to ease visualisation and to allow relevant comparisons (Allain et al., 2018). For example, ecosystem condition metrics can be visualised on a map, but when both the spatial resolution and spatial variation is high, maps become too complex, even unintelligible. It is therefore common to partially aggregate the data and provide a coarser map where different colours are used to distinguish different values. Similarly, one may choose to aggregate such that the spatial resolution matches some meaningful delineation, notably **ecosystem assets** in SEEA EA, which makes it possible to easily compare the ecosystem condition between these areas.

Spatial aggregation of ecosystem condition metrics may also be applied to alleviate issues of spatial auto-correlation. For example, if data is collected opportunistically with sampling sizes or sampling effort varying between areas, then performing partial spatial aggregation to some intermediate-sized, homogeneous areas, will give equal weight or importance to all areas regardless of how many data points are included in each. This approach represents a form of **post-stratification** that is also relevant to process data from hierarchical (e.g. blocked) sampling designs.

Spatial aggregation can have several consequences that may or may not be desirable, such as smoothing out spatial variability, which can mask local patterns and trends. This smoothing out makes the data and its inherent information less suitable for some use cases, such as depicting spatial variation that can be used to support local land-use planning, for aiding a debate about spatial conflicts, or for identification of high risk areas (van Beurden and Douven, 1999).

Table 2: Examples used in this paper, and how they illustrate specific points raised

	Example	Main illustrating point
1	Bilberry	Commensurable spatial scales for variable and reference levels (Section 3.1)
2	Wolves	Spatial compensation and discrepancy between variable and indicator (**?@sec-discrep**)
3	PTI	Compensation and the order of operations (Section 6)
4	Glaciers	Aggregation commutativity and alternative indicator weights (Section 5)

3.1. Matching the scale of variables and reference levels

Similar to variables, the reference levels used for normalising variables also have a spatial assignment, which can be different from that of the variable. For example, variable values may exist for unique 10 × 10 m grid cells, but the reference levels may be created with a different spatial scale in mind, for example municipalities, or they can be uniform across the entire **ecosystem accounting area** (e.g. a natural zero). Variables should not be normalised based on reference levels unless they are at a commensurable spatial scale. The bilberry example (**Example 1**) shows that sometimes variables need to be spatially aggregated before they can be normalised.

Example 1 – Bilberry

This example is to show what it means that the variable and the reference levels need to be at a comensurable spatial scale before doing the normalisition.
Variable: Horizontal coverage (vertical projection) of European blueberry or bilberry (*Vaccinum myrtillus*) recorded in permanent vegetation plots.

Reference levels: X_{100} is defined for each ecosystem asset based on an expert elicitation. Experts were informed by the distribution of the variable values both within and outside protected areas, and the regional distribution of major forest types. They also used their general knowledge about the effect of forestry and on the general vegetation structure of old-growth forests. X_0 is a natural zero (bilberry completely absent).

Table 3: Dummy data for the bilberry example. Variable values (% cover of bilberry) are recorded for each vegetation plot, and aggregated (arithmetic mean) to the ecosystem asset (EA) level. The X_{100} value is defined for the EA level, but in this hypothetical case it is also dis-aggregated to each vegetation plot and used for normalising variable values also at the plot level. The dis-aggregated X_{100} values, and subsequent values that rely on these, are marked with an asterisk (*).

	Plot 1	Plot 2	EA
Variable values	2	36	19
X_{100}	20*	20*	20
Indicator values	0.1*	1.0*	0.95 (0.55*)

The bilberry indicator exemplifies different spatial resolutions for the variable and for the reference levels (Table 3). The variable is recorded at the scale of vegetation plots. The reference level however, is designed with a regional spatial scale in mind, especially because of how it encompasses the known variation in forest types in each ecosystem asset to estimate the mean bilberry coverage under the reference condition. Because the normalisation includes a truncation step, normalising the variable at the plot scale (pathway 1; Figure 2) does not allow overshooting values in plot 2 to compensate for lower values in plot 1 when spatially aggregating the indicator values. When normalising at the plot scale in this case, one is essentially aggregating only the negative deviations from the upper reference level X_{100}, and the aggregated indicator value becomes negatively displaced (0.55) relative to when aggregating variable values (0.9). Given that X_{100} is defined the way it is, this indicator should follow pathway 3 (Figure 3) by spatially aggregating the variable from plot scale to ecosystem asset to allow spatial compensation between plots. At the scale of ecosystem assets, the variable and the reference levels are at a commensurable scale, and the variable can be normalised and potentially aggregated further.

3.2. Fitting data to ecosystem assets

In SEEA EA, information about ecosystem condition is made spatially explicit by assigning variable or indicator values to ecosystem assets. This process requires some spatial manipulations of data, or scale changes (Ewert et al., 2011). The type of manipulation depends on the spatial resolution of the underlying data, as well as the size and configuration of the ecosystem assets. To elaborate on this issue we first make a distinction between two main types of data: spatially exhaustive data and sparse (i.e. spatially discontinuous) data.

Spatially exhaustive, or wall-to-wall data, include remote sensing products, but also other types of pre-aggregated data, where sparse data are assigned to areal units. This last type of data is very common. A lot of demographic information for example is made available at the scale of administrative units, rather than at the level of individuals (which would be very ineffective and also problematic in terms of protecting sensitive information). Similar pre-aggregation is rather common and present in most complete datasets. Consider, as an example, data from LiDAR (Light Detection And Ranging). The raw data is a point cloud, yet the most commonly available datasets are rasters, such as surface or canopy models, i.e. wall-to-wall generalisations of the point cloud. Also data such as satellite images, or maps derived from such, have some inherent pre-aggregation where values are averaged for each raster cell. Often there is little indicator developers can do to affect this pre-aggregation step, but it is important to be aware of it in light of the **ecological fallacy**. This issue will, for example, hamper the detection of true maximum or minimum values (used in *worst rule* (i.e. one out al out) aggregation, for example in the Water Frame Directive - WFD), since these extremes are already smoothed out in the pre-aggregation step (van Beurden and Douven, 1999). This will clearly affect the suitability of such data for identifying areas of high risk (very degraded areas, for example). Similar problems can also occur in subsequent aggregation steps of the indicator calculation workflow, and it is important to ensure that the spatial aggregation function used does not have any unintentional effects on the meaning of the metric.

Sparse data refers to datasets where variable values are assigned to singular points or isolated small areas. In these cases, there will be a lot of area inside each ecosystem asset for which we have no direct information, and some ecosystem assets may have no data at all. Spatial prediction can be used assign variable or indicator values to all areas (as is required in the SEEA EA framework). Both **design-based** and **model-based** approaches are valid under SEEA EA. Model-based approaches (e.g. interpolation) generally make variables easier to aggregate spatially since the spatial structure of the variables will already be accounted for via the prediction process. For example, if using kriging to create local predictions for a variable across an ecosystem asset, then a simple systematic sampling of the field of values across the ecosystem asset will be valid, and give representative grounds for statistical inference (Brus, 2021). However, transparency, validity and simplicity are all very desirable properties from ECAs, which favours a design-based approach that makes no modeling assumptions (Brus, 2021). From here on, we will focus on design-based approaches.

For design-based approaches, one can assign values to areas via simple aggregation functions used on data values that fall within a given ecosystem asset. Many aggregation functions are available, such as sum, worst-rule, different percentiles, arithmetic, geometric, or harmonic means (United Nations, 2024, §5.54). In addition, non-paramteric bootstrapping (Kolstad, 2025) and Bayesian updating (Kolstad et al., 2024) can be used to possibly obtain better descriptions of the uncertainty in the estimates. If the inclusion probabilities are known, or they can be estimated, then the Horvitz-Thomson estimator for the sum or the mean (and variance) of a spatial sample is appropriate and useful, especially when the data originated from a stratified sample (Horvitz and Thompson, 1952). Depending on the random process used to select the sampling points we may need to account for the spatial structure (spatial autocorrelation) of the data when doing this aggregation. This can be addressed in several ways, such as model-assisted approaches (Brus, 2021), e.g. using regression models (Brus, 2000). One can also add an intermediate aggregation step via homogeneous areas (domains), ecosystem assets or some smaller basal spatial units, to control for this spatial non-independence, and thus reduce the sampling bias and variance.

In our experience, the choice of which area units to use when doing this step-wise aggregation is often not reflected much upon. In some cases the areal units are even decided politically, for example to administrative units, with little ecological justification for this choice. However, this decision clearly affects the results of the spatial aggregation via a well-described (but often forgotten?) statistical problem referred to as the **modifiable area unit problem (MAUP)**. The MAUP can lead to inconsistencies between repeated or nested ECAs, leading to confusion and mistrust (Section 5). This is unfortunate, as it is important for decision makers to see that the information they are basing their decision on is robust and insensitive to aggregation methods (van Beurden and Douven, 1999). One option to reduce this discrepancy and arbitrariness is to use ecologically motivated areal units in the step-wise aggregation such as homogeneous ecosystem areas (Vallecillo et al., 2022) or homogeneous impact areas (Kolstad et al., 2024).

4. Aggregation displacement and spatial compensation

Rastetter et al. (1992) showed that when taking the average of two variables, each of which have attribute values (e.g. indicator values) associated with them via some non-linear function, then the attribute of the average variable value differs from the average of the attributes of the original variables. They referred to this as aggregation error and used it to describe some of the dangers associated with **upscaling** in the sense of using precise fine-scale information to explain or predict large scale phenomena. In ECA, the aggregation of both variables and indicators is common practice and raises this issue of aggregation error (Figure 2) when variables have nonlinear relationships to the normalised indicators (Rastetter et al., 1992), which they typically do. However, in our case, the difference between variables and indicators is an intentional one, and we therefore choose to refer to what is essentially the same mathematical effect with the less derogatory term **aggregation displacement** (Figure 2).

Spatial aggregation leads to a divergence in the type of information held in variables and in their associated indicators, to a point where they become qualitatively very different (**Example 2**). Aggregated indicators reflect the average ecosystem condition, where areas in very good or very poor condition have limited ability to compensate for opposite extreme values elsewhere. The spatially aggregated variable on the other hand, may reflect something like a sum of individuals, an average of a population, or some other aspect where values above and below the reference levels are able to compensate for each other. The information held by the indicator is also different from that of the variable since additional ecological knowledge can be introduced via the reference levels.

In the statistical standard and recommended guidelines for ecosystem accounts (United Nations, 2024; 2022), there is no mention of aggregation displacement, and there seems to be little awareness in general of its meening and the ramification of choosing different spatial aggregation pathways for variables. Indicators and variables are sometimes presented side-by-side in ecosystem condition assessments or accounts. This is also recommended practice following the SEEA EA [United Nations (2024); ch. 5.3.4].

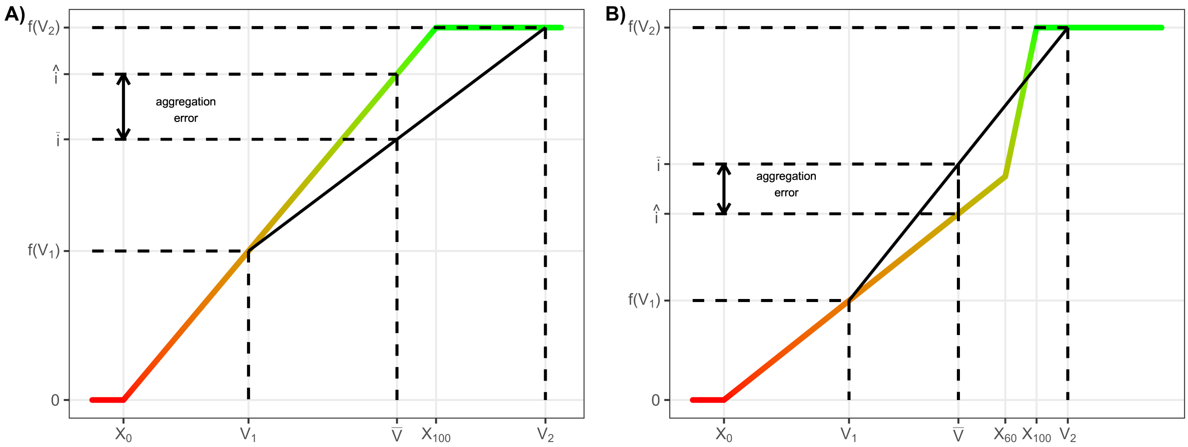

Figure 2: Examples showing the difference in indicator values (y-axis) obtained from taking the mean (V bar) of two variable values (V1 and V1) that are on the original scale (i hat) or on the normalised indicator scale (i bar). Pane A: Due to truncation at X_{100}, the latter results in a comparatively lower indicator value. Pane B: Example where the normalisation function includes a transformation step (see Figure 1 for definition) that anchors X_{60} to 0.6 on the indicator scale. This reverses the order of i hat and i bar compared to example in pane A. The solid coloured line represents the normalisation function f(V). V = variable value, i = indicator value. Modified from Rastsetter (1991).

Example 2 – Wolves

This hypothetical example (Table 4) shows how different the interpretation of a variable and an indicator can become when the information is spatially aggregated. More specifically, it shows shows how spatial compensation in the spatial aggregation of variables leads to aggregation displacement and a discrepancy between the variable and the indicator.
Variable: Number of wolves.

Reference levels: X_{100}= Number of wolves equal to what experts think the ecosystem would support under the reference condition. This is number is informed by data on habitat quality, food supply, and more. X_0 = no wolves.

Table 4: Dummy data for the wolves example. EA = ecosystem asset (e.g. a municipality). EAA = ecosystem accounting area (e.g. country)

	EA 1	EA 2	EA 3	EAA aggregate
Variable values	20	5.0	0	Sum = 25.0
X_{100}	10	10.0	5	Sum = 25.0
Indicator values	1	0.5	0	Mean = 0.5

When species-based indicators are aggregated to the EAA level, it is common for the general public to interpret this value (0.5) as the status for this species, for example the conservation status[1]. However, for the EAA seen overall, the population size is actually equal to the expected population size in the reference condition. Instead, the spatially aggregated indicator value describes the ecosystem condition for the different *areas* in terms of wolf under-abundance. Then we see that the first ecosystem asset has more wolves than we would expect under the reference condition, whereas the other two have less. Because variable values above X_{100} are truncated, the high wolf numbers in ecosystem asset one does not compensate for the low indicator value in assets two and three, and hence the mean indicator value is less than the sum of the variable values divided by the sum of the X_{100}values. But the high wolf numbers in asset 1 *does compensate* when looking at the aggregated variable value.

Generally, because of the normalisation process, indicators are more aligned with the purpose of ECA with describing ecosystem condition in normative terms, than variables. Although variable accounts are allowed under the SEEA EA framework, and are indeed a central feature, we believe they should be seen as interim accounts for metrics that cannot be, or have not yet been, normalised. We would therefore argue for not presenting the original variable once an indicator has been developed. And when only variable estimates are given, extra care is given to describing the spatial aggregation pathway, since unfavourable local variable values (in terms of ecosystem condition) could have become smoothed out during aggregation, hiding potential environmental problems. Sometimes, however, variable values cannot be aggregated spatially in any meaningful way (see **Example 3**).

As we have seen, aggregation displacement causes a divergence in the type of information made available through the spatial aggregation of variables versus indicators. In addition, unavoidable aggregation displace-

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It is sometimes worth going back to the variable, and see if it can be defined differently to avoid this kind of confusion. Wolf numbers could in this example be converted to wolf density.

ment (for good and bad) will also affect the indicator values and the inferences that can be drawn from these. A major determinant of the resulting aggregation displacement from the spatial aggregation of ecosystem condition indicators (Figure 2) is the choice about the order of the different steps in the normalisation and aggregation process, i.e. the aggregation pathway (Figure 3). If normalisation occurs early in the aggregation process, the amount of spatial compensation is limited (**Example 2**). However, sometimes complete or partial compensation is justified (**Example 1** and **3**).

Example 3 – Phytoplankton trophic index (PTI)

Variable: Mean score of algal species present, based on a set of indicator species scored for phosphorus requirements/tolerance. The variable is recorded in water bodies (lakes of 0.5 km^2 or more).
Reference levels: X_{100} = median variable value for water bodies in reference condition. X_0, X_{20}, X_{40}, X_{60} and X_{80} = intercalibrated threshold values, based on dose–response curves.

Table 5: Dummy data for the PTI example. value = value for a hypothetical variable. agg. = spatial aggregation (arithmetic mean); trunc. truncation; stat. = spatial statistics. The transformation step is left out for simplicity. Pathways refer to figure 3.

			Pathway 5				Pathway 6		
Lake	value	X_{100}	trunc.	scale	statistics		scale	agg.	trunc.
A	10	20	10	0.5	High:	50%	0.5	0.85	0.85
B	600	500	500	1.0	Moderate:	50%	1.2		

The Water Framework Directive (WFD) indicators uses aggregation pathway 5 (Figure 3), with truncation, scaling, and transformation, in that order (see worked example in Table 5). The value obtained after the first two steps is called an EQR (ecological quality ratio), and the value obtained after the third step nEQR (normalised EQR). Spatial aggregation, the way that we use the term here, is not done for the WFD. Instead, the proportion of water bodies in each condition class is the aggregated reporting metric. Therefore aggregation displacement is not an issue. When WFD data is put into use in other contexts, however, aggregation becomes important.

Because of how X_{100} is defined based on the median value across reference lakes, overshooting values ($> X_{100}$) should be preserved in the spatial aggregation. Otherwise we get a negative displacement, making it practically impossible to reach an indicator value of 1. This means that neither EQR values nor nEQR values can be uncritically aggregated spatially to be used in a SEEA EA compliant in ECA. One solution, to enable the use of WFD indicators in ECAs, would be to change to pathway 6, with (1) scaling, (2) transforming, (3) aggregating and (4) truncating the values. In our hypothetical example (Table 5) this gives an aggregated value of 0.85, whereas the mean value for the nEQRs would be 0.75 (i.e. negatively displaced).

5. Agreement across nested ECAs

We believe it is a very desirable property that variable and indicator values are comparable across repeated ECAs and harmonised across assessment scales so that accounts from sub-areas can be used to recreate the account of the larger area. This can, however, be difficult or even impossible when ECAs use different aggregation pathways for the same indicator. Cases when two accounts or assessments use what is considered the same metric, but find different values for the same areas, cause confusion and can potentially result in reduced general credibility for ECAs.

We believe one solution to this is to acknowledge that the aggregation pathway can affect the indicators (and indices) so much, sometimes as much as variation in the variable itself, that the use of different pathways imply that metrics are named and treated uniquely, for example using different common names, but perhaps better still, different version numbers or indicator IDs. For each unique indicator the precise aggregation pathway should be specified as part of the indicator metadata. This would show ECA users if two accounts are using different metrics that cannot be assumed to behave similarly or report the same thing, even if they have the same common name and data source.

SEEA EA uses the term aggregation commutativity for the property that the order of vertical and horizontal aggregation is irrelevant to the end result. This is indeed a desirable property, although not always possible. **Example 4** shows a case where the spatial aggregation of an indicator uses area weights that are different from the total extent of the EA (which is what is recommended by SEEA EA). Such alternative weights can be appropriate when the indicator only covers part of an ecosystem, for example if it covers only one of many habitat types. In these cases, each indicator in an index might require different weights when spatially aggregated, but this is of course not possible after the indicators are combined into a single index.

A similar aggregation commutativity can be envisioned for step-wise aggregation of a single indicator, where it does not matter if the original data is aggregated directly from the original measurement scale to the Ecosystem Accounting Area (EAA) level, or via some intermittent scale, such as ecosystem assets or larger regions. This is possible when aggregating metrics using area weighting, and when one is aware of the need for post-stratification when using stratified data sampling. However, **Example 4** demonstrates two factors entailing that indicator-level commutativity is not being fulfilled in this case.

Firstly, some indicators are possible to normalise at the measurement scale, i.e. the finest resolution of the raw data. But others may need to be (pre-) aggregated, for example if the variable is designed to depict a density or a proportion that refers to a spatial unit. In Example 4, there is no obvious definition of the ecosystem assets, and so one must first define those before calculating the variable values for each of them. It turns out that in this case the indicator value at the EAA level is sensitive to the spatial delineation of the EAs.

Secondly, SEEA EA mentions several arithmetic or parametric aggregation functions, such as different means, median, min or max values. It does not mention the possibility of bootstrap resampling (Jakobsson et al., 2021; Kolstad et al., 2024). This method allows for using probability distributions to represent indicator values and uncertainties, and to use weighted resampling to create new joint probability distributions for the spatially aggregated indicator. In Example 4, point estimates for the variable and reference levels are replaced with probability distributions where a 3% uncertainty is introduced based on the reported mapping uncertainty of the raw data. The shape of the aggregated joint distributions depend on the spatial size and configuration of the spatial units where this uncertainty is introduced.

6. Aggregation pathways

We introduce the term aggregation pathway to describe the order of the steps used to go from a variable at the measurement scale, to a spatially aggregated metric, usually an indicator, that describes the ecosystem condition for a larger area. In Figure 3 we show some aggregation pathways that we have come across, and some that we see as potential new pathways. The examples are non-exhaustive, and serve mainly as illustrations. We go on to describe how the aggregation pathways can formally, and succinctly, be described using the names of these operations. The choice about which pathway to use is not trivial, and we want to highlight some of the issues that could arise from having an *ad hoc* approach to these considerations.

Pathway 1 involves early normalisation using the perhaps most common order of the three steps: scaling, truncating and transforming. The three steps may be done simultaneously or in sequence. Finally, the indicator is spatially aggregated.

Pathway 2 involves aggregating the variable before normalising. This preserves the ability for very high or very low variable values to compensate for very low or very high values elsewhere, respectively.

Pathway 3 is similar to pathway 2, but here there are two aggregation steps: one before and one after normalisation. This can for example be the case when variables are aggregated to the scale corresponding to the reference levels before they can be normalised (**Example 1**).

Pathway 4 illustrates the aggregation of a variable, with no normalisation. This is the pathway commonly used for variable accounts in the SEE EA. For this, and all other aggregation pathways, the picture can be made more complicated by adding additional aggregation levels (i.e. a step-wise aggregation, Section 5)

Pathway 5 is a common pathway in the WFD, which does not practice spatial aggregation of indicator values. Instead one reports the number of water bodies in each condition class (spatial statistics). Pathway 6 is a suggested pathway for handling WFD indicator in ECAs (see **Example 3**), where truncation is postponed until after the spatial aggregation in order to allow overshooting values to compensate for low indicator values elsewhere (what we refer to as compensation).

Pathway 7 describes an alternative to pathway 1 for a model-assisted aggregation pathway, where the original sample is the result of a defined sampling strategy, but where a model is used to project (extrapolate or interpolate, depending on the case) values to other spatial points or locations that were not sampled. The resulting map (field of values) is then normalised, (re)sampled (which could imply taking all the discrete population units (e.g. all rivers), and finally aggregated.

Pathways 8 and 9 describe alternative ways to create indices at different spatial scales, either by spatially aggregating the indices (pathway 8), or by aggregating the indicators separately and recalculating the indices at different spatial scales (pathway 9). If perfectly commutative then the two approaches will yield the same result. However, if the indicators that make up the indices use different area weights as part of their spatial aggregation (**Example 4**), then pathway 9 is the only one that gives the same index values across nested accounts (Section 5).

7. Recommendations

Based on the above discussion and examples, we here summarise five recommendations for developers of ecosystem condition indicators and assessments for avoiding some of the pitfalls from having a too casual approach to the choice of aggregation pathways.

1. Report the aggregation pathway, using standardised terminology

ECAs should be accompanied by detailed indicator documentation where a precise description of the steps in the aggregation process is presented. Verbose descriptions can be supplemented or replaced by a standardised short-hand notation that we present in the following: We suggest using the terms as described in Figure 1 and elsewhere in the paper: scale, truncate (abbreviated to *trunc.*), transform (*trans.*), spatial aggregation (*sp. agg.*), thematic aggregation (*th. agg.*) and spatial statistics (*sp. stat.*). These terms can be abbreviated as shown in the parentheses, and placed together into a single string, where operations performed simultaneously are enclosed in square brackets. For example, pathway 1 in Figure 3 can be annotated as $scale - trunc. - trans. - sp.agg.$. If the three normalisation steps are performed simultaneously this can be written as $[scale - trunc. - trans.] - sp.agg.$. If there are more aggregation steps, then the spatial level at each step should be included in the description, e.g. for pathway 3: $sp.agg.(municipalities) - scale - sp.agg.(country)$. "Municipality" and "country" could here be included as footnotes. Note also that in the last example, normalisation only involved a scaling step. The description of indicator pathways can be made even easier by referencing specific aggregation pathways by number, as we have done in this paper using Figure 3 in this paper. Methods used to change either the cover or the extent of the indicator data (see **?@sec-term**) can also be included in the shorthand notation scheme. The three operations we conceive as possible options are extrapolation (extr.), interpolation (inter.), and (sub)sampling. We use the term spatial projection (projection for short) to encompass both extra- and interpolation. Thus, pathway 7 in Fig. 3 can be written as $project - scale - sample - sp.agg. - trunc.$ The type of model used for the spatial projection can be added as a footnote.

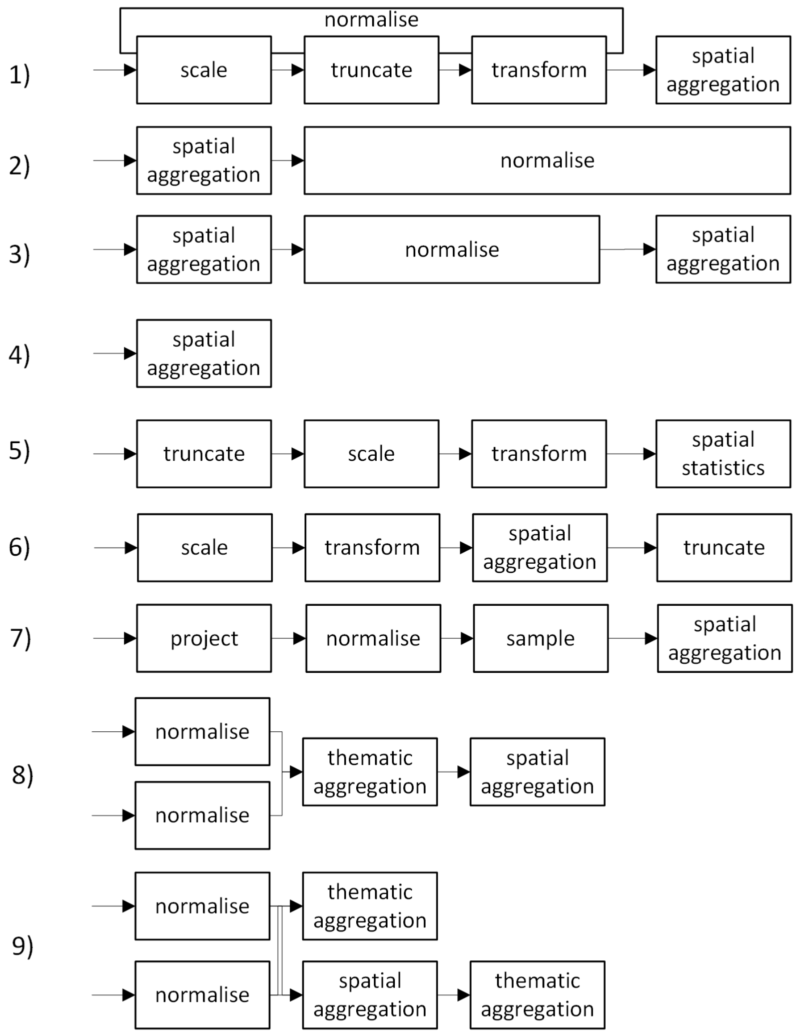

Figure 3: Flowchart showing pathways for the spatial aggregation of variables in ecosystem condition accounting. Normalisation refers to the steps that make a variable conform to the definition of an indicator in SEEA EA, which may include some, but not necesarily all the steps scale, truncate and transform.

Besides making the indicator workflow itself more transparent and reproducible, we believe this recommendation would help raise the general awareness about aggregation displacement in EAs, both among users and developers. It will make the interpretation of ECAs less prone to misunderstanding and misuse, as well as making troubleshooting easier, for example when trying to identify the reason why two ECAs produce dissimilar indicator values from the same underlying data.

2. Normalise variables early, but at the scale where the reference levels are relevant

Normalising variables early in the aggregation pathway means that you are aggregating normative measures of condition, which is generally what you want in ECAs (Section 2). But just like variables and indicators, reference levels also have a spatial resolution, and they should only be used to normalise variables that are at a scale which is relevant to the way the reference levels are defined, i.e. they are at a commensurable scale (**Example 1**).

3. Use a similar aggregation approach for all indicators in the same assessment

It may be premature, or not even possible, to prescribe an aggregation pathway to be used for all ECAs, or even a type of aggregation pathway to be used given the data at hand. However, internal consistency within assessments should be possible, and this can make it easier to communicate and interpret the information conveyed through the indicator values. This can be achieved by for example always scaling early (see recommendation number 2 above) and using the same aggregation levels (same spatial units) and same approach to step-wise aggregation across levels (Section 5), for all indicators.

4. Use unique indicator IDs , also for indicators that are similar, but use different aggregation pathways

Indicators (and variables) often exist in multiple versions, varying slightly in the raw data or in the methods used to produce the data or the metrics. Yet different versions are often referred to by the same common name. This causes confusion about which indicator version is being used, and thus making it difficult to make out which aggregation pathway has been used. We recommend making use of stable and unique indicator IDs. This has for example already been implemented in ecRxiv, a GitHub-based publishing platform for ecosystem condition indicators (Kolstad and Grainger, 2024). On ecRxiv, indicator documentation follows a structured approach to both reporting and peer review (including code review). Each indicator version is given its own ID, and its own fact sheet with a persistent URL, so that ECAs that use these indicators can unequivocally cite specific indicator versions, and how they looked at a given point in time. ecRxiv also includes standardised metadata reporting schemes with fields for ecosystem type (IUCN GET; Keith et al. (2020)) and aggregation pathways (see recommendation number 1 above).

7.0.1. 5. Don't aggregate indices, unless you know all aggregation operations are commutative

When spatially aggregating indices it is no longer possible to use different area weights to each single indicator. If all indicators making up an index are spatially aggregated using the same weights, typically the extent of the spatial units, then the aggregation operations will be commutative and it will not matter if you aggregate vertically then horizontally, or the other way around (Figure 3; Pathway 8 and 9, respectively). However, indicators are not always valid for the entire ecosystem type that the account is made over. They can, for example, retain to only certain habitat or nature types within the ecosystem type, in which case one might want to use different weights when spatially aggregating the indicator that reflect the extent of only the relevant habitat or nature types, and not of the entire ecosystem (see **Example 4**). But when combined with other indicators into a common index, any subsequent aggregation of that index will give equal spatial weight to all indicators (see next paragraph for an exception to this). We therefore recommend caution, and to default to the solution of instead spatially aggregating indicators separately, and then re-calculating indices when needed (Figure 3; Pathway 9). This will ensure that nested accounts will be comparable, i.e. that they will present the same index values independent of which spatial units the indices first are calculated for.

An alternative solution to ensure agreement across nested accounts is to use weights also when performing the vertical or thematic aggregation of indicators into indicators, where indicators are weighted by the area that they are valid over. With this approach one can down-weigh indicators that only cover smaller areas (specific nature types etc.), or which have incomplete spatial coverage. When this weighting is already performed at the vertical aggregation stage, any subsequent horizontal aggregation does not need to account for the unique indicator weights again. However, weighting indicators in vertical aggregation opens a whole other can of worms, and therefore we do not offer this as a generic recommendation.

7.0.2. 6. Don't present variables and their respective indicators as alternative evidences to choose from

Aggregation displacement causes a divergence in the type of information held in ecosystem condition variables versus indicators, and spatially aggregated indicators should not be interpreted as normalised versions of aggregated variables. Therefore, aggregated variables and the associated aggregated indicators cannot act as alternative evidence or interpretations for the state of nature. While this may initially seem like a democratic and transparent approach to reporting, this practice places a significant burden on both the end user and the indicator developer. Misuse can ensue, for example by taking the variable value and assigning it the same interpretation as the indicator value. At the very least, the developer must clarify to the user how the two metrics may have diverged during spatial aggregation and normalisation, complicating the comparison of their respective information.

8. Conclusion

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References

Allain, S., Plumecocq, G., Leenhardt, D., 2018. Spatial aggregation of indicators in sustainability assessments: Descriptive and normative claims. Land Use Policy 76, 577–588. URL: https://linkinghub.elsevier.com/retrieve/pii/S0264837717310396, doi:10.1016/j.landusepol.2018.02.038.

van Beurden, A.U.C.J., Douven, W.J.A.M., 1999. Aggregation issues of spatial information in environmental research. International Journal of Geographical Information Science 13, 513–527. URL: https://doi.org/10.1080/136588199241184, doi:10.1080/136588199241184. publisher: Taylor & Francis _eprint: https://doi.org/10.1080/136588199241184.

Brus, D.J., 2000. Using regression models in design-based estimation of spatial means of soil properties. European Journal of Soil Science 51, 159–172. URL: https://onlinelibrary.wiley.com/doi/abs/10.1046/j.1365-2389.2000.00277.x, doi:10.1046/j.1365-2389.2000.00277.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1046/j.1365-2389.2000.00277.x.

Brus, D.J., 2021. Statistical approaches for spatial sample survey: Persistent misconceptions and new developments. European Journal of Soil Science doi:10.1111/ejss.12988.

Comte, A., Sylvie Campagne, C., Lange, S., Bruzón, A., Hein, L., Santos-Martín, F., Levrel, H., 2022. Ecosystem accounting: Past scientific developments and future challenges. Ecosystem Services 58, 101486. URL: https://www.sciencedirect.com/science/article/pii/S2212041622000821, doi:10.1016/j.ecoser.2022.101486.

Czúcz, B., Keith, H., Maes, J., Driver, A., Jackson, B., Nicholson, E., Kiss, M., Obst, C., 2021. Selection criteria for ecosystem condition indicators. Ecological Indicators 133, 108376. URL: https://linkinghub.elsevier.com/retrieve/pii/S1470160X21010414, doi:10.1016/j.ecolind.2021.108376. publisher: Elsevier B.V.

Edens, B., Maes, J., Hein, L., Obst, C., Siikamaki, J., Schenau, S., Javorsek, M., Chow, J., Chan, J.Y., Steurer, A., Alfieri, A., 2022. Establishing the seea ecosystem accounting as a global standard. Ecosystem Services 54, 101413. URL: https://www.sciencedirect.com/science/article/pii/S2212041622000092, doi:10.1016/j.ecoser.2022.101413.

European Council and Parliament, 2024. Regulation (eu) 2024/3024 of the european parliament and of the council of 27 november 2024 amending regulation (eu) no 691/2011 as regards introducing new environmental economic account modules. URL: https://eur-lex.europa.eu/eli/reg/2024/3024/oj/eng.

Ewert, F., van Ittersum, M.K., Heckelei, T., Therond, O., Bezlepkina, I., Andersen, E., 2011. Scale changes and model linking methods for integrated assessment of agri-environmental systems. Agriculture, Ecosystems & Environment 142, 6–17. URL: https://www.sciencedirect.com/science/article/pii/S016788091100171X, doi:10.1016/j.agee.2011.05.016.

Horvitz, D.G., Thompson, D.J., 1952. A generalization of sampling without replacement from a finite universe. Journal of the American Statistical Association 47, 663–685. URL: https://www.jstor.org/stable/2280784, doi:10.2307/2280784. publisher: [American Statistical Association, Taylor & Francis, Ltd.].

IPBES, 2019. Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Technical Report. IPBES Secretariat. Bonn, Germany. URL: https://doi.org/10.5281/zenodo.3831673.

Jakobsson, S., Evju, M., Framstad, E., Imbert, A., Lyngstad, A., Sickel, H., Sverdrup-Thygeson, A., Töpper, J.P., Vandvik, V., Velle, L.G., Aarrestad, P.A., Nybø, S., 2021. Introducing the index-based ecological condition assessment framework (ibeca). Ecological Indicators 124, 107252. URL: https://linkinghub.elsevier.com/retrieve/pii/S1470160X20311912, doi:10.1016/j.ecolind.2020.107252. publisher: Elsevier B.V.

Keith, D.A., Ferrer-Paris, J.R., Nicholson, E., Kingsford, R.T. (Eds.), 2020. IUCN Global Ecosystem Typology 2.0: descriptive profiles for biomes and ecosystem functional groups. IUCN, International Union for Conservation of Nature. URL: https://portals.iucn.org/library/node/49250, doi:10.2305/IUCN.CH.2020.13.en.

King, S., Agra, R., Zolyomi, A., Keith, H., Nicholson, E., de Lamo, X., Portela, R., Obst, C., Alam, M., Honzák, M., Valbuena, R., Nunes, P.A.L.D., Santos-Martin, F., Equihua, M., Pérez-Maqueo, O., Javorsek, M., Alfieri, A., Brown, C., 2024. Using the system of environmental-economic accounting ecosystem accounting for policy: A case study on forest ecosystems. Environmental Science & Policy 152, 103653. URL: https://www.sciencedirect.com/science/article/pii/S1462901123003027, doi:10.1016/j.envsci.2023.103653.

Kolstad, A., Grainger, M., 2024. ecRxiv - a Publishing Platform for Ecosystem Condition Indicators. URL: https://github.com/NINAnor/ecRxiv.

Kolstad, A.L., 2025. Area of glaciers (ID: NO_glac_001) v. 000.002. URL: ecRxiv:https://view.nina.no/ecRxiv/.

Kolstad, A.L., Grainger, M., Evju, M., 2024. Making use of spatially biased variables in ecosystem condition accounting – a GIS based workflow URL: https://ecoevorxiv.org/repository/view/7221/. publisher: EcoEvoRxiv.

Langhans, S.D., Reichert, P., Schuwirth, N., 2014. The method matters: A guide for indicator aggregation in ecological assessments. Ecological Indicators 45, 494–507. URL: https://www.sciencedirect.com/science/article/pii/S1470160X14002167, doi:10.1016/j.ecolind.2014.05.014.

Lyytimäki, J., Tapio, P., Varho, V., Söderman, T., 2013. The use, non-use and misuse of indicators in sustainability assessment and communication. International Journal of Sustainable Development & World Ecology 20, 385–393. URL: https://doi.org/10.1080/13504509.2013.834524, doi:10.1080/13504509.2013.834524. publisher: Taylor & Francis _eprint: https://doi.org/10.1080/13504509.2013.834524.

Maes, J., Driver, A., Czúcz, B., Keith, H., Jackson, B., Nicholson, E., Dasoo, M., 2020. A review of ecosystem condition accounts: lessons learned and options for further development. One Ecosystem 5, e53485. URL: https://oneecosystem.pensoft.net/article/53485/, doi:10.3897/oneeco.5.e53485. publisher: Pensoft Publishers.

Pedersen, B., Nybø, S., Sæther, S.A., 2016. Nature index for norway 2015. ecological framework, computational methods, database and information systems. NINA rapport 1226 URL: https://brage.nina.no/nina-xmlui/handle/11250/2374610. accepted: 2016-01-22T14:38:08Z ISSN: 1504-3312 Publication Title: 84 pp.

Rastetter, E.B., King, A.W., Cosby, B.J., Hornberger, G.M., O'Neill, R.V., Hobbie, J.E., 1992. Aggregating fine-scale ecological knowledge to model coarser-scale attributes of ecosystems. Ecological Applications 2, 55–70. URL: https://www.jstor.org/stable/1941889, doi:10.2307/1941889. publisher: [Wiley, Ecological Society of America].

Union/EC-JRC, O., 2008. Handbook on Constructing Composite Indicators: Methodology and User Guide. OECD Publishing, Paris. URL: https://doi.org/10.1787/9789264043466-en.

United Nations, 2022. Guidelines on biophysical modelling for ecosystem accounting .

United Nations, 2024. System of Environmental-Economic Accounting-Ecosystem Accounting. Technical Report. URL: https://seea.un.org/ecosystem-accounting.

Vallecillo, S., Maes, J., Teller, A., Babí Almenar, J., Barredo, J.I., Trombetti, M., Abdul Malak, D., Paracchini, M.L., Carré, A., Addamo, A.M., Czúcz, B., Zulian, G., Marando, F., Erhard, M., Liquete, C., Romao, C., Polce, C., Pardo Valle, A., Jones, A., Zurbaran-Nucci, M., Nocita, M., Vysna, V., Cardoso, A.C., Gervasini, E., Magliozzi, C., Baritz, R., Barbero, M., Andre, V., Kokkoris, I.P., Dimopoulos, P., Kovacevic, V., Gumbert, A., 2022. EU-wide methodology to map and assess ecosystem condition: towards a common approach consistent with a global statistical standard. Publications Office of the European Union, LU. URL: https://data.europa.eu/doi/10.2760/13048.