What information is needed for upscaling grassland ecosystem services to landscape scale?

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Abstract

Field measurements of ecosystem services (ES) are laborious and costly, so ES cannot be measured at larger spatial scales. Therefore, ES are upscaled from local measurements to a whole region, based on a restricted number of field-scale measurements combined with environmental and management predictors available for the whole region of interest. The data available to estimate ES are decisive for the quality of the resulting ES maps and the robustness of the conclusions that can be drawn. We present two ES measured in 92 grasslands and determine how well these can be upscaled using different data sources. We developed stepwise models using (i) field-scale agricultural census data, (ii) topographic characteristics, (iii) soil maps, (iv) soil measurement data, (v) detailed management data, and (vi) plant community information. Resulting models reveal forage protein content to be already well predicted by agricultural census data, but for soil carbon stocks considerably more information was needed for a reliable prediction. The explained variance (R^2) of the final models ranges from 0.61 to 0.74, showing a good fit but also considerable uncertainty associated with ES maps, despite the vast data used for the final predictions.

Keywords: ecosystem services, management, protein content, soil carbon stocks, upscaling

Introduction

Ecosystem services (ES) are in the focus of many agricultural policies and, potentially in the future, also part of result-based agri-environmental payments. Field measurements of multiple ES are laborious and costly (Richter *et al.*, 2021), and thus not realistic at larger spatial scales. Therefore, upscaling of ES, from local to regional, based on a restricted number of measurements used to estimate the ES of entire farms or landscapes, is used to produce ES maps, based on readily available environmental and management data (Felix *et al.*, 2022; Le Clec'h *et al.*, 2019). The upscaling process and the data used to estimate ES are decisive for the quality of the resulting maps, determining the reliability of the conclusions drawn from this information. Thus, it is important to know what data is needed to achieve a model that is sufficiently precise for upscaling ES. At present, little is known about data needs and model quality during upscaling, especially when considering the many different ES that are important to meet societal demands.

Materials and methods

We studied 92 permanent grasslands in the Canton of Solothurn, Switzerland, which were (i) either unfertilised or fertilised and (ii) either used as meadow (mostly mown) or pasture (mostly grazed). In fertilised grasslands, the total available nitrogen in annual fertiliser applications per year was on average 85 (SE = 54) kg ha^{-1}, going up to a maximum of 203 kg ha^{-1}. This shows the considerable variability in management intensity in the fertilised grasslands included in the study. On these 92 plots, we measured two highly relevant ES using well-established indicators (Richter *et al.*, 2021). The first indicator was the raw protein content in aboveground plant biomass close to the first harvest date (dry matter). Protein content, a proxy for forage quality, is an important indicator for the provisioning ES obtained by grasslands. Grazing cages ensured biomass was available for sampling, even if livestock were grazing early in the season. Unfertilised meadows had a delayed date for the first cut (June 15th in the lowlands), as all unfertilised grasslands belong to Swiss agri-environmental schemes (biodiversity promotion areas). Yet, this restriction did not apply for extensive pastures. The second indicator was a regulating ES, i.e., the soil organic carbon (SOC) stock, measured in the top 20 cm of the soil and corrected for inorganic carbon. Based on this survey data and further environmental and management information, which was partly measured in the field and partly taken from public sources, we ran stepwise linear regressions in R. The stepwise models were based on (i) agricultural census data at the field scale (i.e., management categories), (ii) topography (from digital elevation model), (iii) soil maps with four classes for agricultural suitability at the field scale (GIS maps), (iv) soil measurement data (field survey, 0–20 cm), (v) management details (based on farmers interviews), and (vi) plant community information (field survey, cover sum of plant functional groups; Tables 1 and 2). The order of the data sources stepwise entering the models was set according to their availability, from readily available data to laborious surveys. Alternative orders were not tested. All models were additionally optimised using AICc (step function in R). Predictors entering the models were allowed to correlate no more than r=0.45 (Spearman correlation). See Table 1 for further details on the predictors used.

Results and discussion

We give detailed results for the stepwise models for SOC stocks (Table 1), while for protein content we only provide model quality for each step (Table 2). We found a significant increase in explained variance (R^2) and a decrease in AICc when including more data in the predictions. This was much less pronounced for protein content, which was already reasonably well predicted by the (interacting) management categories derived from census data. For SOC stocks, in contrast, the initial model performed poorly, highlighting the data demand to precisely predict this ES for upscaling. For the SOC stock, we found a sharp increase in model quality when particularly relevant data was included, i.e., soil measurement data. From the different data sources used, not only the management categories appeared to be important in most cases, but also topography was frequently included in final models. On the other hand, details on grassland management, i.e., fertilizer application levels (more detailed than the categorisation *unfertilized* vs. *fertilized* as given by the management categories based on the census data) and grazing intensities, were of surprisingly little relevance. Potentially, management categories already explained most of the variability related to management. Thus, although nitrogen applications varied widely among fertilised grasslands, the presence of fertilisation appears to be more important for the two ES than exact fertilisation rates.

Note that model 5 was the same as model 4, as additional data did not improve model performance and was thus excluded. Positive and negative estimates (and t-values) abbreviated by ↑ and ↓, respectively. Significance coded as: ***p<0.001, **p<0.01, *p<0.05, (.) p<0.1, n.s.=not significant; / indicates predictors *a priori* not included in the respective model; "-" indicates predictors excluded based on the step function using AICc.

Conclusion

We find models to require different data sources to upscale ES data depending on the specific ES considered. Especially for SOC stocks, more than one data source was needed to achieve a model R^2>0.6, which still leads to considerable errors if such models are used for upscaling. In line with previous research (Le Clec'h *et al.*, 2019), we show the vast data demand inherent to the upscaling of ES, especially if multiple ES are considered and robust results are to be obtained. Future research should seek ways to gather additional ES predictor data at low costs, such as via remote sensing (Muro *et al.*, 2022; Weber *et al.*, 2023), to further improve the quality of ES maps used for future agri-environmental decision-making.

Table 1. Results of linear regressions predicting soil organic carbon stocks, stepwise including more data from model 1 (only i) to model 6 (i to vi).

		Model quality					
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Adj. R^2, model p		0.13 **	0.36 ***	0.38 ***	0.60 ***	0.60 ***	0.61 ***
AICc		−593	−620	−622	−660	−660	−662
		Effect/*p*	Effect/*p*	Effect/*p*	Effect/*p*	Effect/*p*	Effect/*p*
Predictor							
(i) Census data	Pasture (vs. meadow)	↑ n.s.	–	–	–	–	–
	Unfertilized (vs. fertilization allowed)	↓ ***	↓ ***	↓ ***	↓ ***	↓ ***	↓ ***
	Interaction of both previous categories	*	–	–	–	–	–
(ii) Topography	Elevation (m a.s.l.)	/	↑ **	↑ **	↑ ***	↑ ***	↑ ***
	Slope (degree)	/	↑ ***	↑ ***	↑ (.)	↑ (.)	↑ (.)
(iii) Soil maps	Soil permeability	/	/	↑ (.)	–	–	–
	Degree waterlogging	/	/	-	-	-	-
(iv) Soil measurements	Soil pH	/	/	/	↑ ***	↑ ***	↑ ***
	Clay content	/	/	/	↑ ***	↑ ***	↑ ***
(v) Management details	Fertilizer application (available N ha^{-1} $year^{-1}$)	/	/	/	/	–	–
	Livestock-unit-grazing days (ha^{-1} $year^{-1}$)	/	/	/	/	–	–
(vi) Plant community information	Non-leguminous herbs (cover)	/	/	/	/	/	↑ (.)
	Legumes (cover)	/	/	/	/	/	–

Note that model 5 was the same as model 4, as additional data did not improve model performance and was thus excluded. Positive and negative estimates (and *t*-values) abbreviated by ↑ and ↓, respectively. Significance coded as: ***p<0.001, **p<0.01, *p<0.05, (.) p<0.1, n.s.=not significant; / indicates predictors *a priori* not included in the respective model; "-" indicates predictors excluded based on the step function using AICc.

Table 2. Results and quality measures of stepwise linear regression models predicting raw protein content in the first harvest using the same model predictors shown in Table 1.

	Model quality					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Adj. R^2, model p	0.68, ***	0.71, ***	0.72, ***	0.73, ***	0.74, ***	Same model as 5
AICc	-22	-29	-28	-31	-35	

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References

Felix L., Houet T. and Verburg P.H. (2022) Mapping biodiversity and ecosystem service trade-offs and synergies of agricultural change trajectories in Europe. *Environmental Science & Policy* 136, 387–399.

Le Clec'h S., Finger R., Buchmann N., Gosal A.S., Hörtnagl L., Huguenin-Elie O. … and Huber R. (2019) Assessment of spatial variability of multiple ecosystem services in grasslands of different intensities. *Journal of Environmental Management* 251, 109372.

Muro J., Linstädter A., Magdon P., Wöllauer S., Männer F.A., Schwarz L.M. … and Dubovyk, O. (2022) Predicting plant biomass and species richness in temperate grasslands across regions, time, and land management with remote sensing and deep learning. *Remote Sensing of Environment* 282, 113262.

Richter F., Jan P., El Benni N., Lüscher A., Buchmann N. and Klaus V.H. (2021) A guide to assess and value ecosystem services of grasslands. *Ecosystem Services* 52, 101376.

Weber D., Schwieder M., Ritter L., Koch T., Psomas A., Huber N. … and Boch S. (2023) Grassland-use intensity maps for Switzerland based on satellite time series: Challenges and opportunities for ecological applications. *Remote Sensing in Ecology and Conservation*, in press, available online at https://doi.org/10.1002/rse2.372