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Research paper

Spatial modelling provides a novel tool for estimating the landscape level distribution of greenhouse gas balances

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ABSTRACT

A long-term challenge in managing the climate effects of land use is the development of an efficient, comprehensive approach to the identification of greenhouse gas (GHG) balances. The approach would help in establishing robust methods for the cost-effective and climate-friendly targeting of land use options, for example, in peatlands, which are globally important sinks and sources of GHGs. The aims of this study were to create spatial models with the maximum entropy method Maxent so as to 1) identify the environmental variables that control the distribution of GHG sinks and sources in forestry-drained peatlands in Finland and 2) predict the landscape-level distribution of GHG balances in two regional mire complex zones (the aapa mire and the raised bog zone). Several environmental datasets were used as sources of explanatory variables. Even though the significance of the explanatory variables were different between mire complex zones, the variables describing habitat conditions, such as drainage intensity and site fertility, contributed most to the models. Drainage intensity describes indirectly the moisture conditions and can thereby be used as a proxy for the water table. The results showed that relatively coarse-scale environmental data (25 ha grid cells) combined with spatial modelling have potential in explaining and predicting GHG balances at the landscape level. To our knowledge, this is the first time that spatial Maxent models have been used to model the distribution of GHG balances.

1. Introduction

The mitigation of climate change by reducing greenhouse gas (GHG) emissions has paramount importance in the context of current global change and for the agendas of the EU Climate and Energy Package 2020 (European Commission, 2016) and the Kyoto Protocol (United Nations, 2014). Northern peatlands contribute significantly to carbon storage and have therefore a major role in global GHG balance (Gorham, 1991). Their drainage is known to accelerate the decomposition of peat (Jaatinen et al., 2008) and thereby increase the emissions of carbon dioxide (CO_2) from the soil (Silvola et al., 1996). Drainage also improves the conditions for the production of nitrous oxide (N_2O) (Martikainen et al., 1993), whereas methane (CH_4) emissions diminish or even cease after peatland drainage (Abdalla et al., 2016; Maljanen et al., 2010).

Knowledge of the spatial distribution of GHG sinks and sources and of the environmental factors behind them is needed to optimize land use so that climate change can be mitigated effectively. The need to develop cost-efficient methods to extrapolate GHG balances from site measurements to larger scales has been expressed in several studies (e.g. Klemedtsson et al., 2005; Mander et al., 2010; Ojanen et al., 2010). However, spatial data on GHGs are still virtually missing and are too expensive to acquire in extensive areas by direct measurements.

The spatial distribution of GHG fluxes has been studied previously using either GIS data (Geographical Information Systems) (e.g. Brocks et al., 2014; Mander et al., 2010) or statistical models (e.g., Leppelt et al., 2014; Zhu et al., 2013). With GIS-based methods, the fluxes are first linked to specific classes of environmental conditions in the flux measurement location and then the extrapolation is done based on the area of each class. The relationship between the fluxes and environmental conditions affecting them may remain uncertain if there are only classes that reflect, for example, land use on a very general level. Statistical models are used to specify the relationship, but usually the models are built with environmental data measured at the site. These environmental data cannot be utilized when extrapolated to other areas, since comprehensive data on these fine-scale variables may not be available. The statistical models have been extrapolated using spatial data, but not all the necessary data, for example, water table data, are

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available for spatially extensive areas (Leppelt et al., 2014). Thus, there is a pressing need to clarify whether variables derived from spatially comprehensive environmental data sets, including several potential proxies for the water table, can be used to produce spatial predictions of GHG balances.

Statistics-based spatial models have proven valuable for generating biogeographical information that can be applied across a broad range of fields, including ecology, land use planning and climate change (e.g. Barbet-Massin et al., 2012; Bolliger et al., 2007; Thuiller et al., 2008). The models may effectively exploit the limited empirical data and dispense a useful basis for environmental assessments. Spatial modelling methods thus provide increasing possibilities to develop models for explaining and predicting the distribution of GHG balances for extensive areas with measured flux and available spatial environmental data.

In this paper, a grid-based approach and the maximum entropy method Maxent (Phillips et al., 2006) were utilized to model soil GHG sinks and sources at a landscape-scale resolution (25 ha) in boreal forestry-drained peatlands (peatlands drained by ditching for forestry) in Finland. With almost 5 million hectares of forestry-drained peatlands (Finnish Forest Research Institute, 2014) and extensive and easily available environmental data sets, Finland provides an excellent setting for studying the relationship between environmental conditions and GHG balances. Specifically, the aims were to 1) find the environmental variables that control the distribution of GHG sinks and sources and 2) predict the spatial distribution of GHG balances. The advantage of the modelling of balances instead of fluxes is that it provides a simple surrogate that estimates whether the target area is a sink or source. Land use planning in particular can benefit from this approach. To our knowledge, this is the first time that Maxent models have been used for modelling the distribution of GHG balances.

2. Material & methods

2.1. Study area

The study was carried out in Finland, at a location between 60° and 70° northern latitudes in Northern Europe (Fig. 1a). The study area covers almost the entire country, excluding the northernmost part (the palsa mire zone) due to the lack of forestry-drained peatlands there. The study area was divided into grid cells of 25 ha (500 m × 500 m) and the cells in which forestry-drained peatlands covered less than 2.5% were excluded from the study. Thus, the study area consists in total of 680 541 grid cells (170 000 km^2).

The study area was divided in two zones (the aapa mire zone: 53.3% of grid cells; the raised bog zone: 46.5% of grid cells) because of the different mire complexes prevailing in the zones (Fig. 1b). Mire complexes are large landscape units of peatlands with similar climatic conditions, hydrology, macro- and microtopography and peat stratigraphy (Ruuhijärvi, 1982). Raised bogs characterise southern Finland, whereas aapa mires are common in northern Finland (Seppä, 2002). The nutrient status of raised bogs usually varies within the bog due to the convex topography: the central area of the bog is nutrient poor whereas the edge receives nutrients from the surrounding mineral soils (Eurola et al., 1984). Aapa mires are wetter and concave in topography. The nutrient status varies relatively little within aapa mires, which are generally richer in nutrients than raised bogs (Ruuhijärvi, 1983).

The annual mean temperature in the study area declines from south (+5 °C) to north (−2 °C). Moreover, there is maritime impact on the climate in coastal areas, while the continental impact intensifies inland and eastward. The annual mean precipitation sum varies between 450 and 750 mm (Pirinen et al., 2012). 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 landscape is dominated by lakes, coniferous forests, and peatlands.

2.2. GHG data

GHG balances of 76 measurement sites were utilized in this study (Fig. 1b). Fluxes from 68 sites were measured between May and October in 2007 and 2008. The sites were chosen from the permanent sample plots of the 8th National Forest Inventory (Natural Resources Institute Finland, 2011) to include equally different site types of forestry-drained peatlands of those parts of Finland where forestry is economically viable. The momentary soil-atmosphere fluxes of CH_4, N_2O, and heterotrophic respiration were measured. Based on these measurements and litter production estimates, annual soil balances of CH_4, N_2O, and CO_2 were estimated (see Ojanen et al., 2010 for more details for CH_4 and N_2O and Ojanen et al., 2013 for CO_2).

Fluxes of CH_4 and N_2O were measured from eight drained sites between May and October in 2014 and 2015 (unpublished data). These sites cover the nutrient-poorest site types that were poorly represented in the previous data. The momentary fluxes of CH_4 and N_2O were measured similarly to Ojanen et al. (2010) with the exception that samples were taken from 6 measurement points (instead of 4) at 5, 10, 15 and 20 min (instead of 5, 15, 25 and 35) after inserting the chamber. Annual balances were calculated similarly to Ojanen et al. (2010).

The measurement sites were defined either as sinks or sources of each gas based on the calculated annual balances. The sites with a measured balance value of 0 were set as sinks. In the aapa mire zone, the numbers of measurement sites were 11 and 17 respectively for CH_4 sinks and sources, 15 and 9 for CO_2 sinks and sources, and 9 and 19 for N_2O sinks and sources. In the raised bog zone, the respective numbers were 34 and 14 (CH_4), 21 and 23 (CO_2), and 2 and 46 (N_2O) for sinks and sources. The size of each measurement site was around 100 m^2. All sites were drained at least 20 years before the GHG measurements, thus representing the well-established state of the forestry-drained peatlands in Finland.

2.3. Environmental data

The explanatory variables were selected to represent important environmental gradients of climate, topography and habitat features. The correlations between environmental variables were tested and only variables with low correlations (Spearman's rho < 0.7) were selected in order to minimize the potential effect of multicollinearity in the modelling. In total 13 environmental variables describing moisture, drainage intensity, temperature and volume of tree biomass (Table 1) were calculated for all 25 ha grid cells using ESRI ArcGIS software (version 10.3.1) and were then used in the modelling.

The mean temperature of the snow-free period from May to October (TEMP, °C) and mean water balance (WAB, mm) for the years 1981–2010 were calculated from data of the Finnish Meteorological Institute (Pirinen et al., 2012). WAB (Fig. 2a) describes the water available in the ecosystem considering both precipitation and evapotranspiration. It was calculated according to Skov and Svenning (2004) as the monthly difference between precipitation and potential evapotranspiration (PET, mm), summed over a year and then averaged for the period 1981–2010. PET was calculated as

$$PET = 58.92 \times T_{above0\ ^{\circ}C}$$

where $T_{above0\ ^{\circ}C}$ is the annual mean of monthly mean temperatures with negative values adjusted to zero (Holdridge, 1967; Lugo et al., 1999).

The topographic wetness index (TWI) describes the effect of topography on the moisture conditions. High values indicate wet conditions. TWI was derived from the digital elevation model (NLS, 2016). TWI was calculated using the formula by Burrough and McDonnell (1998)

$$TWI = \ln(\alpha/\tan\beta)$$

where α is the upslope contributing area per width, orthogonal to the flow direction, while tanβ is the local slope in radians.