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SPATIAL DISTRIBUTION OF GHG SINKS AND SOURCES IN FORESTRY-DRAINED BOREAL PEATLANDS

Mari Parkkari*, Miia Parviainen, Paavo Ojanen and Anne Tolvanen

Natural Resources Institute Finland (Luke), Finland

**Corresponding author: mari.keranen@luke.fi*

SUMMARY

Boreal peatlands contribute significantly to the global carbon store and have a major role in global greenhouse gas (GHG) balances. The peatland drainage for forestry purposes has an effect on CO_2, CH_4 and N_2O fluxes and thereby on GHG balances. In Finland, there is a remarkable area of drained peatlands, which indicates that decisions made for future peatland uses have effects on GHG emissions at a larger than national scale. Identification of reliable measures of GHG balances is needed to estimate whether suitable conditions for GHG sinks may be generated through peatland management. As extensive GHG data is expensive to acquire, alternative methods to obtain data from larger areas are needed. Statistically-based spatial models provide a cost-efficient approach for mapping and analysing GHG balances. The aim of this study is to explore the possibility of modelling and mapping the GHG balances of CO_2, CH_4 and N_2O in forestry-drained boreal peatlands using different environmental datasets, Geographic Information Systems (GIS) and spatial modelling method Maxent. With the aid of spatial methods it is possible to produce prediction maps showing the locations of GHG sinks and sources and identify the environmental factors controlling the GHG balance. The visual presentations are important not only for researchers but also for land use management and political decision making, since they help to implement climate-friendly land use options in critical geographical locations.

***Keywords**: peatlands, drainage, greenhouse gas, spatial modelling, GIS*

INTRODUCTION

Peat soils have a notable effect on greenhouse gas (GHG) balance (Frolking *et al*., 2006; Gorham, 1991). In Finland, more than half of the 9 million ha of originally pristine mires have been drained for forestry (Finnish Forest Research Institute, 2009), which has led to changes in the greenhouse gas balance (Maljanen *et al*., 2010; Minkkinen *et al*., 1999; Nykänen *et al*., 1998). The changes, however, are diverse and the balance is affected by various environmental factors. Some sites are sinks of GHGs after the drainage whereas some are sources (Lohila *et al*., 2011; Maljanen *et al*., 2010; Ojanen *et al*., 2010). It is a challenge to identify the suitable locations for GHG sinks, but the identification is nevertheless important for climate friendly peatland management (Mander *et al*., 2010).

The spatial distribution of GHG fluxes in various ecosystems has been presented in previous studies (e.g. Ernfors *et al*., 2008; Huang *et al*., 2013; Leppelt *et al*., 2014; Mander *et al*., 2010; Petrescu *et al*., 2010; Xiao *et al*., 2008; Zhu *et al*., 2013). Both Petrescu *et al*. (2010) and Zhu *et al*. (2013) presented the distribution of CH_4 fluxes from northern wetlands with the spatial resolution of 0.5 °. Petrescu *et al.* (2010) used process-based models to estimate the CH_4 emissions, whereas Zhu *et al*. (2013) created a statistical model to extrapolate flux measurements for their study area.

Ernfors *et al*. (2008) presented the distribution of N_2O emissions from drained organic forest soils in Sweden based on soil CN ratio. Brocks *et al*. (2014) estimated N_2O emissions from agricultural soils in Germany, by combining flux measurements with spatially explicit data on land use, climate and soil properties. Mander *et al*. (2010) estimated the distribution of CH_4 and N_2O emissions from rural lands in Estonia based on land use. Leppelt *et al*. (2014) used statistical models to estimate the N_2O fluxes from European organic soils and to identify the important drivers within different land use types, presenting the distribution with 1 km^2 grids.

The distribution of fluxes has also been estimated using remote sensing based variables (e.g. Huang *et al*., 2013; Jägermeyer *et al*., 2014; Xiao *et al*., 2008). For example, Huang *et al*. (2013) studied the distribution of soil respiration in Tibetan alpine grasslands with a resolution of 25 ha. They used remote sensing based vegetation indices as explanatory variables in the model. Xiao *et al.* (2008) estimated the net ecosystem exchange of different ecosystems in USA with the spatial resolution of 1 km^2. They used remote sensing variables as explanatory variables to upscale from the tower measurements to continental level.

The need for a reliable extrapolation method has been expressed in several studies (e.g. Klemedtsson *et al*., 2005; Mander *et al*., 2010; Ojanen *et al*., 2010). The spatial models that cover a spatial distribution of an ecological phenomenon (Jørgensen, 2008) have proved valuable for generating, for example, biogeographical information that can be applied across a broad range of fields and scales (e.g. Austin & van Niel, 2011; Elith & Leathwick, 2009; Guisan and Zimmermann, 2000; Zimmermann *et al.,* 2010). Spatial modelling has been utilized mostly in species distribution studies (e.g. Arundel, 2005; Parviainen *et al*., 2008; Thuiller *et al*., 2008; Williams *et al*., 2009) and for example Maxent modelling has been designed particularly for species distribution modelling (Phillips *et al.,* 2006). The same modelling method could be used to identify the controlling environmental conditions and the locations of sinks and sources of GHGs.

The aim of this study is to explore the possibility of modelling and mapping the GHG balances (CO_2, CH_4 and N_2O) of forestry-drained boreal peatland soils using environmental information and Maxent modelling technique. We use Geographic Information Systems (GIS) and different available environmental datasets as sources of explanatory variables. In this paper, we present the study setting and some preliminary results.

METHODS

Study area

The study was performed in total of 809 363 grids of 25 ha situated in the zones of aapa mires and raised bogs in Finland, excluding the northernmost part of Finland because of the lack of measured GHG data. Advantages of the grid approach are the possibility to split the study areas objectively into comparable sampling units and the opportunity to utilize GIS and RS data as a source of explanatory variables. Most of the study area belongs to the boreal zone and only the southernmost part belongs to the hemi-boreal zone (Ahti *et al*., 1968). The mean annual temperature in Southern Finland is ca. +5 °C and in Northern Finland ca. −2 °C. Annual precipitation is between 400 and 750 mm (FMI).

GHG data

The GHG fluxes used in this study has been measured between May and October in 2007 and 2008 from 68 peatland sites drained for forestry in Finland (Figure 1). All sites were drained at least 20 years before the GHG measurements. The momentary fluxes of CH_4, N_2O and heterotrophic respiration were measured and based on the measurements, yearly balances of CH_4, N_2O and CO_2 were estimated (see Ojanen *et al.* 2010 for more details of CH_4 and N_2O and Ojanen *et al*. 2013 for CO_2). We used these balances for the modelling and created separate models for sinks and sources of each GHG both in aapa mire and in raised bog zones (excluding N_2O sink in raised bog zone). The data was treated as presence only in the creation of the model, but as presence/absence in the evaluation of the models.

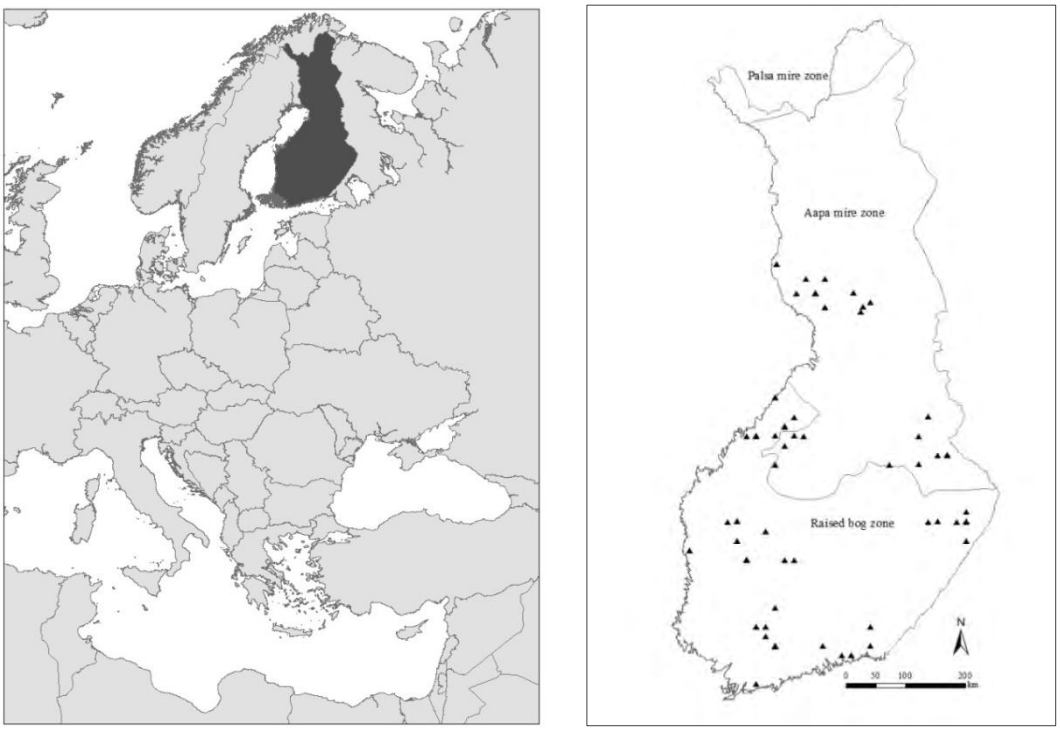

Figure 1: The location of GHG measurement sites (triangles) in Finland in northern Europe.

Environmental variables

The environmental variables used in this study were selected to represent important ecological gradients that may influence the GHG balances. In total, 13 environmental variables were calculated at 25 ha resolution: the mean summer temperature (Finnish Meteorological Institute FMI), water balance (FMI), land surface temperature (Landsat TM 5), wetness component derived from Tasseled Cap transformation (Landsat TM 5), soil adjusted vegetation index SAVI (Landsat TM 5), topographical wetness index (Digital Elevation Model), root biomass, mean diameter of trees and proportion of drained peatland types in the grid cells derived from Multi-source National Forest Inventory (MS-NFI) of Finland (Natural Resources Institute Finland Luke). Distinct sets of environmental predictors were used depending on the modelled GHG balance. The correlations between variables were tested to minimize the effect of multicollinearity in the multivariate study setting.

Modelling procedure

For the modelling, we used Maxent (Maximum Entropy), which applies the principle of maximum entropy to predict the potential distribution of phenomenon of interest from presence-only data and environmental variables (Phillips *et al*., 2006). High predicted environmental suitability indicates the locations where environmental conditions are similar to those, where modelled phenomenon is known to occur. Maxent uses generalising approach, rather than discriminating, so it can utilise training data with limited occurrence information (Phillips *et al.,* 2006). It has been observed to achieve better discrimination capability compared to other modelling techniques (e.g. Phillips *et al.,* 2006; Wisz *et al.,* 2008). We composed the models using linear, quadratic and hinge features and 4-fold cross validation with random seed.

The performances of the models were evaluated by calculating AUC (area under the curve of a receiver operating characteristic plot ROC) (Fielding & Bell, 1997) value and implementing visual interpretations of the predictions maps. AUC value indicates the discriminations ability of the models which refers to the ability to separate the potential locations of sinks and sources from each other. The discriminating ability was considered as low if AUC < 0.7, fair if 0.7 < AUC < 0.8, good if 0.8 < AUC 0.9 and excellent if AUC > 0.9 (Swets 1988). Finally, we calculated the AUC value with SPSS (IBM SPSS Statistics 22) for sinks using the locations of sources as absence data and for sources using the locations of sinks as absence data. We evaluated the models visually.

PRELIMINARY RESULTS

The AUC values ranged from 0.506 (CH_4 sink in raised bog zone) to 0.824 (CH_4 source in raised bog zone). The variables that contributed the most in the models varied between different models (Figure 2). The proportion of *Vaccinium vitis-idaea* (Ptkg) and Dwarf shrub drained peatland types (Vatkg) were the most important variables in three models.

For some gases, the predicted suitable locations are different for sinks and sources (for example CO_2 in aapa zone) but for some models predict suitable environmental conditions in same areas. Especially the suitable locations for CH_4 sinks and sources in raised bog zone overlapped greatly.

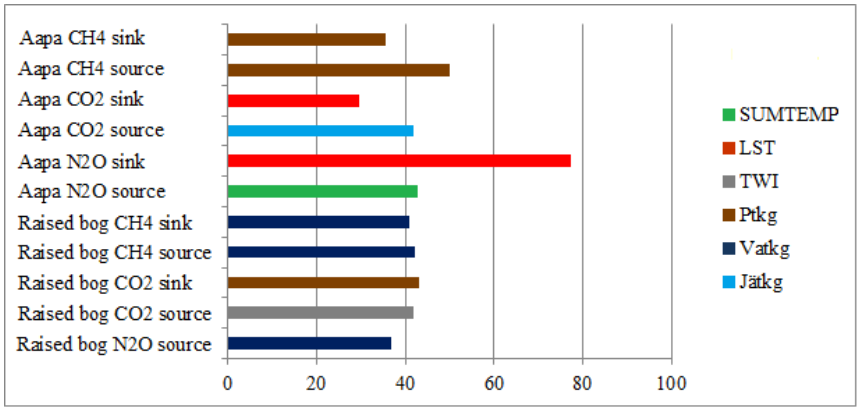

Figure 2: The relative contributions of the most important environmental variable in each model. SUMTEMP mean summer temperature, LST land surface temperature, WAB water balance, TWI topographic wetness index, Ptkg *Vaccinium vitis-idaea* type, Vatkg Dwarf shrub type and Jätkg *Cladina* type

DISCUSSION AND CONCLUSIONS

The performance of the models varied from low to good based on AUC values (Swets 1988). The model for source of CH_4 in raised bog zone achieved the best discrimination ability whereas the model for sink of CH_4 in the same zone had the weakest ability. The visual interpretation revealed that predicted sinks and sources

overlapped especially in the case of CH_4 in raised bog zone. This may be explained by rather coarse resolution of the study (25 ha); there can be both potential sinks and sources of a GHG in the same grid and thus it may cause uncertainty to the models. Also Huang *et al*. 2013 noticed the problem with heterogeneity in their study of 25 ha. However, because some of the environmental data have coarse spatial resolution, the use of smaller modelling scale would not bring extra information.

The variables describing the proportions of different drained peatland types contributed to the models because they are proxies of for example nutrient conditions of a grid and thereby affect also the vegetation, tree growth and GHG fluxes. The variables describing the small-scale conditions seemed to work better than variables of a large scale. However, we underline that these are preliminary results so the models need to be further calibrated and the results should be evaluated with more than AUC value and visual interpretation.

Spatial models combined with environmental data have been used to acquire distribution data of ecological phenomena and in this study we found out that they could be utilized also in studying the distribution of GHG balances. To our knowledge, Maxent has not been previously utilized in this kind of GHG study. Our study provides new insights to identify GHG sinks and sources in a landscape scale resolution. With the information of the GHG distribution, land use management can be used as a tool to maximize carbon sequestration and help to mitigate climate change.

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