Horizontal aggregation of spatially biased ecosystem condition indicators – a GIS based workflow

A Short Subtitle

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Abstract

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1. Introduction

Ecosystem condition accounting is the game of compiling relevant data on the status, trends and qualities of ecosystems (i.e. nature) and communicating this in a structured format. Its purpose is to make it easier to account for nature in policy by making the environmental costs of certain policies and practices visible to decision makers. As natural capital keeps declining all over the world, it is becoming increasingly urgent to make the message clear to decision makers about. A statistical standard for ecosystem accounting, including ecosystem condition accounting, was developed by the UN and adopted by the UN Statistical Commission in 2021 and is called SEEA EA (United Nations (2021); System of Environmental-Economic Accounting - Ecosystem Accounting). The standard, or framework, is a set of rules, principles and best practices for compiling Ecosystem accounts, mainly aimed at national accounts.

Central to ecosystem condition accounts are variables and indicators. These are parameters chosen to reflect the central condition characteristics of the ecosystems, and that can be quantified and ideally monitored over time to reflect the status and trends in condition. Indicators are (data) variables that are normalised (rescaled) against upper and lower reference values to become bound between the values 0 and 1. This normalisation ensures that indicators are more comparable because an indicator value of 1 will mean the same for all indicators, i.e. that the variable equals the upper reference value which again reflect the value of the variables under the reference condition. Similarly, a value of 0 mean that the variable is the worst possible state. The reference condition needs to be defined for each Ecosystem Condition Assessment separately, but SEEA EA gives some suggestion, such as an an ecosystem with no or minimal anthropogenic disturbance.

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A general requirement for indicators in the SEEA EA framework is that they should give an unbiased representation of the condition inside the ecosystem assets (Czúcz et al., 2021b, table 1; see also United Nations, 2021, §2.87) Ecosystem assets are defined as "ecological entities [meaning areas] about which information is sought and about which statistics are ultimately compiled (United Nations, 2021). This requirement for indicator validity means that spatially biased data are ill suited, especially if sampling intensity varies along gradient of anthropogenic pressures and hence ecosystem condition. SEEA EA is spatially explicit, which in practice means that indicators that are in some way sampled (i.e. not complete wall-to-wall data like remotely sensed imagery), the values are projected on to areas on the map, so that all areas inside the ecosystem accounting area get assigned value for that indicator. There are at least 3 general ways to achieve this complete areal coverage of indicator values:

a. Using wall-to-wall data (e.g. remotely sensed data)
b. Predict values using a model (e.g. by accounting for environmental variation)
c. Simple projection of some best estimate, typically a central tendency from area representative data

The need for an unbiased estimation of indicator values is unquestionable, but nonetheless, this requirement puts a large limitation on what types of data one can use. Ecosystem condition assessments are generally limited by data availability, and the choice of variables and indicators to include in assessments are more often or not a pragmatic and opportunistic one which is unlikely to reflect the full scope of the ecosystem condition characteristics. Note that the same is true for thematic biases. For example reflected in the scarcity of data included on insects or soil biota, even though most will agree they represent key ecosystem characteristics. Also having data from only one or a subset of nature types inside what is defined as the ecosystem in the assessment, is a typical thematic bias in ecosystem accounting. However, in this paper we chose to focus on spatial bias.

Being able to make use of spatially biased data would greatly alleviate data shortage problems in ecosystem condition accounts. One way to achieve this is modelling (option b in the list above). Models can describe the general associations between the spatially sampled data and the context (e.g. the set of environmental variables) where it was samples, and use these relationships to predict and project indicator values to areas that where not originally sampled. Depending on the data that goes into these models, they can be very reliable and make good indicators. This is especially true when the ecosystem assets are large (e.g. regions or nations). But when they are small, like the scale of a municipality, and when the indicator is more likely to be used as the evidence base in concrete physical land use planning, then the inherent level of uncertainty from such models becomes unacceptable.

In this study we explore the potential for using a stratified aggregation technique to make use of spatially biased field data in ecosystem condition accounting. We demonstrate this technique using a generic GIS-based workflow for compiling ecosystem condition accounts that can be applied at any spatial scale, and we highlight the opportunities for local use-cases of this workflow by contrasting our findings across three neighboring municipalities in Norway. The main question is how much generalisation can we perform on the data we have before the resulting indicator looses its practical value in local governance processes. We end by interviewing end-users from the relevant municipalities about the perceived benefits and shortcomings of our condition indicators.

2. Material and Methods

This study makes use of a data set from from a standardised field survey of nature types in Norway that started in 2018 and which is still ongoing (Norwegian Environmental Agency, 2024). In this survey, selected nature types are delineated on a map (over 140 000 polygons at the end of 2023), and each locality is scored on a range of variables relevant for describing the state and quality of nature (Agency). The surveys are commissioned with the goal of producing data relevant for immediate land-use decisions, and is therefore spatially biased, typically towards areas with high human impact or expected impact. In addition there is a thematic and size bias in the sampling protocol. For examples, for the forest ecosystem, rare, endangered or calcareous forest types are delineated, whereas more common or ordinary forest types are not. For that reason we we focused on open mire ecosystems in Norway where the thematic bias is less severe. Of all possible mire types, the survey only maps the following:

- Southern ombrotrophic mires > 2500 m^2
- Northern ombrotrophic mires > 10.000 m^2
- All semi-natural mires (minerotrophic fens)
- Calcareous southern fens >500 m^2
- Calcareous northern fens >1000 m^2

In the above, *southern* refers to boreonemoral and southboreal zones, and *northern* refers to mid-boreal, north boreal, and alpine zones (AsbjørnMoen, 1998). In addition, the northern fens need to be even more calcareous than the southern fens in order to be surveyed. We included data from 2018 to 2023. In this paper we assume the survey is representative for the entire mire ecosystem in Norway. Although it is possible that smaller or less calcareous mires will score systematically different than the ones that are surveyed we do not think this is so much the case for our variables (see below). However, we do assume that alien plants are slightly less common on bogs relative to fens, and therefore that this variable will be biased since that variable for only recorded in fens. The other variables are recorded in all delineated mires.

From the survey data set we identified six relevant variables (variable 1-6 in Table 1) which we attribute to three different ecosystem condition characteristics that describe the typical behavior of open mire ecosystems in the reference condition (Figure S1). Variables 1 -5 were were originally recorded along binned frequency ranges Agency . Because the data was strongly right skewed we used the lower limit for each frequency range to convert them into percentages. Variables 2-5 describe very related aspects, and are attributed to the same ecosystem condition characteristic (vegetation intactness) and so they where combined into a single indicator called antropogenic disturbance to soil and vegetation (ADSV; Figure S1). This was done by summing the two variables after they had been converted to percentages. This was not a perfect solution, especially since some localities only had one of the variables recorded, but we chose this, rather than for example using a *worst rule* principle, in order to better separate the localities in terms of their indicator values. Variable 6 is different from the preceding variables in Table 1 in that it includes an estimation of future effects that the observed trenches are projected to have on mire vegetation, function or structure over time. This is not a favorable trait in a metric used to evaluate the ecosystem condition as it is today, yet we include it here nonetheless because there is a general shortage of data on mire hydrology, which is a fundamental part of mire integrity.

To turn the remaining three variables into indicators we scaled them using three normative reference values each: an upper (best possible condition), a lower (worst possible condition), and a threshold value that defines the breaking point between good and poor condition. The reference values are numerical representation of the reference condition. We define the reference condition as one where ecosystems are subject to little or no human influence, with a climate as in the period 1961-1990 and a native species pool similar as today.

For the indicators Alien species and ADSV, the lower and upper reference values were defined as 100% and 0%, respectively. The threshold for *good ecosystem condition* was defined as 10%, which was then mapped to the value 0.6 on the rescaled indicators, thus creating a non-linear rescaling of the variable (Figure S2). The variable 7GR-GI was rescaled into the indicator named *Trenching* by using the lower and upper reference values 1 and 5, respectively, and a threshold value of 2.5 (Figure S2). A variable value of 1 indicates an intact mire, and a value of 5 indicates a mire transitioning away from a wetland. A value of 2 indicates observable change within the range expected for the same mapping unit, and a value of 3 indicates a mire transitioning into a neighboring (ecologically speaking) mapping unit. See Figure S1 and Figure 2 for a schematic workflow for the indicator development.

According to the SEEA ECT, *Alien species* can be attributed to ECT class B1 - Compositional state characteristics and *ADSV* and *Trenching* attributed to ECT class A1 - Physical state characteristics (Czúcz et al., 2021a).

We used an ecosystem delineation map for open mires in southern Norway, produced using remotely sensed data and a deep learning model (Bakkestuen et al., 2023). This model, which has a 90.9% precision when tested against independent field data, estimates 12.7% of the area in southern Norway is mire (Bakkestuen et al., 2023). Mires are ecologically and socially important in Norway simply doe to its large extent, and due to its role in climate mitigation as mires store a large amount of carbon. There has not been a national assessment of the ecosystem condition of mires in Norway, but the authors recent contributed on a report which presented several new indicators that can be used in future national assessments for this ecosystem (Nybø et al., 2023; see also Kolstad et al., 2023)). The current study builds on the work in that report.

We chose three municipalities in Norway to test out the indicators. The municipalities differ in several aspects, such as the amount of mire area, the total area surveyed, and the prevalence of infrastructure (Table 2, Figure 1, Figures S3, S4).

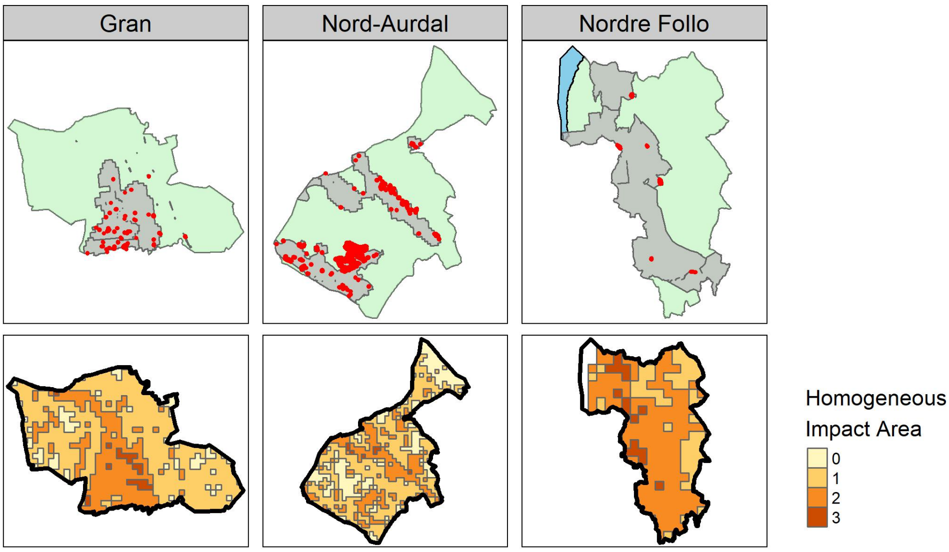

Figure 1: Map of the three focal municiaplities. For each municipality the maps in the top row shows ocean in blue and non-ocean in green. The survey coverage maps are in grey, and the mapped mires are in red, with polygon borderes made extra thich to make them visible, but then also exagerating their size. The bottom row shows the delineation for homogeneous impact areas which is an ordinal gradient from 0–3 with increasing presence of human instrastructure.

Table 1: Variables used in this study

id	Variable code	Variable name	Measurement unit	Description	Reference
1	7FK	Prevalence of alien species	Unitless, ordinal, non-linear scale from 1 (no alien species) to 7 (only alien species)	The fraction of the species composition made up from alien species	Halvorsen and Bratli (2019)
2	7SE	Human caused abration or abration-caused erosion	Unitless, ordinal, non-linear scale from 1 to 4.	Measures the frequency of imagined 4 m^2 quadrats layed over the area that has some sign of abration	Halvorsen and Bratli (2019)
3	PRSL	*as above*	Unitless, ordinal, non-linear scale from 0 to 7.	Same as 7SE, but recorded at a higher resolution	Miljødirektoratet (2022)
4	7TK	Tracks from large vehicles	Unitless, ordinal, non-linear scale from 1 to 4.	Measures the frequency of imagined 100 m^2 quadrats layed over the area that has some signs of vehicle tracks	Halvorsen and Bratli (2019)
5	PRTK	*as above*	Unitless, ordinal, non-linear scale from 0 to 7.	Same as 7TK, but recorded at a higher resolution	Miljødirektoratet (2022)
6	7GR-GI	Trenching intensity	Unitless, ordinal scale from 1 to 5	Describes the effect that drainage ditches is estimate to have on the species composition and environmental variables ones the system reached its new equilibrium	Miljødirektoratet (2022)
7	Infrastructure Index	Infrastructure Index	Unitless linear scale from 0 to 13.2	Unitelss index ranging from from 0 to 13.2	Erikstad et al. (2023)

8	HIA	Homogeneous Impact Area	Ordinal, non-linear scale from 1 to 4	A categorical representation of the infrastructure index	this paper

Table 2: Information for the three target municipalities in Norway

Municipality	Total terrestrial area (km^2)	% of terrestrial area surveyed	% open mires in relation to total terrestrial area	Total mire area (km^2)	%of mire area inside survey area	Number of mire polygons in survey	Mean Infrastructure Index value
Nordre Follo	203	40	0.3	0.6	18.6	6	1.8
Gran	756	21	2.7	20.2	0.5	56	1.2
Nord-Aurdal	906	26	11.1	100.7	18.1	236	1

Because the nature type survey data is spatially biased, we cannot assume that they are area representative. In an attempt to overcome this issue we divided the area of Norway into four non-overlapping Homogeneous Impact Areas (HIAs) based on an infrastructure index for the year 2022 Table 1. This index is a continuous variable that represnets the frequency of different infrastructure types inside 500 m radius circles around each 100×100 m pixel. We then categorised this continuous variable into four classes (0–3) using the following value ranges: 0 = <1; 1 1 > 6; 6 2 >12; 3 12. The name HIAs is not a perfect representation of the information found in the infrastructure index, but we introduce this name here as a general term which is aligned with the concept of Homogeneous Ecosystem Areas, *sensu* Vallecillo et al. (2022). We plotted the HIA map over an area in Norway that we are familiar with and confirmed a sensible separation of areas from areas with no roads of major infrastructure (HIA = 0) to urban areas (HIA = 3). We then aggregated the data to 1×1 km pixels to ease computations, and vectorized it.

We then took the nature type polygons with the indicator values and intersected with the HIA map and a map of municipal outlines in Norway. The relationship between the HIA classes and indicator values was examined visually. For each HIA and municipality combination we then created a probability distribution for the area weighted mean indicator values using Bayesian updating of a uniform prior between 0 and 1, informed by the standard deviation (SD) of the indicator values in the national data set [Figure 2 C; Appendix C, line XXX]. The resulting distributions are assumed normally distributed, and we therefore simply carried the mean and SD from the posterior distributions over to individual polygons in the ecosystem delineation map, for each HIA class separately, and for each polygon we then sampled random numbers from a normal distribution with this same mean and SD. The number of m^3 dictated the number of samples for each polygon, thus ensuring that large polygons end up counting more towards the indicator value in the entire municipality. We then drew 1000 random values from this much large vector of possible indicator values and created a probability distribution for the indicators for the entire municipalities (i.e. the ecosystem accounting areas). When there were no indicator values for a given HIA class, we ignored that class also in the municipal estimate.

3. Results

The three indicators showed some association with the HIAs when we lookad at data from all of Norway with 9026 individual mires. The indicators mostly showed a worsening of condition with increasing presence of human infrastructure (Figure 3). This relationship was much stringer for the indicator Trenching, and weakest for the indicator Alien species. Alien species also had the highest indicator values overall, with most mirer having no alien species recorded. For Trenching, 57% of mires in HIA-3 had some trenches, whereas in HIA-0 this number was 10%. However, only in Gran municipality was there a significant difference in the Trenching indicator between HIAs, with HIA-2 having worse condition than HIA-1 (Figure 4). Conversely, the ADSV indicator in Gran showed worse condition in HIA-1 compared to HIA-2. Nordre-Follo had considerably fewer data points compared to Gran, and especially to Nord-Aurdal who had the most data points, and this paucity of data is reflected in the wide credible intervals for all three indicators in Nordre Follo. The credible intervals are widest for the Trenching indicators, and this is because the national data set showed more variation in the underlying variable 7GR-GI, and this information is informing the Bayesian updating process (see Section 2). None of the three municipalities had data for all four HIAs. Therefore, when we transferred the mean and SD for each HIA over to the ecosystem delineation map (Figure 5), some mire polygons did not get assigned any data, and were therefore dropped from any further analyses. At the municipality level (i.e. the ecosystem accounting area level) the three municipalities show some differentiation. Nordre-Follo had the highest (the best) indicator values for ADSV, but the lowest for Trenching, which was also the only instance of an indicator crossing the threshold from good to deteriorated condition (Figure 6; Table S1).

4. Discussion

5. Conclusion

CRediT authorship contribution statement

Anders L. Kolstad: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation, Writing - Original Draft, Visualization, Project administration, Funding acquisition. **Matthew Grainger**: ... **Marianne Evju**: ...

Declaration of Competing Interest

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Kwaku Peprah Adjei Hanno Sandvik

Data availability

This manuscript is written in Quarto, and the source file (Appendix B) also contains code for all the analyses underlying this study, including data exploration and cleaning. For a rendered version of the source file, with all code and calculation visible, see Appendix C. The source files and the data are also located on GitHub (https://github.com/anders-kolstad/HIAs). The exception is the large nature type survey data which was downloaded locally, but which is freely available (see Norwegian Environmental Agency (2024)).

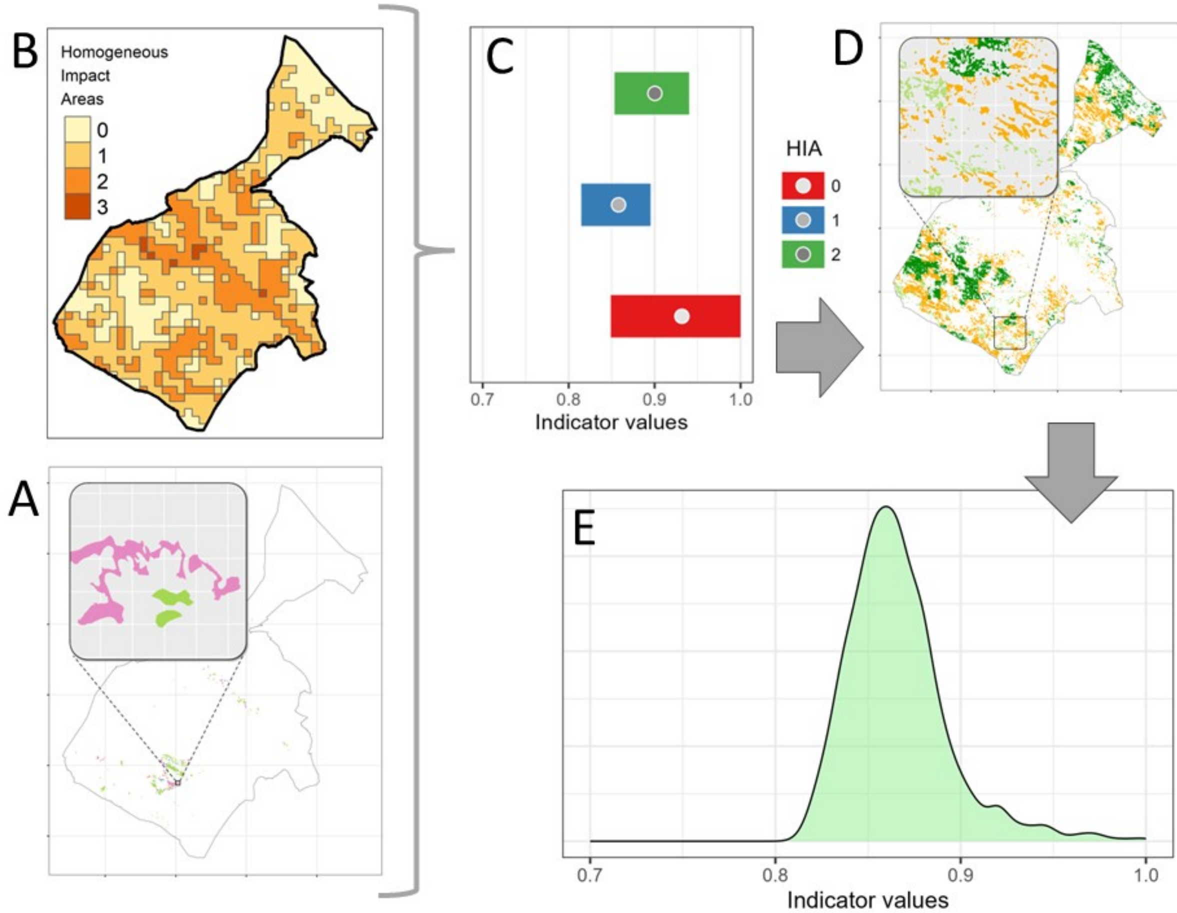

Figure 2: Simplified schematic showing the workflow (Figures A-E) for horizontal aggregation of a spatially biased ecosystem condition indicator. Figure A shows a spatially explicit indicator. The colors indicator different indicator values (highlighted in the inset). The outline is the ecosystem accounting area (EEA). Figure B shows the location of four homogeneous impact areas (HIAs) inside the EEA. The indicator values in Figure A are used, in combination with the HIA map in Figure B, to update a uniform prior and produce a posterior probability distribution for the mean indicator value for each HIA (Figure C; here simplified to only show the mean (circles) and 95% credible intervals (colored bands)). The bayesian updating is informed by the standard deviation for the indicator in a much bigger national data set. Unlike an arithmetic approach, the width of the posterior distribution responds both to variation in the data and to the sample size, giving a religable measure for the uncertainty around the indicator even with a singe observation. The distributions in Figure C are assumed normally distributed. Note that because in this example there were no indicator data for HIA-3, indicator values are only aggregated for HIAs 0–2. In Figure D the mean and SD from the posterior distributions are transferred to individual polygons in an ecosystem delineation map, for each HIA seperately. For each ecosystem occurence (i.e. ecosystem assets) in Figure D, we draw one random value for each square meter of area from a normal distribution with the mean and SD that is associated with that polygon. In Figure E we randomly sample 1000 values from the entire vector of samples in the previous step, and we get an area weighted probability distribution for the mean indicator value for the EEA.

Figure 3: Proportion of localities with different indicator values for three ecosystem condition indicators along a gradient of infrastructure densities.

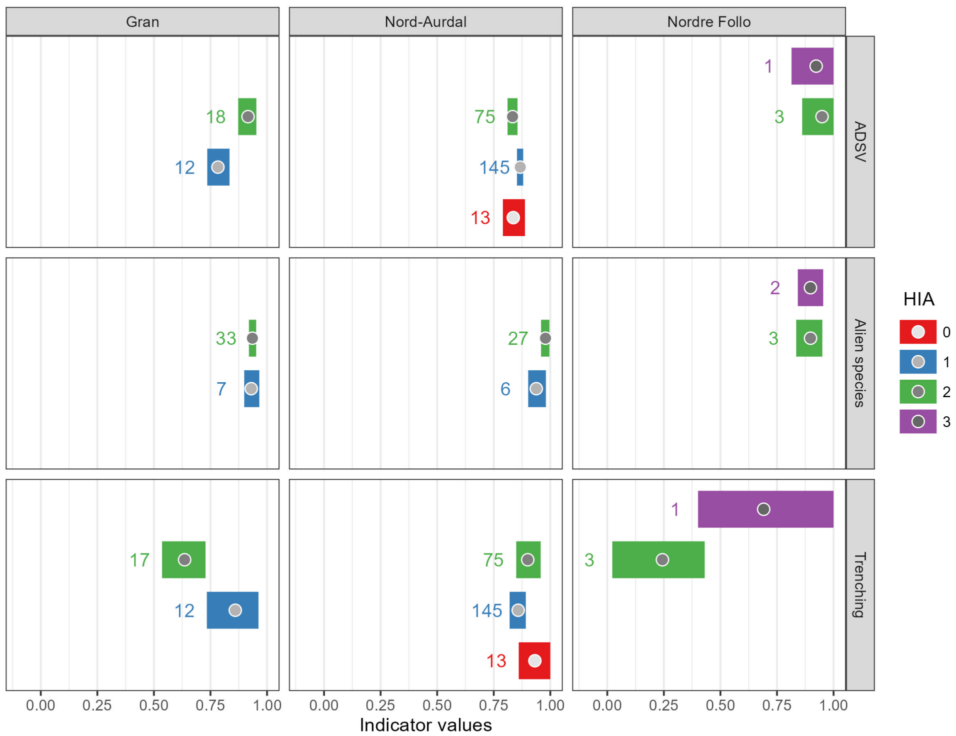

Figure 4: Indicator values (circles = mean; bars = 95% credible intervals) for three mire ecosystem condition indicators in three Norwegian municipalities. The indicator values are calculated uniquely for each Homogeneous Impact Area (HIA) in each municipality. The numbers to the left of each bar is the sample size, i.e. the number of surveyed mires.

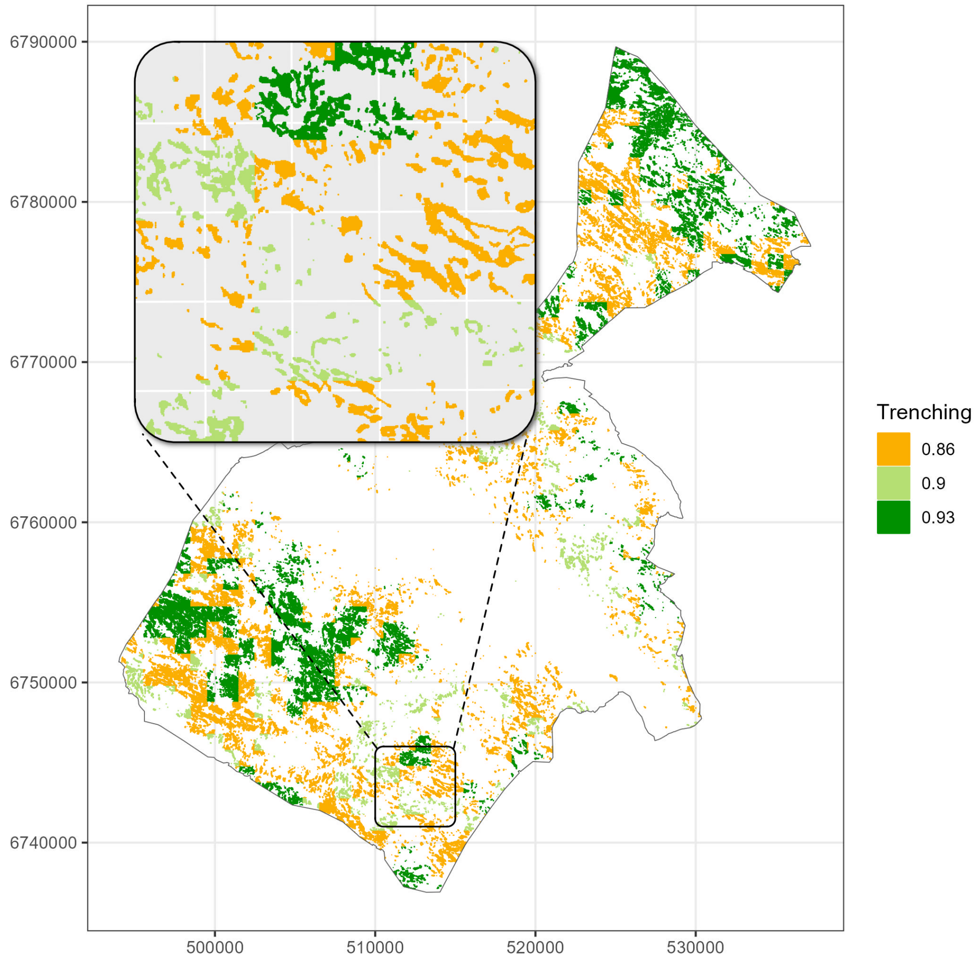

Figure 5: An indicator for mire trenching shown for Nord-Aurdal municipality. Individual mire polygons are colored by the mean indicator values for the homogenous impact area where it lies. Colors are chosen to best reflect categorical differences and exagerates the absolute difference between areas. The inset it just a visual aid. Coordinate reference system is EPSG 25832. Axis are in meters.

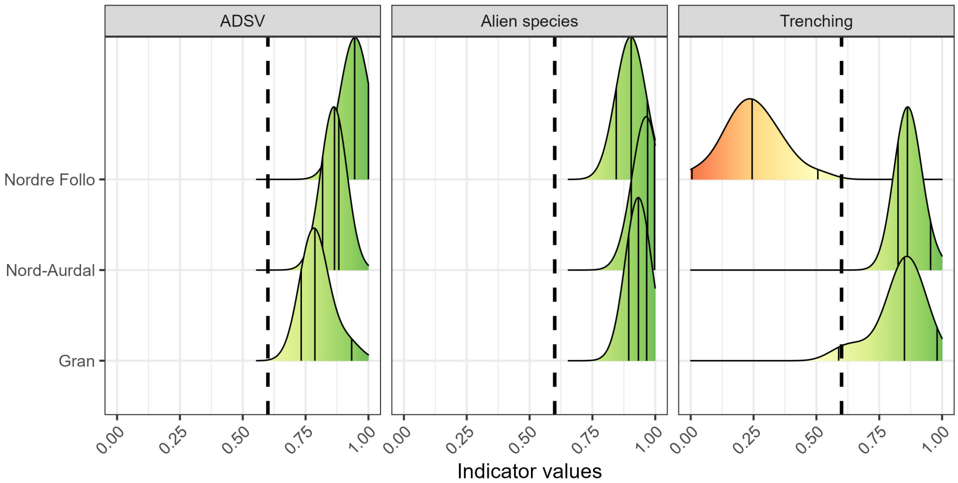

Figure 6: Distributions for three ecosystem condition indicators in the Norwegian municiaplities. The color gradient reflects the value of the x-axis. The dotted vertical line represnet the threshold for what is considered reduced ecosystem condtion (< 0.6). Vertical lines under the density curves are 2.5%, 50% (the median) and 97.5% percentiles.

References

Agency, N.E., . Mapping manual – Mapping of terrestrial Ecosystem Types following NiN2. Technical Report M-2209. Norwegian Environmental Agency.

AsbjørnMoen, 1998. Vegetation. National Atlas for Norway, Statens Kartverk, Hønefoss.

Bakkestuen, V., Venter, Z., Ganerød, A.J., Framstad, E., 2023. Delineation of Wetland Areas in South Norway from Sentinel-2 Imagery and LiDAR Using TensorFlow, U-Net, and Google Earth Engine. Remote Sensing 15, 1203. URL: https://www.mdpi.com/2072-4292/15/5/1203, doi:10.3390/rs15051203. number: 5 Publisher: Multidisciplinary Digital Publishing Institute.

Czúcz, B., Keith, H., Driver, A., Jackson, B., Nicholson, E., Maes, J., 2021a. A common typology for ecosystem characteristics and ecosystem condition variables. One Ecosystem 6, 1–16. doi:10.3897/oneeco.6.e58218. publisher: Pensoft Publishers.

Czúcz, B., Keith, H., Maes, J., Driver, A., Jackson, B., Nicholson, E., Kiss, M., Obst, C., 2021b. 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.

Erikstad, L., Simensen, T., Bakkestuen, V., Halvorsen, R., 2023. Index Measuring Land Use Intensity—A Gradient-Based Approach. Geomatics 3, 188–204. URL: https://www.mdpi.com/2673-7418/3/1/10, doi:10.3390/geomatics3010010. number: 1 Publisher: Multidisciplinary Digital Publishing Institute.

Halvorsen, R., Bratli, H., 2019. Dokumentasjon av NiN versjon 2.2 tilrettelagt for praktisk naturkartlegging: utvalgte variabler fra beskrivelsessystemet. – Natur i Norge, Artikkel 11 (versjon 2.2.0). Technical Report. Trondheim.

Kolstad, A.L., Grainger, M., Sandvik, H., Venter, Z., Speed, J.D., Nater, C., Evju, M., Åstrøm, J., 2023. Indicators for ecosystem condition in norway. URL: https://ninanor.github.io/ecosystemCondition/index.html.

Miljødirektoratet, 2022. Naturtyper - miljødirektoratets instruks.

Norwegian Environmental Agency, 2024. Naturtyper etter Miljødirektoratets Instruks. URL: https://kartkatalog.miljodirektoratet.no/Dataset/Details/2031.

Nybø, S., Kolstad, A.L., Sandvik, H., Bakkestuen, V., Evju, M., Framstad, E., Grainger, M., Jepsen, J.U., Nater, C.R., Speed, J.D., Töpper, J.P., Venter, Z., Åström, J., Åström, S.C., Bargmann, T.B., Silvennoinen, H.M., Sydenham, M.A., 2023. Indikatorer for økologisk tilstand i våtmark, semi-naturlig mark og naturlig åpne områder under skoggrensa. Technical Report. Norwegian Institute for Nature Research. URL: https://brage.nina.no/nina-xmlui/handle/11250/3096724.

United Nations, 2021. System of Environmental-Economic Accounting-Ecosystem Accounting White cover (pre-edited) version. 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.