

<sup>1</sup> On the spatial aggregation of condition metrics for ecosystem accounting

<sup>2</sup> Anders Lorentzen Kolstad<sup>a,\*</sup>, Hanno Sandvik<sup>a</sup>, Bálint Czúcz<sup>a</sup>, Chloé R. Nater<sup>a</sup>

<sup>a</sup>Norwegian Institute for Nature Research, Department of Terrestrial Ecology, Pb 5685 Torgarden, Trondheim, 7485

---

<sup>3</sup> **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.

<sup>4</sup> *Keywords:* SEEA EA, ecosystem condition, ecosystem accounting, indicators, aggregation bias,  
<sup>5</sup> aggregation error, aggregation displacement, upscaling

---

<sup>6</sup> **1. Introduction**

<sup>7</sup> The world is facing a nature crisis of a magnitude that requires urgent political decision making and  
<sup>8</sup> international coordination ([IPBES, 2019](#)). Ecosystem accounting has been fronted as a framework for  
<sup>9</sup> providing a knowledge base for this. EAs are environmental assessments aimed at communicating on the  
<sup>10</sup> status and trends in the extent and condition of ecosystems at a scale and in a format that is relevant for  
<sup>11</sup> decision makers ([Edens et al., 2022](#), [Comte et al. \(2022\)](#)). For ecosystem condition accounting (ECA) and  
<sup>12</sup> assessments, this often requires that **metrics** (terms in bold are explained in Table 1) used to describe the  
<sup>13</sup> condition of ecosystems are **aggregated spatially** to produce a single value for a larger area. This represents  
<sup>14</sup> a type of knowledge synthesis, aimed at condensing the complexity of the real world into something that is  
<sup>15</sup> 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](mailto:anders.kolstad@nina.no) (Anders Lorentzen Kolstad), [hanno.sandvik@nina.no](mailto:hanno.sandvik@nina.no) (Hanno Sandvik), [balint.czucz@nina.no](mailto:balint.czucz@nina.no) (Bálint Czúcz), [chloe.nater@nina.no](mailto:chloe.nater@nina.no) (Chloé R. Nater)

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

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

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

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

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).
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.

Term or concept	Definition and deliberation
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 nomenclature $X_n$ 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 <i>Transformation</i> ).
Normalisation	This is the mathematical process of turning a condition variable into an indicator <i>sensu</i> SEEA EA. It consists of three distinct steps: scaling, truncation, and transformation (see also ( <b>fig-term?</b> )). <b>Scaling</b> 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. <b>Truncation</b> means to recode scaled variable above 1 to become 1, and values below 0 to become 0. <b>Transformation</b> 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 [ <i>sensu</i> WFD; EU (2000)] 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 <b>rescaling</b> 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).
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.

Term or concept	Definition and deliberation
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. It means going from fine-resolution data to less fine or coarse resolution data. In related fields of study this operation may be described as <i>increasing the support</i> or <i>reducing the grain</i> (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 <i>upscaleing</i> 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 <b>index</b> ( <i>plural: indices</i> ).
Spatial prediction	It refers to any estimation of the value of a variable at an unobserved location, and therefore include both inter- and extrapolation. <b>Interpolation</b> means to <i>fill in the gaps</i> , or to increase the density of the data. <b>Extrapolation</b> 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 sophisticated ways to essentially <i>spread</i> 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 spatial and statistical prediction. Design-based approaches relies on classical sampling theory and uses what is known 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 sought, made up of contiguous spaces of a specific ecosystem type. The ecosystem accounting area is the ' <i>geographical territory for which an ecosystem account is compiled</i> ' (United Nations 2024)

Term or concept	Definition and deliberation
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 than 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 ( <i>modifiable</i> ), 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 interpretation of indicator values.
Post-stratification	A statistical technique used to correct for a biased sample by forcing the sample to match the main population in some key characteristics. 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 <i>post-processing</i> , e.g. by doing a step-wise spatial aggregation via the same strata.

## 49 2. Reasons for normalising variables

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

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

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

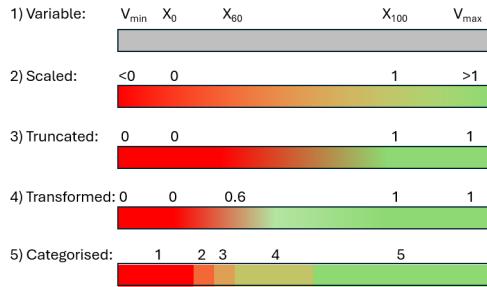


Figure 1: Examples of how important terms are used in this manuscript. Note that the meaning of the terms may differ from how they are used in other fields, such as mathematics. The variable (1), in original units, has a minimum ( $V_{\min}$ ) and a maximum value ( $V_{\max}$ ), as well as points anchoring 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.

### 74 3. The challenges and rationale for spatial aggregation in ecosystem condition accounting

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

80 Generally, spatial aggregation increases the clarity and accessibility of a metric because it simplifies or com-  
 81 presses the information, sometimes into just a single number (**total aggregation**). This may be necessary  
 82 in some cases of ecosystem accounting when information is required at a relatively high administrative level  
 83 (e.g. nations) and when variables and indicators need to be presented in standardised tables which don't  
 84 allow for describing a lot of spatial variation.

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

90 Data may also be only **partly aggregated**, or the same metric may be presented at different levels of  
 91 aggregation ([Allain et al., 2018](#)). A minimum level of aggregation may be decided based on uncertainties in  
 92 the data: high spatially resolute data may be imprecise at fine scales, leading to false sense of certainty and  
 93 potential misinterpretation ([Lyytimäki et al., 2013](#)), but these same data seen over a larger area may be  
 94 assumed to converge on some true value, making spatially aggregated data better suited for communication  
 95 to users. Other common arguments for performing spatial aggregation are to ease visualisation and to allow  
 96 relevant comparisons ([Allain et al., 2018](#)). For example, ecosystem condition metrics can be visualised on  
 97 a map, but when both the spatial resolution and spatial variation is high, maps become too complex, even  
 98 unintelligible. It is therefore common to partially aggregate the data and provide a coarser map where  
 99 different colours are used to distinguish different values. Similarly, one may choose to aggregate such that

100 the spatial resolution matches some meaningful delineation, notably **ecosystem assets** in SEEA EA, which  
101 makes it possible to easily compare the ecosystem condition between these areas.

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

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

113 Similar to variables, the reference levels used for normalising variables also have a spatial assignment, which  
114 can be different from that of the variable. For example, variable values may exist for unique  $10 \times 10$  m grid  
115 cells, but the reference levels may be created with a different spatial scale in mind, for example municipalities,  
116 or they can be uniform across the entire **ecosystem accounting area** (e.g. a natural zero). The bilberry  
117 example (**Example 1**) shows that, to ensure variables and reference levels are at a commensurable spatial  
118 scale, sometimes variables need to be partly 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 commensurable spatial scale before doing the normalisation.

*Variable:* Horizontal coverage (vertical projection) of European blueberry or bilberry (*Vaccinium 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 2: 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 2). 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 4) 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.

120

#### 121 4. Spatial prediction: fitting data to ecosystem assets

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

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

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

156 For design-based approaches, one can assign values to areas via simple aggregation functions used on data  
157 values that fall within a given ecosystem asset. Many aggregation functions are available, such as sum,

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

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

## 179 5. Aggregation displacement and spatial compensation

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

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

198 In the statistical standard and recommended guidelines for ecosystem accounts ([United Nations, 2024;](#)  
199 [2022](#)), there is no mention of aggregation displacement, and there seems to be little awareness in general of  
200 its meaning and the ramification of choosing different spatial aggregation pathways for variables. Indicators  
201 and variables are sometimes presented side-by-side in ecosystem condition assessments or accounts. This is  
202 also recommended practice following the SEEA EA [[United Nations \(2024\)](#); ch. 5.3.4].

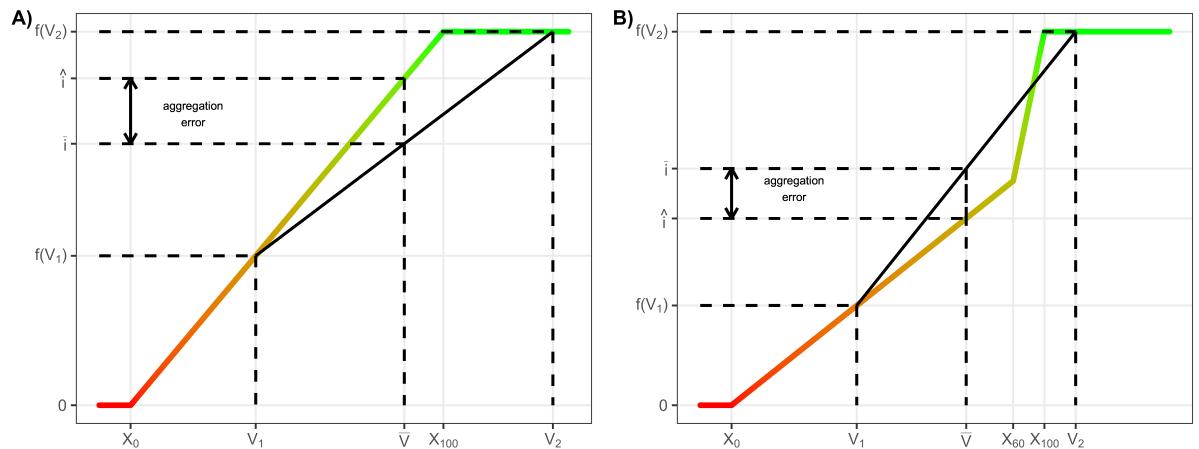


Figure 2: Examples showing the difference in indicator values (y-axis) obtained from taking the mean ( $\bar{V}$ ) of two variable values ( $V_1$  and  $V_2$ ) that are on the original scale ( $i$  hat) or on the normalised indicator scale ( $i$  bar). Pane A: Due to truncation at  $X_{100}$ , the latter 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 3) shows how different the interpretation of a variable and an indicator can become when the information is spatially aggregated. More specifically, it 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 number is informed by data on habitat quality, food supply, and more.  $X_0$  = no wolves.

Table 3: 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. 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.

203  
204 As we have seen, aggregation displacement causes a divergence in the type of information made available  
205 through the spatial aggregation of variables versus indicators. In addition, unavoidable aggregation displacement  
206 (for good and bad) will also affect the indicator values and the inferences that can be drawn from these.  
207 A major determinant of the resulting aggregation displacement from the spatial aggregation of ecosystem  
208 condition indicators (Figure 2) is the choice about the order of the different steps in the normalisation and  
209 aggregation process, i.e. the aggregation pathway (Figure 4). If normalisation occurs early in the aggrega-  
210 tion process, the amount of spatial compensation is limited (**Example 2**). However, sometimes complete  
211 or partial compensation is justified (**Example 1** and **3**).

## Example 3 – Water Framework Directive, indicator ASPT

Variable: ASPT (*average score per taxon*) is the mean eutrophication tolerance score of invertebrate species present in a river water body.

Reference levels:  $X_{100}$  = median variable value recorded in reference water bodies.  $X_{80}$  = lower boundary of variable values in reference water bodies.  $X_0$  = natural zero (no species present).  $X_{20}$ ,

212

$X_{40}$ , and  $X_{60}$  = intercalibrated threshold values, based on dose-response curves.

The Water Framework Directive (WFD) indicators use aggregation pathway 5 (Figure 4), with truncation, scaling, and transformation, in that order. The value obtained after the first two steps is called an EQR (ecological quality ratio), and the value obtained after the third step is called nEQR [normalised EQR, and true indicator values *sensu* SEEA EA; [Van De Bund and Solimini \(2007\)](#)]. Spatial aggregation, the way that we use the term here, is not done for the WFD. Instead, the aggregated reporting metric is the proportion of water bodies in each of the five condition classes (“bad”, “poor”, “moderate”, “good”, “high”), separated by the non-terminal reference levels.

When WFD data is put into use in other contexts, however, aggregation becomes important, and it is crucial that aggregation is done after the (scaling and) transformation step, because the transformation (using a stepwise-linear function) adds ecological meaning to the data. As the example in Figure 3 shows, the ecologically meaningful interpretation is that the EAA has “poor” condition at time 1, improving to “moderate” condition at time 2. When aggregation is erroneously done before transformation, however, the same measurements suggest that condition is “bad” and deteriorating. This illustrates that an ecosystem condition indicator account cannot be derived directly from an ecosystem condition variable account in conjunction with reference levels, as suggested by SEEA EA ([United Nations \(2024\)](#): 5.76 and table 5.3). The reason in the case of ASPT is that the transformation function is non-linear, and aggregation displacement therefore occurs in the spatial aggregation of variables and indicators. Reference levels are the same throughout the entire EAA, and variation in reference levels is thus not part of the problem here.

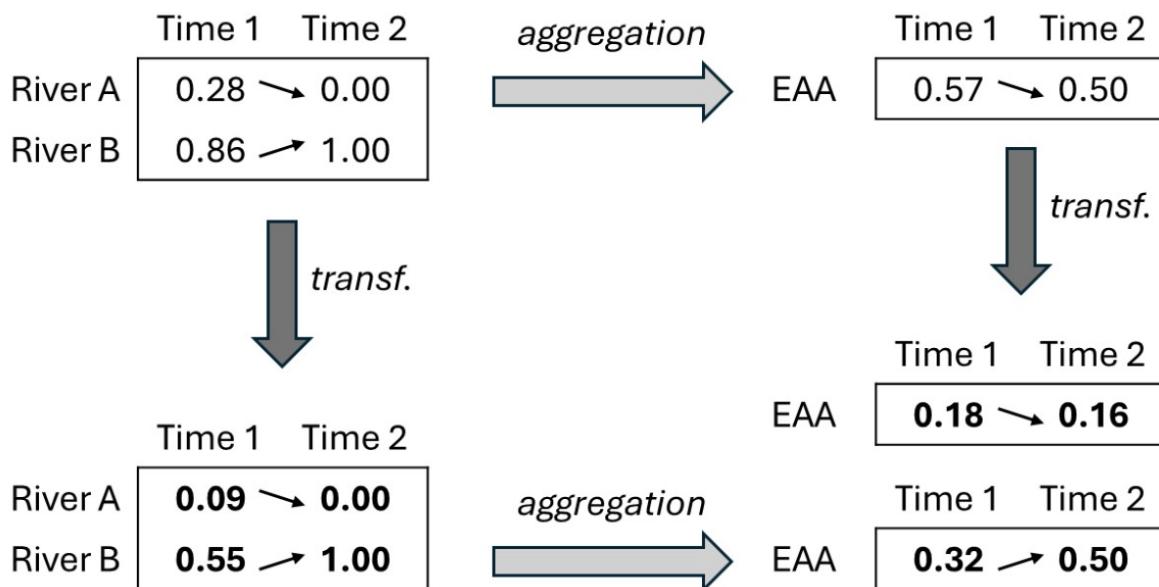


Figure 3: Different aggregation pathways can result in different indicator values, exemplified by the ASPT indicator from the WFD. Two ecosystem assets (Rivers A and B) are measured at two points in time. Regular font numbers are EQR values; boldface numbers are nEQR values (indicator values *sensu* SEEA EA). When EQR values are first aggregated and then transformed (“transf.”), ASPT incorrectly indicates a deteriorating and “bad” condition. When EQR values are first transformed and then aggregated, ASPT correctly indicates an improvement from “poor” to “moderate” condition.

Another issue that can be illustrated with ASPT (or other WFD indicators) is the effect of truncation. Aggregation pathway 5 uses truncation as the first step. When WFD data is used in ecosystem

condition accounting, however, truncation needs to be the final step, applied only after aggregation. This is because  $X_{100}$  is defined as the median of variable values measured in reference water bodies. In other words, half of the values measured in reference water bodies is expected to be above  $X_{100}$ . When truncation is done as the first step, the average indicator value of reference water bodies will be around 0.95, i.e. it would be prevented from actually reaching 1.0. Overshooting values therefore need to be preserved until after aggregation (spatial compensation), and only after aggregation should overshooting values be truncated to 1.0.

Likewise, in the case where model-based extrapolation of a WFD indicator is used, it is important to postpone truncation until after the modelling and extrapolation. Otherwise the distribution of the extrapolated values may be severely distorted, at least if many of the original measurements are in or close to the  $X_{100}$  value.

214

## 215 6. Aggregation pathways

216 We introduce the term aggregation pathway to describe the order of the steps used to go from a variable at  
217 the measurement scale, to a spatially aggregated metric, usually an indicator, that describes the ecosystem  
218 condition for a larger area. In Figure 4 we show some aggregation pathways that we have come across,  
219 and some that we see as potential new pathways. The examples are non-exhaustive, and serve mainly as  
220 illustrations. We go on to describe how the aggregation pathways can formally, and succinctly, be described  
221 using the names of these operations. The choice about which pathway to use is not trivial, and we want to  
222 highlight some of the issues that could arise from having an *ad hoc* approach to these considerations.

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

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

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

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

234 Pathway 5 is a common pathway in the WFD, which does not practice spatial aggregation of indicator  
235 values. Instead one reports the number of water bodies in each condition class (spatial statistics). Pathway  
236 6 is a suggested pathway for handling WFD indicator in ECAs (see **Example 3**), where truncation is  
237 postponed until after the spatial aggregation in order to allow overshooting values to compensate for low  
238 indicator values elsewhere (what we refer to as compensation).

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

244 Pathways 8 and 9 describe alternative ways to create indices at different spatial scales, either by spatially  
245 aggregating the indices (pathway 8), or by aggregating the indicators separately and recalculating the indices  
246 at different spatial scales (pathway 9). If perfectly commutative then the two approaches will yield the same  
247 result. However, if the indicators that make up the indices use different area weights as part of their spatial

248 aggregation (**Example 4**), then pathway 9 is the only one that gives the same index values across nested  
 249 accounts.

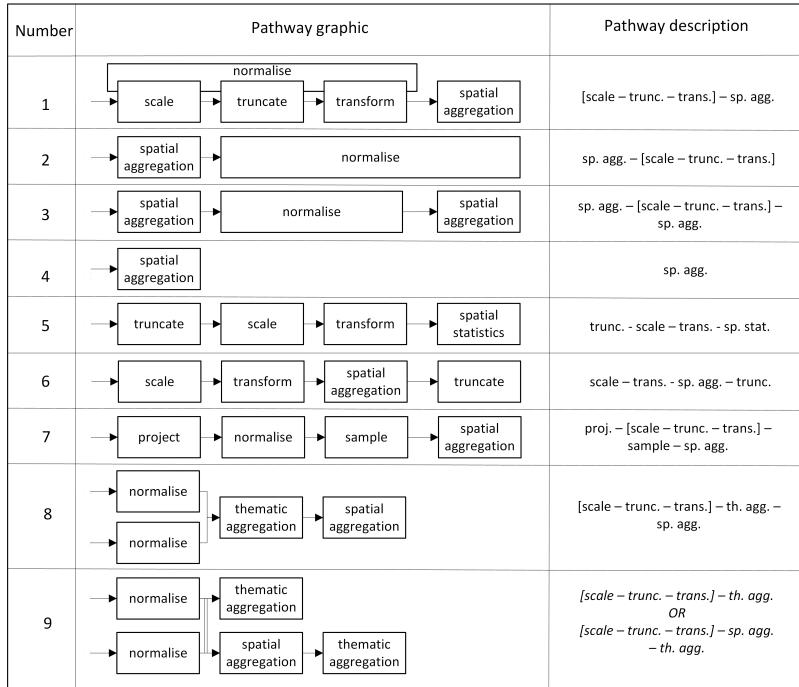


Figure 4: Flowchart showing a selection of nine possible pathways for the spatial aggregation of variables in ecosystem condition accounting. Normalisation refers to the steps that make a variable conform to the definition of an indicator in SEEA EA, which may include some, but not necessarily all, of the steps scale, truncate and transform. The pathway description used the standardised shorthand aggregation pathway terminology, where trunc. = truncation, trans. = transformation, sp. agg. = spatial aggregation, proj. = project (extrapolation or interpolation), sample = sub-sampling from a larger dataset, th. agg. = thematic aggregation.

## 250 7. Recommendations

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

### 254 1. Report the aggregation pathway, using standardised terminology

255 ECAs should be accompanied by detailed indicator documentation where a precise description of the  
 256 steps in the aggregation process is presented. Verbose descriptions can be supplemented or replaced by a  
 257 standardised short-hand notation that we present in the following: We suggest using the terms as described  
 258 in Figure 1 and elsewhere in the paper: scale, truncate (abbreviated to *trunc.*), transform (*trans.*), spatial  
 259 aggregation (*sp. agg.*), thematic aggregation (*th. agg.*) and spatial statistics (*sp. stat.*). These terms can be  
 260 abbreviated as shown in the parentheses, and placed together into a single string, where operations performed  
 261 simultaneously are enclosed in square brackets. For example, pathway 1 in Figure 4 can be annotated as  
 262 *scale – trunc. – trans. – sp.agg..* If the three normalisation steps are performed simultaneously this can  
 263 be written as *[scale – trunc. – trans.] – sp.agg..* If there are more aggregation steps, then the spatial level  
 264 at each step should be included in the description, e.g. for pathway 3: *sp.agg.(municipalities) – scale –*  
 265 *sp.agg.(country)*. “Municipality” and “country” could here be included as footnotes. Note also that in  
 266 the last example, normalisation only involved a scaling step. The description of indicator pathways can be  
 267 made even easier by referencing specific aggregation pathways by number, as we have done in this paper

268 using Figure 4 in this paper. Methods used to change either the cover or the extent of the indicator data  
269 (see Table 1) can also be included in the shorthand notation scheme. The three operations we conceive  
270 as possible options are extrapolation (extr.), interpolation (inter.), and (sub)sampling. We use the term  
271 spatial projection (projection for short) to encompass both extra- and interpolation. Thus, pathway 7 in  
272 Figure 4 can be written as *project – scale – sample – sp.agg. – trunc.* The type of model used for the  
273 spatial projection can be added as a footnote.

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

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

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

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

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

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

293 Indicators (and variables) often exist in multiple versions, varying slightly in the raw data or in the methods  
294 or aggregation pathway used to produce the data or the metrics. Yet different versions are often referred to  
295 by the same common name, for example in nested or repeated ECAs. This causes confusion about which  
296 indicator version is being used, and thus making it difficult to make out which aggregation pathway has  
297 been used. We need to acknowledge that the aggregation pathway can affect the indicators (and indices) so  
298 much that the use of different pathways imply that metrics are named and treated uniquely. We recommend  
299 making use of stable and unique indicator IDs and version numbers. This has for example already been  
300 implemented in ecRxiv, a GitHub-based publishing platform for ecosystem condition indicators used in the  
301 Norwegian national pilot ECA ([Kolstad and Grainger, 2024](#)). On ecRxiv, indicator documentation follows  
302 a structured approach to both reporting and peer review (including code review). Each indicator version  
303 is given its own ID, and its own fact sheet with a persistent URL, so that ECAs that use these indicators  
304 can unequivocally cite specific indicator versions, and how they looked at a given point in time. ecRxiv also  
305 includes standardised metadata reporting schemes with fields for ecosystem type (IUCN GET; [Keith et al.](#)  
306 ([2020](#))) and aggregation pathways (see recommendation number 1 above).

#### 307 7.0.1. 5. Don't aggregate indices, unless you know all aggregation operations are commutative

308 When spatially aggregating indices it is no longer possible to use different area weights to each single  
309 indicator. If all indicators making up an index are spatially aggregated using the same weights, typically the  
310 extent of the spatial units, then the aggregation operations will be commutative and it will not matter if you  
311 aggregate vertically then horizontally, or the other way around (Figure 4; Pathway 8 and 9, respectively).  
312 However, indicators are not always valid for the entire ecosystem type that the account is made over. They  
313 can, for example, retain to only certain habitat or nature types within the ecosystem type, in which case one  
314 might want to use different weights when spatially aggregating the indicator that reflect the extent of only

315 the relevant habitat or nature types, and not of the entire ecosystem (see **Example 4**). But when combined  
316 with other indicators into a common index, any subsequent aggregation of that index will give equal spatial  
317 weight to all indicators (see next paragraph for an exception to this). We therefore recommend caution,  
318 and to default to the solution of instead spatially aggregating indicators separately, and then re-calculating  
319 indices when needed (Figure 4; Pathway 9). This will ensure that nested accounts will be comparable,  
320 i.e. that they will present the same index values independent of which spatial units the indices first are  
321 calculated for.

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

#### 329 7.0.2. 6. *Don't present variables and their respective indicators as alternative evidences to choose from*

330 Aggregation displacement causes a divergence in the type of information held in ecosystem condition  
331 variables versus indicators, and spatially aggregated indicators should not be interpreted as normalised  
332 versions of aggregated variables. Therefore, aggregated variables and the associated aggregated indicators  
333 cannot act as alternative evidence or interpretations for the state of nature. While this may initially seem  
334 like a democratic and transparent approach to reporting, this practice places a significant burden on both  
335 the end user and the indicator developer. Misuse can ensue, for example by taking the variable value and  
336 assigning it the same interpretation as the indicator value. At the very least, the developer must clarify to  
337 the user how the two metrics may have diverged during spatial aggregation and normalisation, complicating  
338 the comparison of their respective information. Generally, because of the normalisation process, indicators  
339 are more aligned with the purpose of ECA with describing ecosystem condition in normative terms, than  
340 variables. Although variable accounts are allowed under the SEEA EA framework, and are indeed a central  
341 feature, we believe they should be seen as interim accounts for metrics that cannot be, or have not yet been,  
342 normalised.

## 343 8. Conclusion

344 This paper has described the reasons why we need to do spatial generalisation in ecosystem accounting,  
345 and clarified several misconceptions about this process. We have showed that indeitical raw data, when  
346 spatially aggregated through different pathways, can yield fundamentally different types of information  
347 about ecosystems condition. The recommendations offered here is intended to help researchers design  
348 ecosystem condition metrics that better align with the type of information they aim to communicate from  
349 the data, while also improving transparency through the use of a standardised terminology. With a clearer  
350 understanding of the challenges inherrent to spatial generalisation, we that hope future ecosystem condition  
351 accounts will be more internally consistent, more comparable between each other, and less susceptible to  
352 unintended mathematical artefacts.

## 353 References

- 354 Allain, S., Plumecocq, G., Leenhardt, D., 2018. Spatial aggregation of indicators in sustainability assessments: Descriptive  
355 and normative claims. Land Use Policy 76, 577–588. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0264837717310396>,  
356 doi:[10.1016/j.landusepol.2018.02.038](https://doi.org/10.1016/j.landusepol.2018.02.038).
- 357 van Beurden, A.U.C.J., Douven, W.J.A.M., 1999. Aggregation issues of spatial information in environmental research. In-  
358 International Journal of Geographical Information Science 13, 513–527. URL: <https://doi.org/10.1080/136588199241184>,  
359 doi:[10.1080/136588199241184](https://doi.org/10.1080/136588199241184). publisher: Taylor & Francis.
- 360 Brus, D.J., 2000. Using regression models in design-based estimation of spatial means of soil properties. European Journal of Soil  
361 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](https://doi.org/10.1046/j.1365-2389.2000.00277.x). \_eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1046/j.1365-2389.2000.00277.x>.

- 363 Brus, D.J., 2021. Statistical approaches for spatial sample survey: Persistent misconceptions and new developments. European  
 364 Journal of Soil Science doi:[10.1111/ejss.12988](https://doi.org/10.1111/ejss.12988).
- 365 Comte, A., Sylvie Campagne, C., Lange, S., Bruzón, A., Hein, L., Santos-Martín, F., Levrel, H., 2022. Ecosystem accounting:  
 366 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](https://doi.org/10.1016/j.ecoser.2022.101486).
- 367 Czúcz, B., Keith, H., Maes, J., Driver, A., Jackson, B., Nicholson, E., Kiss, M., Obst, C., 2021. Selection criteria for  
 368 ecosystem condition indicators. *Ecological Indicators* 133, 108376. URL: <https://linkinghub.elsevier.com/retrieve/pii/S1470160X21010414>, doi:[10.1016/j.ecolind.2021.108376](https://doi.org/10.1016/j.ecolind.2021.108376). publisher: Elsevier B.V.
- 369 Edens, B., Maes, J., Hein, L., Obst, C., Siikamaki, J., Schenau, S., Javorsek, M., Chow, J., Chan, J.Y., Steurer, A., Alfieri,  
 370 A., 2022. Establishing the sea 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](https://doi.org/10.1016/j.ecoser.2022.101413).
- 371 European Council and Parliament, 2024. Regulation (eu) 2024/3024 of the european parliament and of the council of 27  
 372 november 2024 amending regulation (eu) no 691/2011 as regards introducing new environmental economic account modules.  
 373 URL: <https://eur-lex.europa.eu/eli/reg/2024/3024/oj/eng>.
- 374 Ewert, F., van Ittersum, M.K., Heckelei, T., Therond, O., Bezlepkinia, I., Andersen, E., 2011. Scale changes and model linking  
 375 methods for integrated assessment of agri-environmental systems. *Agriculture, Ecosystems & Environment* 142, 6–17. URL:  
 376 <https://www.sciencedirect.com/science/article/pii/S016788091100171X>, doi:[10.1016/j.agee.2011.05.016](https://doi.org/10.1016/j.agee.2011.05.016).
- 377 Horvitz, D.G., Thompson, D.J., 1952. A generalization of sampling without replacement from a finite universe. *Journal of the  
 378 American Statistical Association* 47, 663–685. URL: <https://www.jstor.org/stable/2280784>, doi:[10.2307/2280784](https://doi.org/10.2307/2280784). publisher:  
 379 [American Statistical Association, Taylor & Francis, Ltd.].
- 380 IPBES, 2019. Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform  
 381 on Biodiversity and Ecosystem Services. Technical Report. IPBES Secretariat. Bonn, Germany. URL: <https://doi.org/10.5281/zenodo.3831673>.
- 381 Jakobsson, S., Evju, M., Framstad, E., Imbert, A., Lyngstad, A., Sickel, H., Sverdrup-Thygeson, A., Töpper, J.P., Vandvik, V.,  
 382 Velle, L.G., Aarrestad, P.A., Nybø, S., 2021. Introducing the index-based ecological condition assessment framework (ibeca).  
 383 *Ecological Indicators* 124, 107252. URL: <https://linkinghub.elsevier.com/retrieve/pii/S1470160X20311912>, doi:[10.1016/j.ecolind.2020.107252](https://doi.org/10.1016/j.ecolind.2020.107252). publisher: Elsevier B.V.
- 384 Keith, D.A., Ferrer-Paris, J.R., Nicholson, E., Kingsford, R.T. (Eds.), 2020. IUCN Global Ecosystem Typology 2.0: descriptive  
 385 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](https://doi.org/10.2305/IUCN.CH.2020.13.en).
- 386 King, S., Agra, R., Zolyomi, A., Keith, H., Nicholson, E., de Lamo, X., Portela, R., Obst, C., Alam, M., Honzák, M., Valbuena,  
 387 R., Nunes, P.A.L.D., Santos-Martin, F., Equihua, M., Pérez-Maqueo, O., Javorsek, M., Alfieri, A., Brown, C., 2024. Using  
 388 the system of environmental-economic accounting ecosystem accounting for policy: A case study on forest ecosystems.  
 389 *Environmental Science & Policy* 152, 103653. URL: <https://www.sciencedirect.com/science/article/pii/S1462901123003027>, doi:[10.1016/j.envsci.2023.103653](https://doi.org/10.1016/j.envsci.2023.103653).
- 390 Kolstad, A., Grainger, M., 2024. ecRxiv - a Publishing Platform for Ecosystem Condition Indicators. URL: <https://github.com/NINAnor/ecRxiv>.
- 391 Kolstad, A.L., 2025. Area of glaciers (ID: NO\_glac\_001) v. 000.002. URL: [ecRxiv:https://view.nina.no/ecRxiv/](https://ecRxiv:https://view.nina.no/ecRxiv/).
- 392 Kolstad, A.L., Grainger, M., Evju, M., 2024. Making use of spatially biased variables in ecosystem condition accounting – a  
 393 GIS based workflow URL: <https://ecovorxiv.org/repository/view/7221/>. publisher: EcoEvoRxiv.
- 394 Langhans, S.D., Reichert, P., Schuwirth, N., 2014. The method matters: A guide for indicator aggregation in ecological as-  
 395 sessments. *Ecological Indicators* 45, 494–507. URL: <https://www.sciencedirect.com/science/article/pii/S1470160X14002167>, doi:[10.1016/j.ecolind.2014.05.014](https://doi.org/10.1016/j.ecolind.2014.05.014).
- 396 Lyttimäki, J., Tapio, P., Varho, V., Söderman, T., 2013. The use, non-use and misuse of indicators in sustainability as-  
 397 sessment and communication. *International Journal of Sustainable Development & World Ecology* 20, 385–393. URL:  
 398 <https://doi.org/10.1080/13504509.2013.834524>, doi:[10.1080/13504509.2013.834524](https://doi.org/10.1080/13504509.2013.834524). publisher: Taylor & Francis \_eprint:  
 399 <https://doi.org/10.1080/13504509.2013.834524>.
- 400 Maes, J., Driver, A., Czúcz, B., Keith, H., Jackson, B., Nicholson, E., Dasoo, M., 2020. A review of ecosystem condition  
 401 accounts: lessons learned and options for further development. *One Ecosystem* 5, e53485. URL: <https://onecosystem.pensoft.net/article/53485/>, doi:[10.3897/oneco.5.e53485](https://doi.org/10.3897/oneco.5.e53485). publisher: Pensoft Publishers.
- 402 Pedersen, B., Nybø, S., Sæther, S.A., 2016. Nature index for norway 2015. ecological framework, computational methods,  
 403 database and information systems. NINA rapport 1226 URL: <https://brage.nina.no/nina-xmlui/handle/11250/2374610>.  
 404 accepted: 2016-01-22T14:38:08Z ISSN: 1504-3312 Publication Title: 84 pp.
- 405 Rastetter, E.B., King, A.W., Cosby, B.J., Hornberger, G.M., O'Neill, R.V., Hobbie, J.E., 1992. Aggregating fine-scale ecological  
 406 knowledge to model coarser-scale attributes of ecosystems. *Ecological Applications* 2, 55–70. URL: <https://www.jstor.org/stable/1941889>, doi:[10.2307/1941889](https://doi.org/10.2307/1941889). publisher: [Wiley, Ecological Society of America].
- 407 Union/EC-JRC, O., 2008. Handbook on Constructing Composite Indicators: Methodology and User Guide. OECD Publishing,  
 408 Paris. URL: <https://doi.org/10.1787/9789264043466-en>.
- 409 United Nations, 2022. Guidelines on biophysical modelling for ecosystem accounting .
- 410 United Nations, 2024. System of Environmental-Economic Accounting-Ecosystem Accounting. Technical Report. URL: <https://sea.un.org/ecosystem-accounting>.
- 411 Vallecillo, S., Maes, J., Teller, A., Babí Almenar, J., Barredo, J.I., Trombetti, M., Abdul Malak, D., Paracchini, M.L., Carré,  
 412 A., Addamo, A.M., Czúcz, B., Zulian, G., Marando, F., Erhard, M., Liqueite, C., Romao, C., Polce, C., Pardo Valle, A.,  
 413 Jones, A., Zurbaran-Nucci, M., Nocita, M., Vysna, V., Cardoso, A.C., Gervasini, E., Magliozzi, C., Baritz, R., Barbero, M.,  
 414 Andre, V., Kokkoris, I.P., Dimopoulos, P., Kovacevic, V., Gumbert, A., 2022. EU-wide methodology to map and assess

- 428 ecosystem condition: towards a common approach consistent with a global statistical standard. Publications Office of the  
429 European Union, LU. URL: <https://data.europa.eu/doi/10.2760/13048>.
- 430 Van De Bund, W., Solimini, A., 2007. Ecological Quality Ratios for Ecological Quality Assessment in Inland and Marine  
431 Waters. volume EUR 22722 EN. Office for Official Publications of the European Communities., Luxembourg. URL: <https://publications.jrc.ec.europa.eu/repository/handle/JRC36757>.
- 432