Modelling ground lichen distribution as a proxy for the ecosystem service of reindeer meat provision –

An example from the project “National monitoring for assessing and valuating ecosystem services in Fennoscandian alpine and boreal landscapes

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Within the project “National monitoring for assessing and valuating ecosystem services in Fennoscandia alpine and boreal landscapes”, data provided by the National Inventory of Landscapes in Sweden (NILS) are used to describe the quantity, quality and spatial distribution of Ecosystem Services (ESS) in the northern part of the country. We combine survey data with remote sensing data to produce maps of single ESS as an input variable for a decision support tool. Mat-forming ground lichens are the most important source of food for reindeers throughout the winter in forested areas of northern Sweden and an essential limiting factor for the population size. Therefore the occurrence and distribution of ground lichens can be seen as a proxy for the potential production of reindeer meat within a region.

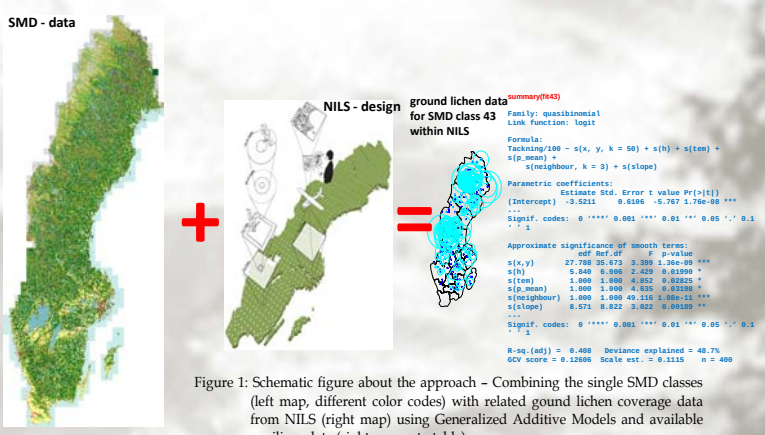

Figure 1: Schematic figure about the approach – Combining the single SMD classes (left map, different color codes) with related gound lichen coverage data from NILS (right map) using Generalized Additive Models and available auxiliary data (right summaty table).

Methods

The Swedish Landcover data (Svenska Marktäckedata, SMD) has 55 classes of land cover, encompassing different types of forest, other land use types and mountain vegetation. The SMD map was created from a combination of remote sensing and National Forest Inventory (NFI) data (Reese et al 2003). The SMD data are available for all of Sweden with a pixel resolution of 30m x 30m. Data about ground lichen coverage collected by NILS (7570 sample units) were matched with the SMD classes; within each of the classes the distribution of ground lichens were modeled using Generalized Additive Models (GAM) in combination with relevant auxiliary data such as elevation, mean temperature, mean rain fall, biomass, forest age, slope and aspect (Figure 1). To include potential spatial dependencies, a variable called ‘neighbour’ was additionally introduced. This variable is based on the number of surrounding SMD pixels that have the same SMD class as the pixel of interest. For the modeling process the package mgcv (Wood 2011) within the open source platform R (R Core Team 2014) was used. The method Best Subset Selection (e.g. Hastie et al. 2009) was applied for model selection.

Figure 2: Example of field validation – Predicted values were controlled and documented by photos in the field

Results

It was possible to provide adequate models (adjusted r^2 between 0.5 and 0.89) for 20 SMD classes which covered most parts of the forested and mountain areas of northern Sweden. Several of the remaining SMD classes were not of interest within this study as they occur only in the south or were related to different agricultural areas or e.g. water bodies. In general the resulting maps of ground lichen occurrence provide good match between areas with lichen occurrence and areas without lichen occurrence (Figure 2). Within these 20 classes two different types of problems occurred: the first was due to the fact that the data collected by NILS did not represent the whole gradient of ground lichen cover (high abundances were rarely found) and therefore the models underestimated the real occurrence of ground lichens (Figure 3). The second problem occurred because the sample intensity of NILS within the boreal region of Sweden is lower than in the continental or in the mountain region. For example, the SMD class “Coniferous forest on open bedrock” can only be described by sample plots from the south, even though this class occurs in the northern parts of Sweden as well. The results of the prediction for this class in the north have to be interpreted therefore with caution.

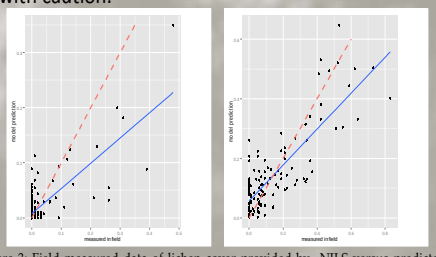

Figure 3: Field measured data of lichen cover provided by NILS versus predicted values. Predicted values are more or less underestimating the true measurements. Left panel: SMD class 46 “Coniferous forest on mires”, right panel: SMD class 47 “Coniferous forest on open bedrock”. Red line = first bisecting line, blue line = estimated trend.

Discussion

In general, using remote sensing data for pre-classification of the landscape to build landscape specific models of ground lichen cover seems to be a good way to reduce variance introduced by unknown landscape variables. The relative proportion between lichen occurrence and non-occurrence was successfully modeled (Figure 2). The problem of missing data of ground lichen cover with high abundance within NILS data cannot be easily solved. It is linked to the fact that sampling intensity of NILS (as the NFI) is able to describe common phenomena with good quality, but sparse and rare phenomena are underrepresented. In terms of modeling, such underestimation can only be avoided by including extra data that were not collected by standard landscape surveys. Including samples from the NFI that are only randomly visited in field (i.e., temporary plots) will not solve this problem; nevertheless they can give important information about the natural variance within ground lichen cover. As the SMD were established in 2009 these data are not up to date and might not match all current landscape patterns adequate today. The use of current satellite pictures is therefore required for the future work of this project

Literatur:
Reese H, Nilsson M, Granqvist Pahlén T, Hagner O, Joyce S, Tingelöf U,Egberth M, and Olsson H, (2003) Countrywide estimates of forest variablesusing satellite data and field data from the National Forest Inventory. Ambio,32(8):542-548
R Core Team (2014). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.
Wood SN (2011) Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. Journal of the Royal Statistical Society (B) 73(1):3-36
Hastie T, Tibshirani R, Friedman J (2009) The Elements of Statistical Learning, Second Edition, Springer, New York, 745 pp.