

Mapping peatland heterogeneity: A key to assessing carbon balance and its radiative effect within a northern boreal landscape

Running Title: Boreal peatland heterogeneity and carbon balance

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Abstract

Boreal peatlands are highly heterogeneous and play a significant role in the global carbon (C) cycle. However, the effects of the peatland-dominated heterogeneity within the boreal landscape are rarely quantified. Here, we use field-based measurements, high-resolution land cover classification, and biogeochemical and atmospheric models to estimate the C budget and corresponding radiative effect (RE) for a boreal landscape (Kaamanen) that is rich in peatlands and aquatic ecosystems. The average present-day, landscape-scale CO₂ and CH₄ budgets were -108 ± 10 and 2.28 ± 0.19 g C m⁻² yr⁻¹, respectively. We find that peatland heterogeneity accounts for 88% of the variability in CH₄-C budget across the Kaamanen landscape despite only comprising 26% of the area. Moreover, peatland heterogeneity dominates the variability in RE that combines CO₂ and CH₄ exchanges within the landscape, accounting for 65% and 79% over the 100-yr and 25-yr time horizons, respectively. Future warming tends to enhance this heterogeneity. Aggregating peatland classification or mis-classifying peatlands can significantly alter the estimated magnitude and even the sign of the RE due to landscape-scale C exchanges. Scrutiny of global land cover products revealed significant shortcomings in their representation of boreal peatlands, calling for improved mapping of boreal peatland heterogeneity to reduce the uncertainty in C budgets and C-climate feedback.

Keywords: boreal, landscape, peatland, heterogeneity, carbon, radiative effect

1 Introduction

The boreal biome, consisting of forest, peatland, and lake ecosystems, occurs in continental interiors at 45.5-71.4°N and covers about 15.1 million km² or 10.3% of Earth's land surface area (Helbig et al., 2020; Olson et al., 2001). This vast and patterned area stores more carbon (C) than the atmosphere (~ 1000 GtC vs. 860 GtC), most of which resides in soils and peatlands (Bradshaw & Warkentin, 2015; Friedlingstein et al., 2020; Hugelius et al., 2020; Nichols & Peteet, 2019). Moreover, the boreal ecosystems are vulnerable to environmental changes (Åberg, Jansson, & Jonsson, 2010; Hopple et al., 2020; Loisel et al., 2021), and thus their functioning in the changing climate is vital to the global C budget (Comyn-Platt et al., 2018; Gauthier, Bernier, Kuuluvainen, Shvidenko, & Schepaschenko, 2015; Tagesson et al., 2020).

Landscape processes are important for the upscaling of C budget across a biome since Earth System Models (ESMs) or statistical models such as machine learning are generally performed based on grid cells that are composed of multiple land units (Lawrence et al., 2018). A typical boreal landscape shows a mosaic of diverse forests, peatlands, and water bodies with large differences in their abiotic and biotic characteristics (Chapin III, Matson, & Vitousek, 2011; Hugelius et al., 2020; Verpoorter, Kutser, Seekell, & Tranvik, 2014). Therefore, the exploration of C budget and its climate impact at the landscape scale by considering the mosaic structure is crucial for accurately estimating the C budget across the boreal biome and hence for better understanding global C-climate feedbacks.

85 Despite their significance, our understanding of the landscape-scale C dynamics,
86 including both carbon dioxide (CO₂) and methane (CH₄), in the circumpolar region
87 mainly derives from tundra (Sturtevant & Oechel, 2013; Treat et al., 2018; Weller et
88 al., 1995) and the transition zone between the tundra and boreal biomes (Christensen et
89 al., 2007; O'Shea et al., 2014; Tang et al., 2015). Within the boreal biome, most studies
90 have been aimed at the C dynamics of individual ecosystems (Clemmensen et al., 2013;
91 Guo et al., 2020; Johansson et al., 2006) or the entire boreal zone (Kicklighter, Melillo,
92 Monier, Sokolov, & Zhuang, 2019; Tagesson et al., 2020), with only a few landscape-
93 scale studies that consider both CO₂ and CH₄ exchange and forest, peatland, and aquatic
94 ecosystems at the same time. These studies have advanced our understanding for
95 example by showing the difference between short- and long-term C dynamics within a
96 catchment (Juutinen et al., 2013), the need for integrating terrestrial and aquatic fluxes
97 at the landscape scale (Aurela et al., 2015; Chi et al., 2020; Juutinen et al., 2013), and
98 the application of airborne measurements of CO₂ and CH₄ fluxes to regional upscaling
99 (O'Shea et al., 2014). In spite of these advances, there are major knowledge gaps. First,
100 a fine-resolution mapping of different land cover types (LCTs) within a peatland
101 complex, and thus the detailed quantification of heterogeneity in peatland C dynamics
102 relative to the landscape-scale heterogeneity, is lacking. Second, remote sensing-based
103 land cover classification is prone to classification errors. For example, peatlands
104 adjacent to or embedded in forests may become classified as forests (Thompson,
105 Simpson, & Beaudoin, 2016), and peatlands adjacent to lakes and flooded areas
106 classified as lakes (Matthews, Johnson, Genovese, Du, & Bastviken, 2020). Little is
107 known about how such LCT aggregation or misclassification affects the estimated
108 landscape-scale C budgets. Third, our knowledge of the potential trajectories of the
109 LCT-specific C budget heterogeneity under future warming conditions is limited. These

knowledge gaps undermine current C inventories, remote sensing-based upscaling products and procedures, and especially ESMs, in which the peatlands are considered as a single block entity, if at all (Loisel et al., 2021). This points to an urgent need to better understand what level of detail is needed to characterize the heterogeneous boreal landscapes and their response to warming.

To fill these research gaps, we conducted an in-depth study in a typical northern boreal landscape located in northern Finland. We performed a high-resolution land cover classification based on multi-source remote sensing and field data. We collected large amounts of LCT-specific data including ecosystem-atmosphere fluxes of CO₂ and CH₄, soil and vegetation properties, and meteorological and hydrological variables. With these data, we calibrated and validated terrestrial and aquatic biogeochemical models, and simulated daily greenhouse gas (GHG) fluxes under present and future conditions. In addition, we estimated the potential development of the radiative effect of these fluxes. With these analyses, we aim to quantify the heterogeneity in peatland C dynamics and their radiative effect relative to that in the landscape scale and demonstrate the importance of accurately mapping the small-scale variation in peatland types within a typical boreal landscape. To assess the need for improved peatland mapping within the boreal zone, we surveyed how accurately the peatlands within the study area are depicted in current global, continental, and national land cover products.

2 Materials and methods

2.1 Study area

This study was conducted in a 32.8 km² northern boreal catchment situated in northern Finland (69.13-69.26°N, 27.21-27.45°E; 155 m a.s.l), about 200 km south of the Arctic Ocean ([Figure 1](#)). The catchment is characterized by subarctic climate (Aurela, Laurila, & Tuovinen, 2001). The mean annual air temperature during the period from 1981 to 2010 at the Inari Ivalo weather station (59 km south of Kaamanen) was -0.4 °C, with the warmest and coldest monthly air temperature being 14.0 °C and -12.8 °C in July and January, respectively (Pirinen et al., 2012). During the aforementioned period, the mean annual precipitation was 472 mm, and the mean annual relative humidity was 79% (Pirinen et al., 2012).

2.2 Land cover classification

Land cover in the study area was classified using a geographic object-based image analysis approach, following the methodology described by Räsänen, Juutinen, Tuittila, Aurela, and Virtanen (2019) and Räsänen and Virtanen (2019). Object-based approaches have been documented to be effective in particular when analyzing high-spatial resolution remote sensing imagery (Blaschke et al., 2014; Chen, Weng, Hay, & He, 2018), and it has been shown that inclusion of multi-source (*i.e.*, multiple types of remote sensing data) and multi-temporal remote sensing data increases land cover classification accuracy (Amani et al., 2017; Chasmer et al., 2020; Halabisky, Babcock, & Moskal, 2018; Karlson et al., 2019; Räsänen & Virtanen, 2019). Specifically, a WorldView-2 satellite image (WV-2, DigitalGlobe Inc., Westminster, CO, USA) was segmented with a full lambda schedule segmentation with an average segment size of 0.2 ha. For each segment, 352 features, including spectral, topographic, vegetation

height, and texture features, were calculated from the WorldView-2 image, four PlanetScope satellite images (PS, Planet Labs Inc., San Francisco, CA, USA) from different phenological stages and aerial lidar data (National Land Survey of Finland) (Table S1).

Training data were collected from 16 transects of 0.25-1.0 km in length and visual interpretation of an aerial orthophoto. In total, there were 1058 training segments (18-383 in each LCT). A supervised random forest classification (Breiman, 2001) was used to classify 11 LCTs (excluding streams) (Table 1; Figure S1). Accuracy of the classification was assessed with a pixel-based approach utilizing 359 vegetation plots, of which 137 were circular plots with a radius of 5 m (of which 59 were in transects, and 78 randomly sampled), 204 were quadrats with a 50 cm side length (in transects), and 18 were circular plots with a radius of 20 cm (Räsänen & Virtanen, 2019).

After the random forest classification, the stream LCT was added to the map from National Land Survey of Finland topographic database. Owing to large differences in hydrology and C dynamics (Figures S2-S7; Table S2), the fen string LCT was split into string top and string margin fractions by assuming that 59.2% of the string belong to tops and 40.8% to margins as per the land cover classification conducted for a peatland area within the landscape (Heiskanen et al., 2021; Räsänen & Virtanen, 2019) (Table 2).

2.3 Flux measurements

The ecosystem-atmosphere fluxes of CO₂ and CH₄ were measured on the dominant peatland surfaces, *i.e.*, pine bog, string top, string margin, tall sedge fen, and flark fen, using a static chamber technique (Heiskanen et al., 2021; Juutinen et al., 2013; Laine, Riutta, Juutinen, Välimäki, & Tuittila, 2009). The measurements were made repeatedly during the growing seasons 2005, 2006, 2017, and 2018 (Heiskanen et al., 2021; Juutinen et al., 2013; Laine et al., 2009). Permanent chamber bases were installed in replicate for each peatland type.

Net ecosystem CO₂ exchange (NEE) was measured using transparent chambers equipped with a fan and an infra-red gas analyzer (in 2005-2006, EGM-3, PP-systems, MA, USA; in 2017-2018, Picarro G2401, Picarro Inc., CA, USA), and was determined from several (2-4) replicate measurements. Ecosystem respiration (ER) was measured using opaque chambers. Fluxes were calculated from concentration changes using standard methods (Heiskanen et al., 2021; Juutinen et al., 2013; Laine et al., 2009). Gross primary productivity (GPP) was calculated as the difference between NEE and ER. Positive fluxes in this study indicate a C flux to the atmosphere, while negative values represent C uptake by the ecosystem.

In 2005-2006, the CH₄ fluxes were determined in aluminum chambers equipped with a fan, and CH₄ concentration was measured using gas chromatographs (HP-5710A and HP-5890A, Palo Alto, CA, USA) equipped with a flame ionization detector (Juutinen et al., 2013). In 2017-2018, the CH₄ flux measurements were conducted with the CO₂ chamber flux set-up.

In the pine forest (69.1°N, 27.3°E), NEE was measured using the eddy covariance (EC) technique from June 2017 to December 2018 (Heiskanen et al., 2021). The NEE data for birch forest were derived from the EC measurements conducted at Petsikko (69.28°N, 27.14°E) in June–September 1996 (Aurela, Tuovinen, & Laurila, 2001).

At a lake within the study landscape, the CO₂ and CH₄ fluxes were measured manually with a Picarro G2401 (Picarro Inc., CA, USA) and floating chambers during the summer season (June–August) of 2017 (Juutinen et al., 2013).

2.4 Terrestrial ecosystem modeling

Ecosystem C dynamics of the terrestrial land cover types in the study landscape were simulated using a process-based biogeochemistry model, NEST-DNDC (Zhang, Sachs, Li, & Boike, 2012). It integrates a widely used biogeochemical model DeNitrification-DeComposition (DNDC) (Kou et al., 2020; Li, Aber, Stange, Butterbach-Bahl, & Papen, 2000) with the Northern Ecosystem Soil Temperature model (NEST) (Zhang, Chen, & Cihlar, 2003). Thus, the model can effectively simulate C dynamics in LCTs of the cold circumpolar regions (Deng et al., 2017; Treat et al., 2018; Zhang et al., 2012). In the model, all LCTs share common climate and atmospheric environmental conditions (*e.g.*, atmospheric CO₂ and nitrogen (N) concentration), but they differ in their assigned land types, soil, and vegetation characteristics. Therefore, the model is particularly suitable to work with ecosystem C dynamics in fragmented circumpolar landscapes (Zhang et al., 2012).

In this study, the simulations with the NEST-DNDC model for the terrestrial LCTs were conducted through the following three steps. First, the datasets required for model input were prepared, including data associated with climate, soil, and vegetation. Of them, the climate dataset, shared by all LCTs, include historical meteorological observations for 1996 and 2005-2018, and future data for 2019-2099. The historical climate dataset, including daily mean, maximum, and minimum air temperatures, precipitation, wind speed, global radiation, and relative humidity, were derived from the Utsjoki Kevo weather station (69.8°N, 27.0°E) of the Finnish Meteorological Institute. The future climate data was extracted from the bias-corrected dataset of the International Impact Model Intercomparison Project (ISIMIP) output from HadGEM2-ES (Frieler et al., 2017).

The LCT-specific soil variables that were used to drive the model consisted of texture, bulk density, pH, soil C concentration, and soil C:N ratio ([Table S2](#)). The soil texture was loamy sand for forests and pristine peat for peatlands. In all peatlands, soil samples of a known volume were collected from layers 0–5 cm and 15–20 cm beneath the litter layer (the layer where vascular plant and moss leaf structures are still discernible) using a knife and scissors. The samples were dried (48 h at 75 °C) and weighted for dry mass. Bulk density was calculated based on the volume and dry mass of the samples. Parts of dry samples were ground using a ball mill and 0.2 g subsamples of ground material were analyzed for total C and N concentrations using a LECO CNS-2000 analyzer (LECO Corporation, Saint Joseph, MI, USA). Soil pH was estimated in the field in water collected at the depth of 30 cm. In models, means of the two peat layers were used for bulk density, C concentration, and C:N ratio. In pine, birch and pine-birch mixed forests, pits were dug to a depth of 100 cm and horizontal soil cores (length 5

cm, diameter 3 cm) were collected from the organic (O) and eluvial (E) horizons, from the top and bottom parts of the illuvial (B) horizon, and at the depth of 50 and 100 cm. These samples were analyzed following the procedures described for peatland samples except that the pH was measured from O horizon samples and samples collected at 30 cm depth in distilled water solution. In models, means of values of all available soil horizons were used for forest soil bulk density, C concentration, C:N ratio, and pH. Vegetation data included in the models consisted of aboveground plant biomass and leaf area index (LAI) of different LCTs ([Tables S3-S4](#)). The aboveground biomass and LAI of each LCT was determined based on 130 circular plots with a 5 m radius (71 random plots, 59 plots in transects) distributed among the LCTs (see [Supplementary Text for detailed information](#)).

Second, we calibrated and validated the model for different LCTs ([Figures S2-S15](#)). The observed C fluxes used for the model calibration included the 1996 data of birch forest, the 2006 data of pine bog, string margin, tall sedge fen, and flark fen, and the 2017 data of string top and pine forest. The calibrated models were then validated with the remaining C flux data, from 2005 for pine bog, string margin, tall sedge fen, and flark fen, from 2017 for string margin, and from 2018 for string top, string margin, and pine forest. Finally, we ran the calibrated and validated model for the period 2005-2018 for the dominant terrestrial LCTs. To explore the potential trajectory of RE heterogeneity under warming, we then drove the model for the period 2019-2099 with variable temperature from two Representative Concentration Pathway scenarios, RCP4.5 and RCP8.5, keeping other climatic and atmospheric inputs constant (2005-2018 averages) (Lucht et al., 2002). The C budget of mixed forest and open forest was simulated based on parameters from pine/birch forest and their own soil and vegetation

data. The pine bog simulation was also used for birch swamp (covering only 0.12% of study area) in the landscape-scale estimation of C budget and RE since observations were lacking for birch swamp.

2.5 Aquatic ecosystem modeling

The Arctic Lake Biogeochemistry Model (ALBM), which is a one-dimensional process-based climate-sensitive lake biogeochemistry model, was used to simulate the CO₂ and CH₄ fluxes from lakes in the study area (Guo et al., 2020; Tan, Zhuang, & Anthony, 2015; Tan et al., 2017). For lake C fluxes, the model simulates both the diffusive and the ebullitive emission. The model was first calibrated against observations of water temperature and C fluxes of the lake using the Monte Carlo method with 10,000 parameter sample sets. The optimum parameter set was then selected based on the total root-mean-square error of the modeled CO₂ and CH₄ fluxes. Finally, we run simulations over the same period forced by the same meteorological data as for the other LCTs (Figure S16). The lake simulation was also used for streams in the landscape-scale estimation of C budget and RE.

2.6 Radiative effect of greenhouse gas fluxes

The annual CO₂ and CH₄ flux densities (g m⁻² yr⁻¹) of each LCT during the period of 2005-2099 were used as input to estimate the radiative effect (RE) of these fluxes, *i.e.*, their contribution to Earth's radiative balance. We expressed this effect as the cumulative RE due to an annual emission or uptake pulse over time horizons of 25 and 100 yr, which was calculated using a dynamic radiative forcing (RF) model (Lohila et al., 2010; Mathijssen et al., 2017; Piilo et al., 2020). Even though we used a RF model here, it is important to note that we refer to this quantity as RE, as it does not represent

a forcing that would result from a perturbation to Earth's energy balance (Neubauer, 2021). This modelling is performed in order to obtain a common metric for the CO₂ and CH₄ fluxes, in a similar vein to the CO₂-equivalent fluxes derived from the global warming potential concept; however, using RE as the common metric provides additional flexibility as we can dynamically account for the effect of changing background concentrations.

In the RF model, CO₂ and CH₄ pulses were assumed to be instantaneously and completely mixed in the atmosphere (Myhre et al., 2013). The resulting atmospheric concentration pulses were modeled to decay according to characteristic time scales related to global biogeochemical cycles. For CO₂, these dynamics were implemented as a weighted sum of four exponential functions, where the shortest perturbation time was 4.3 yr and the slowest decay function effectively corresponded to a permanent atmospheric change for 22% of each annual pulse (Joos et al., 2013). The evolution of the atmospheric CH₄ concentration perturbation was calculated as an exponential decay with a single atmospheric perturbation time scale of 12.4 yr (Myhre et al., 2013).

The annual emission/uptake pulses were integrated over time by accounting for their timing and decay, resulting in time series of atmospheric CO₂ and CH₄ concentration changes. Atmospheric oxidation of the emitted CH₄ molecules to CO₂, which generates an indirect RE, was included in the model assuming an 80% efficiency for the CH₄-to-CO₂ conversion (Boucher, Friedlingstein, Collins, & Shine, 2009). The instantaneous RE resulting from the modeled CO₂ and CH₄ concentration changes was calculated with a radiative efficiency parameterization (Etminan, Myhre, Highwood, & Shine, 2016). This parameterization takes into account the spectral interactions between CO₂, CH₄,

and nitrous oxide. The model also includes an estimate for the indirect CH₄-induced RE due to ozone and stratospheric water vapor changes (Myhre et al., 2013). The RE due to ecosystem-atmosphere fluxes was calculated as a marginal change with respect to specified, variable background concentrations (Lohila et al., 2010). These concentrations were adopted from the RCP scenarios (Meinshausen et al., 2011). In this study, the total RE refers to the sum of the RE due to CO₂ and CH₄.

2.7 Statistical analysis

The landscape-scale C budget and RE were estimated by weighting the C budget and RE of each LCT (except non-vegetated) with the corresponding relative area within the catchment. The role of peatlands in the landscape-scale heterogeneity in C budget and RE was quantified at two levels, based on the LCT-specific C fluxes expressed (1) per unit area ('LCT-based heterogeneity') and (2) as area-weighted budgets ('area-based heterogeneity'). For the LCT-based heterogeneity, we calculated the Sum of Squared Deviations (SSD) from the arithmetic mean among peatland LCTs and that among all LCTs within the landscape and then divided the peatland SSD by the landscape SSD. For the area-based heterogeneity, we calculated the ratio between the SSD from the area-weighted mean among peatland LCTs and that among all LCTs within the boreal landscape.

To illustrate the uncertainty in the landscape-scale results due to aggregation or misclassification of peatlands, we tested the statistical difference among different land cover scenarios (*i.e.*, scenarios that peatlands are combined, and scenarios that peatlands are mis-classified as non-peatland LCTs) with Least Significant Difference (LSD). Combining peatland LCTs is relevant because peatland LCTs in the current

circumpolar peatland maps are generally expressed as a uniform land cover type (Hugelius et al., 2020; Xu, Morris, Liu, & Holden, 2018), without capturing spatial heterogeneity among different peatland types. In remote sensing-based products, peatlands can also be confused with other terrestrial or aquatic LCTs. Most commonly, forested peatland is mis-classified as forest (Thompson et al., 2016) and open water-logged peatland with low vegetation as a lake (Matthews et al., 2020).

When estimating potential trajectories of RE heterogeneity among different LCTs under future warming scenarios, the relative importance of CO₂ and CH₄ in explaining the trend of total RE heterogeneity was analyzed with the random forest technique (Delgado-Baquerizo et al., 2018).

2.8 Survey of land cover products

We surveyed seven widely used global land cover products in our study area and assessed how well peatlands are presented in them by calculating the fractional peatland/wetland area and estimating the spatial agreement with our LCT data by error matrices (Frey & Smith, 2007; Krankina et al., 2008). Moreover, we included in the comparison one continental and one national land cover product. The nine products considered are detailed in [Table 3](#).

3 Results

3.1 Landscape heterogeneity

Twelve LCTs were distinguished within the studied boreal landscape with high spatial resolution land cover classification ([Figures 1, S1; Tables 1-2](#)), with an overall accuracy of 73.1% ([Table S5](#)). Four of these LCTs were forests (*i.e.*, pine, birch, mixed, and open

forests, occupying 60.6% of the landscape), two were water bodies (*i.e.*, lake and stream, 13.2%), one represents non-vegetated areas (0.7%), and five were peatlands (25.5%) that were distributed along a gradient from forests to water bodies (Table 1). Among the peatland LCTs, pine bog (9.3%), birch swamp (0.1%), and fen string (including thin, elongated, and smaller, rounded elevated microforms; 2.7% string top and 1.8% string margin) were characterized as dry communities as their water tables were below the peat surface (Tables 2, S2). Of these, pine bog and birch swamp represent forested dry peatlands while string top and margin represent open dry peatland habitats (Table 1). The two water-logged peatland LCTs, *i.e.*, tall sedge fen (5.6%) and flark fen (6.0%), represent open wet peatland habitats (Tables 1-2, S2).

3.2 Carbon budget under present climate

The various LCTs differ in vegetation, soil, and hydrological characteristics (Figures S2-S16; Tables 1, S2-S4), leading to heterogeneity in the ecosystem-atmosphere fluxes of CO₂ and CH₄ (Figure 2). For the total C budget (sum of CO₂-C and CH₄-C budgets), the terrestrial LCTs (peatlands and forests) functioned as C sinks, while lakes functioned as a significant C source (mean $\pm$ 95% confidence interval: 27 ± 2 g C m⁻² yr⁻¹) during the period 2005-2018 (Figure 2a). Among the peatland LCTs, the C budget ranged from a large C sequestration in pine bog (-141 ± 17 g C m⁻² yr⁻¹) to a small sequestration in tall sedge fen (-17 ± 3 g C m⁻² yr⁻¹), while among the forest types, the largest C sink was found for pine forest (-154 ± 17 g C m⁻² yr⁻¹) and the smallest for open forest (-45 ± 6 g C m⁻² yr⁻¹) (Figure 2a). The variability and magnitude of the total C budget was dominated by CO₂ (Figure 2b). Most peatland LCTs emitted CH₄ to the atmosphere, with the largest emission from the water-logged peatland LCTs (tall sedge fen: 19 ± 1 g C m⁻² yr⁻¹; flark fen: 17 ± 2 g C m⁻² yr⁻¹) (Figure 2e). Forests functioned

as weak CH₄ sinks (-0.23 ± 0.02 to -0.26 ± 0.02 g C m⁻² yr⁻¹), while lakes were CH₄ sources (1.33 ± 0.09 g C m⁻² yr⁻¹) (Figure 2e).

By quantifying the role of peatlands in the landscape-scale heterogeneity in C budget at the LCT level, we found that the variability in the total C mass budget among peatland LCTs accounted for 38 ± 5 % of the variability due to all landscape LCTs combined (Figure 2f). The CO₂-C budget, GPP, and ER heterogeneity had a similar peatland contribution (33 ± 5 %, 36 ± 1 %, and 39 ± 2 %, respectively) (Figure 2f). Compared to them, peatlands explained a significantly larger part of the variability (81 ± 0.5 %) in the CH₄-C budget (Figure 2f).

The landscape-scale C budget, obtained by weighting the CO₂ and CH₄ exchange rates of each LCT by the corresponding areas (Table 2), was -106 ± 11 g C m⁻² yr⁻¹ in 2005-2018. It was dominated by the CO₂ uptake of -108 ± 10 g C m⁻² yr⁻¹ while the CH₄ emission was 2.28 ± 0.19 g C m⁻² yr⁻¹ (landscape mean in Figure 2a-e). Peatlands explained a smaller part of the variability in total C budget (19 ± 3 %), CO₂-C budget (15 ± 3 %), GPP (16 ± 1 %), and ER (19 ± 1 %) compared to the LCT level (Figure 2g). These proportions were also less than the proportion of the total peatland area within the landscape (26%) (Table 2). However, peatlands explained as much as 88 ± 0.1 % of the CH₄ flux variability when scaling them with LCT areas (Figure 2g).

3.3 Radiative effect of present carbon budget

The different heterogeneities in CO₂-C and CH₄-C budgets, together with the different radiative impacts of CO₂ and CH₄ (Myhre et al., 2013), led to a further layer of LCT

heterogeneity in the C flux effect on radiative balance (Figure 3). The total RE generated by CO₂ and CH₄ fluxes varied greatly among the peatland LCTs (Figure 3a). Specifically, pine bog had the greatest negative RE (-37 ± 4 fW m⁻² over the 100-yr time horizon, 1 fW = 10⁻¹⁵ W), followed by string top (-25 ± 3 fW m⁻²). In contrast, tall sedge fen exhibited the largest positive RE among all the LCTs (69 ± 6 fW m⁻²), followed by flark fen (52 ± 7 fW m⁻²). Consequently, the RE generated by different peatland types spanned a range of 107 ± 9 fW m⁻², which was more than twice that among the forest and aquatic LCTs (56 ± 5 fW m⁻²) (Figure 3a).

Despite comprising just 26% of the landscape area, the variability among peatland types accounted for 77 ± 3 % to 81 ± 1 % of the total variability in RE at the LCT level and 65 ± 4 % to 79 ± 2 % when considering LCT areas, depending on the time horizon (Figure 3d-e). These were similar to the corresponding SSD ratio for the CH₄-C budget (LCT-based: 81 ± 0.5 %; area-based: 88 ± 0.1 %) and much larger than those for the CO₂-C budget (LCT-based: 33 ± 5 %; area-based: 15 ± 3 %) (Figure 3d-e).

3.4 Uncertainty due to biased peatland classification

The area-weighted total RE resulting from the CO₂ and CH₄ budgets was -20 ± 3 fW m⁻² per unit area of the region over the 100-yr time horizon (CO₂: -30 ± 3 fW m⁻²; CH₄: 10 ± 1 fW m⁻²; landscape mean in Figure 3a-c).

Using this result as a baseline (Scenario 1, Figure 4), we analyzed the potential deviation in RE for scenarios in which peatland LCTs were combined (Scenario set 2 in Figure 4) or mis-classified as forests or lakes (Scenario set 3 in Figure 4). Regarding

scenarios in which peatland LCTs are combined, our results showed that the negative RE over the 100-yr time horizon significantly decreased when all the peatland LCTs were pooled into the forested dry peatland class (pine bog, -32 ± 3 fW m⁻², Scenario 2a) or treated as string top (-29 ± 3 fW m⁻², Scenario 2b) (Figure 4a). On the other hand, the negative RE significantly increased when all the peatland LCTs were classified as water-logged peatland (tall sedge fen, -5 ± 3 fW m⁻², Scenario 2d; flark fen, -10 ± 4 fW m⁻², Scenario 2e) (Figure 4a). This suggests that, to accurately estimate the regional RE, the LCT mapping must be able to distinguish between the water-logged and dry peatland areas within the landscape. Consistent with this point, when all the water-logged peatland areas were classified as tall sedge fen and all the dry peatland LCTs were classified as string top, RE did not change significantly (Scenario 2f, Figure 4a).

Regarding scenarios that peatlands are confused with other terrestrial or aquatic LCTs, our results showed that the uncertainty in RE was insignificant if pine bog (the dominant forested peatland in the landscape) was identified as pine forest (-21 ± 4 fW m⁻², Scenario 3a, Figure 4a). This was associated with the comparable CO₂ budgets and the consistently small CH₄ emissions of the forested peatlands and their corresponding forest types (Figure 2). Similarly, when flark fen, an open water-logged peatland with low vegetation cover, was classified as a lake, the modeled RE did not change significantly (Scenario 3b, Figure 4a). However, when the two above-mentioned misclassification scenarios were adopted simultaneously and the remaining open peatland LCTs were represented by a single open dry peatland type (string top), the negative RE decreased significantly (Scenario 3c, Figure 4a). Our results demonstrate the potentially high sensitivity of the modeled RE to peatland classification (Figure 4a).

Further analyses showed that over a shorter time horizon (25 yr) this sensitivity involved not only the magnitude but also the sign of RE (Figure 4b).

Like RE, our results also demonstrated that the aggregation or misclassification of peatlands could significantly alter the estimated landscape-scale C budget, although the differences among various scenarios were smaller compared to RE (Figure 4c). Moreover, we found that the landscape-scale CO₂ budget and its RE did not differ significantly ($p > 0.05$) from those calculated with the full LCT classification (Scenario 1) in any peatland aggregation or misclassification scenario (Figure 4d-f). In contrast, there were significant differences in the landscape-scale CH₄ budget and its RE among different scenarios (Figure 4d-f).

3.5 Radiative effect of future carbon budget

Based on our RE calculations with the LCT fluxes modeled until 2099, we found that the variation in total RE due to the C budget of different peatland LCTs significantly increased during 2005-2099 under both RCP scenarios considered ($p < 0.001$; Figure 5a-b). Even though the radiative efficiency (*i.e.*, RE per atmospheric GHG change) is concurrently reduced as background concentrations increase (Etminan et al., 2016; Meinshausen et al., 2011), the warming-induced changes in GHG fluxes resulted in an amplified variability in the RE of total C budget among peatland LCTs. Compared to the present period (2005-2018), the peatland heterogeneity in total RE during 2086-2099 was enhanced by 143% under RCP4.5 and by 243% under RCP8.5 (Figure 5a-b). Moreover, the SSD of total RE among all the landscape LCTs also significantly increased under the two RCP scenarios ($p < 0.001$; Figure 5a-b), indicating an amplified

heterogeneity in RE at the landscape scale as well. Similar to the total RE, the SSD of CH₄-induced RE among the peatland LCTs significantly increased with warming under both climate change scenarios ($p < 0.001$; Figure 5c-d). Moreover, our results showed that, compared to CO₂-C exchange, the RE heterogeneity due to CH₄-C budget had a larger relative importance in explaining the trend of total RE heterogeneity among peatlands during 2005-2099 (Figure 5e-f).

3.6 Survey of different land cover products

Compared to the 25.5% areal coverage of peatlands within the Kaamanen landscape revealed by our classification, there was no peatland/wetland specified in the global land cover map of GLCC, MODIS.LCT or GLWD; the coverage was 0.1% in both GlobCover2009 and FROM-GLC10, as high as 58.0% in GLC2000, and 24.8% in PEATMAP (Figure 6; Table 3). Although the proportion of peatlands was similar in PEATMAP and this study, the spatial agreement between their areas was only 48.5% (Table 3). The corresponding spatial agreement for GLC2000, GlobCover2009, and FROM-GLC10 were 21.8%, 0.1%, and 0.01%, respectively (Table 3). Regarding the peatland/wetland heterogeneity, there was only one peatland/wetland type defined in any of the considered global products including such a LCT, *i.e.*, ‘regularly flooded shrub and/or herbaceous cover’ in GLC2000, ‘closed to open (>15%) grassland or woody vegetation on regularly flooded or waterlogged soil’ in GlobCover2009, ‘wetland’ in FROM-GLC10, and ‘peatland’ in PEATMAP (Figure 6).

The European-level product, CLC2018EU.25ha, has a similar peatland representation to PEATMAP, *i.e.*, one peatland category (‘peatbog’), with a 25.3% areal coverage and

44.8% spatial agreement (Figure 6; Table 3). Unlike the larger scale products, the national data base CLC2018FI.20m provides multiple peatland classes for the Kaamanen landscape ('Broad-leaved forest on peatland', 'Coniferous forest on peatland', 'Mixed forest on peatland', 'Transitional woodland/shrub cc 10-30% on peatland' (cc = canopy closure), 'Peatbog', 'Terrestrial inland marsh', and 'Aquatic inland marsh'), with a relatively accurate peatland area (28.6%) and a high score of spatial agreement (62.0%) (Figure 6; Table 3). On the other hand, the 'Peatbog' class, which in CLC2018FI.20m is defined as open peatlands smaller than 25 ha (<https://ckan.ymparisto.fi/dataset/corine-maanpeite-2018>), alone occupied about 84% of the total peatland/wetland area (Figure 6). This indicates that, although there are multiple peatland/wetland classes and forested peatlands are separated from forests and open peatlands, there is no separation of small peatland patterns in CLC2018FI.20m either.

4 Discussion

This study couples a detailed land cover classification of a typical boreal landscape with quantification of spatial heterogeneity in C budget and its climate impact (RE); based on these comprehensive data, we assessed the effect of peatland classification accuracy on C budget and RE, derived potential trajectories of RE heterogeneity under future warming conditions and surveyed peatland representation in global land cover products. This was motivated by the fact that landscapes including peatlands are widespread across the boreal biome. By overlaying two maps, *i.e.*, the map of terrestrial ecoregions of the world (Olson et al., 2001) and the latest northern peatland map with 10-km pixels (Hugelius et al., 2020), we find that there are approximately 150,400 10-km pixels within the boreal zone, of which 140,700 (*i.e.*, 94%) contain peatlands

(peatland area fraction > 0) (Figure S17a). Our results jointly advocate the detailed delineation of peatland heterogeneity, *i.e.*, determining a sufficient number of LCTs with differing characteristics, so that we can reduce uncertainties in C budget estimates of the boreal biome. This conclusion is further supported by previous studies that focused on individual boreal peatland ecosystems (Heiskanen et al., 2021; Li et al., 2016; Lund et al., 2010).

Indeed, recently, there have been multiple attempts to produce local, regional, national, and circumpolar databases of northern peatlands. In part of these attempts, however, all peatlands and wetlands have been lumped into one class (Hird, DeLancey, McDermid, & Kariyeva, 2017; Hugelius et al., 2020; Karlson et al., 2019; Tanneberger et al., 2017; Xu et al., 2018), but there exist approaches that include separate classes for different peatland types (Amani et al., 2017; Bourgeau-Chavez et al., 2017; Korpela, Haapanen, Korrensalo, Tuittila, & Vesala, 2020; Mahdianpari et al., 2020; Olefeldt et al., 2021; Räsänen & Virtanen, 2019). Currently, the most detailed circumpolar database uses existing GIS datasets and machine learning modeling to estimate the fractional coverage of five different wetland classes in 0.5° grid cells (Olefeldt et al., 2021). Also some other data products have relied on existing GIS databases (Hugelius et al., 2020; Tanneberger et al., 2017; Xu et al., 2018), while others have used remotely sensed data that enable construction of higher spatial resolution datasets (Amani et al., 2017; Bourgeau-Chavez et al., 2017; Hird et al., 2017; Karlson et al., 2019; Mahdianpari et al., 2020; Räsänen & Virtanen, 2019).

To generate locally accurate maps of peatland LCTs, it has been shown that ultra-high spatial resolution (pixel size < 1 m) airborne or drone data are required (Korpela et al.,

2020; Räsänen & Virtanen, 2019). Nevertheless, the use of such data is presently impossible for large regions, but maps based on high-resolution satellite data (pixel size < 30 m) are, at least in some cases, sufficient to predict the proportional area of different LCTs (Bartsch, Hofler, Kroisleitner, & Trofaier, 2016; Mahdianpari et al., 2020; Treat et al., 2018). In practice, however, even the national-scale land cover product (CLC2018FI.20m), while showing possible guidelines for larger scale maps and the best performance of the products compared in this study, depicts peatlands at much coarser than the nominal 20-m pixel level.

Both at small and large scales, peatland LCT detection requires multiple remote sensing data sources that bring complementary information, including, *e.g.*, optical data depicting spectral properties of land cover, lidar data providing information about topography and vegetation structure, and synthetic aperture radar (SAR) data sensitive to moisture and surface structure (Amani et al., 2017; Bourgeau-Chavez et al., 2017; Hird et al., 2017; Karlson et al., 2019; Mahdianpari et al., 2020; Räsänen, Manninen, Korkiakoski, Lohila, & Virtanen, 2021; Räsänen & Virtanen, 2019). Freely available high-resolution remote sensing datasets, such as Sentinel-1 SAR, optical Sentinel-2 and Landsat 8, and ArcticDEM topographic data would enable the generation of circumpolar maps of peatland LCTs. Such maps could be upscaled from local peatland maps and field inventories; vice versa, circumpolar maps could be downscaled to locally accurate products with high resolution datasets, such as airborne or drone lidar and hyperspectral data.

Besides the large spatial heterogeneity, boreal peatlands can also vary temporally under environmental changes. Our modeling results showed that the LCT-based RE

heterogeneity among peatland types could be enhanced in future warming conditions, suggesting that peatland heterogeneity in climate feedback to C fluxes would change with environmental changes irrespective of land cover change. The reason why we did not consider changes in peatland area or LCT distribution within the Kaamanen landscape is that paleoecological evidence indicates that there has not been any major changes in the surface microtopography and vegetation taxonomic composition since the formation of the irregular string and flark pattern ca. 1000 yr ago (Piilo et al., 2020). Furthermore, there is no permafrost within the study area (Aurela, Laurila, et al., 2001), and hence permafrost thawing, which could induce drastic changes in peatland types and distribution (Helbig et al., 2017; Johansson et al., 2006; Payette, Delwaide, Caccianiga, & Beauchemin, 2004), has no effect there. However, as 77% of the 10-km peatland pixels of the boreal map do contain permafrost (Figure S17b), the heterogeneity of peatlands potentially increases across the northern boreal landscape with permafrost thawing. Overall, vegetation and hydrology changes affecting the peatland distribution and characteristics within the boreal zone cannot be ruled out. These potential changes under environmental changes highlight not only the delineation of the spatial heterogeneity of peatlands, but also their temporal dynamics.

5 Conclusions

Based on an extensive set of field data including CO₂ and CH₄ fluxes, soil and vegetation characteristics, and an explicit land cover classification, we modeled the C budgets and their radiative climate effects both for the boreal landscape and its individual LCTs. The average present-day, landscape-scale budgets of CO₂ and CH₄ were -108 ± 10 and 2.3 ± 0.2 g C m⁻² yr⁻¹, respectively. We show that, despite only comprising 26% of the study area, peatlands within the Kaamanen boreal landscape

621 account for 88% of the area-based heterogeneity in CH₄-C budget, and 65% and 79%
622 of that in the total radiative effect over the 100-yr and 25-yr time horizons, respectively.
623 Misclassifying peatlands or inadequately representing the heterogeneity among the
624 peatland types can alter the magnitude of the modeled radiative effect significantly over
625 the 100-yr time horizon, and even change the sign over the 25-yr time horizon.
626 Warming tends to enhance the RE heterogeneity of peatland C budgets. We also
627 observed that global land cover products have obvious biases in their classification of
628 boreal peatlands. Overall, this study implies the great significance of resolving land
629 cover specifics, especially peatland heterogeneity, in sufficient detail across the boreal
630 biome for constraining the circumpolar C-climate nexus.

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Author contributions

D.K., T.V., C.C.T., J-P.T., N.J.S. and A.K. designed research and led the discussion, A.R. and T.V. conducted the land cover classification, S.J., M.A., L.H. and J-P.T. performed the flux measurement, J.M., A.R. and T.V. conducted the soil and vegetation mapping, S.J., S.R.P., M.V., M.H., J.W. and T.J. collected data from peatland and water body properties, D.K., C.C.T., N.J.S., J.D., Y.Z., Q.Z. and M.G. performed the biogeochemical modelling, J-P.T., D.K. and C.C.T. conducted the radiative forcing analysis, D.K., C.C.T. and J-P.T. analyzed data and integrated results, D.K., J-P.T., C.C.T., N.J.S. and A.K. drafted the manuscript. All authors contributed to the writing.

Competing interests

The authors declare that they have no competing interests.

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955 **Table 1. Land cover types (LCTs) and their dominant species in the tree, understory, and ground layers.**

Land cover type	Tree layer	Field layer	Ground layer
Pine forest	Canopy cover > 10%, pine (<i>Pinus sylvestris</i>) cover > 2/3 of total canopy cover	Evergreen shrubs (e.g., <i>Vaccinium vitis-idaea</i> , <i>Empetrum nigrum</i> , and <i>Calluna vulgaris</i>), and also some deciduous shrubs	Feather mosses and lichens
Birch forest	Canopy cover > 10%, birch (<i>Betula pubescens</i>) cover > 2/3 of total canopy cover	Evergreen and deciduous shrubs	Feather mosses and lichens
Mixed forest	Multiple tree species, including pine, birch, and few aspen (<i>Populus tremula</i>), canopy cover > 10%, cover of minority species > 1/3	Evergreen (<i>Vaccinium vitis-idaea</i>) and deciduous (<i>Vaccinium myrtillus</i> , <i>Vaccinium uliginosum</i>) shrubs	Feather mosses and lichens
Open forest	Forest with tree canopy cover < 10%	Evergreen shrubs, and some deciduous shrubs	Lichens, and some feather mosses
Pine bog	Peatland with coverage of pine trees > 1%	Evergreen (<i>Rhododendron tomentosum</i>) and deciduous (<i>Vaccinium uliginosum</i> , <i>Betula nana</i>) shrubs, and some forbs (<i>Rubus chamaemorus</i>) and graminoids (mostly <i>Carex</i> spp.)	<i>Sphagnum</i> , feather mosses, and lichens
Birch swamp	Peatland with coverage of birch trees > 2%	Forbs, grasses, and shrubs	<i>Sphagnum</i> and feather mosses
String	Peatland with few trees (< 1% coverage)	Evergreen and deciduous dwarf shrubs as well as forbs (esp. <i>Rubus chamaemorus</i>)	<i>Sphagnum</i> and feather mosses, and some lichens
Tall sedge fen	None	Sedges, also deciduous shrubs (e.g., <i>Betula nana</i> , <i>Salix</i> spp.) and forbs	<i>Sphagnum</i> , wet brown mosses, and open water
Flark fen	None	Grasses and forbs	Open water, bare peat, and wet brown mosses
Lake	None	None	Open water
Stream	None	None	Open water
Non-vegetated	None	None	Mostly human made bare areas, sand with some stones, and all roads in the area

956

957 **Table 2. The area extent of different land cover types (LCTs).**

Major LCT	Specific LCT	Area (km ²)	Area fraction (%)
Peatland	Pine bog	3.06	9.32
	Birch swamp	0.04	0.12
	String top	0.87	2.65
	String margin	0.60	1.83
	Tall sedge fen	1.85	5.64
	Flark fen	1.96	5.97
Forest	Pine forest	17.36	52.89
	Birch forest	0.14	0.43
	Mixed forest	1.94	5.91
	Open forest	0.44	1.34
Water body	Lake	4.32	13.16
	Stream	0.02	0.06
Non-vegetated		0.22	0.67
Total		32.82	100

958

959 **Table 3. Assessment of peatland/wetland representation in different land cover products for the Kaamanen boreal landscape.**

Product	Reference	Scale	Version	Methodology	Spatial resolution	Peatland/wetland relevant class label	Peatland/wetland area (%)	Spatial agreement (%)
Global Land Cover Characterization (GLCC)	Loveland et al. (2000)	Global	version 2	Remote sensing	1 km	-	0	0
Moderate Resolution Imaging Spectroradiometer Land Cover Type (MODIS.LCT)	Sulla-Menashe, Gray, Abercrombie, and Friedl (2019)	Global	MCD12Q1 v006	Remote sensing	500 m	-	0	0
Global Land Cover 2000 (GLC2000)	Bartholomé and Belward (2005)	Global	Global Product v1.1	Remote sensing	1 km	Regularly flooded shrub and/or herbaceous cover	58.0	21.8
Global Land Cover Map for 2009 (GlobCover2009)	Arino et al. (2012)	Global	v2.3	Remote sensing	300 m	Closed to open (>15%) grassland or woody vegetation on regularly flooded or waterlogged soil	0.1	0.1
First 10-m resolution global land cover product (FROM-GLC10)	Gong et al. (2019)	Global	v01	Remote sensing	10 m	Wetland	0.1	0.01
Global Lakes and Wetlands Database (GLWD)	Lehner and Döll (2004)	Global	level 3	Database	30 second	-	0	0
PEATMAP	Xu et al. (2018)	Global	Finland	Meta-analysis	Shapefile	Peatland	24.8	48.5
CORINE Land Cover 2018 EU, 25 ha (CLC2018EU.25ha)	https://land.copernicus.eu/pan-european/corine-land-cover/clc2018	Continental	2018, 25 ha	Remote sensing and database	Shapefile (minimum unit 25 ha)	Peatbog	25.3	44.8

	CORINE Land Cover 2018 FI, 20 m (CLC2018FI.20m)	https://ckan.ymparisto.fi/dataset/corine-maanpeite-2018	National	2018, 20 m	Remote sensing and database	20 m	BFPL, CFPL, MFPL, TWPL, peatbog, TIM, and AIM	28.6	62.0
960	Note: BFPL, CFPL, MFPL, TWPL, TIM, and AIM indicate <i>Broad-leaved forest on peatland, Coniferous forest on peatland, Mixed forest on</i>								
961	<i>peatland, Transitional woodland/shrub cc 10-30% on peatland (cc = canopy closure), Terrestrial inland marsh, and Aquatic inland marsh,</i>								
962	respectively.								

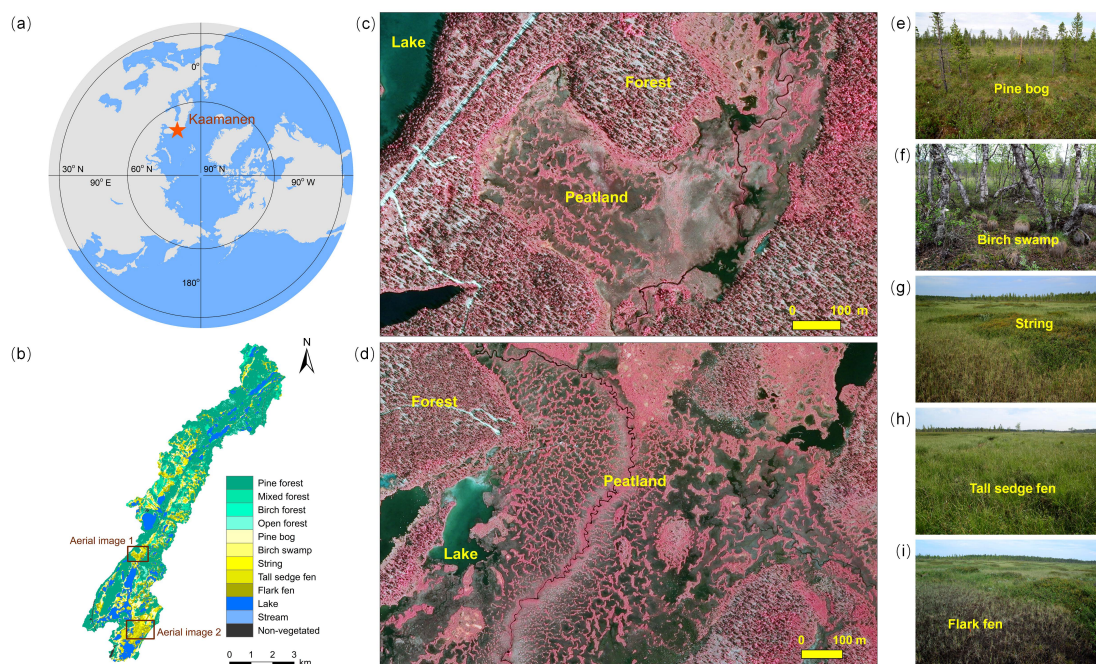


Figure 1. Location (a), land cover types (b), 0.5-m resolution false color aerial images (c-d), and photographs of different peatland types (e-i) of the Kaamanen catchment. Panels (c) and (d) correspond to Aerial image 1 and 2, respectively, in panel (b).

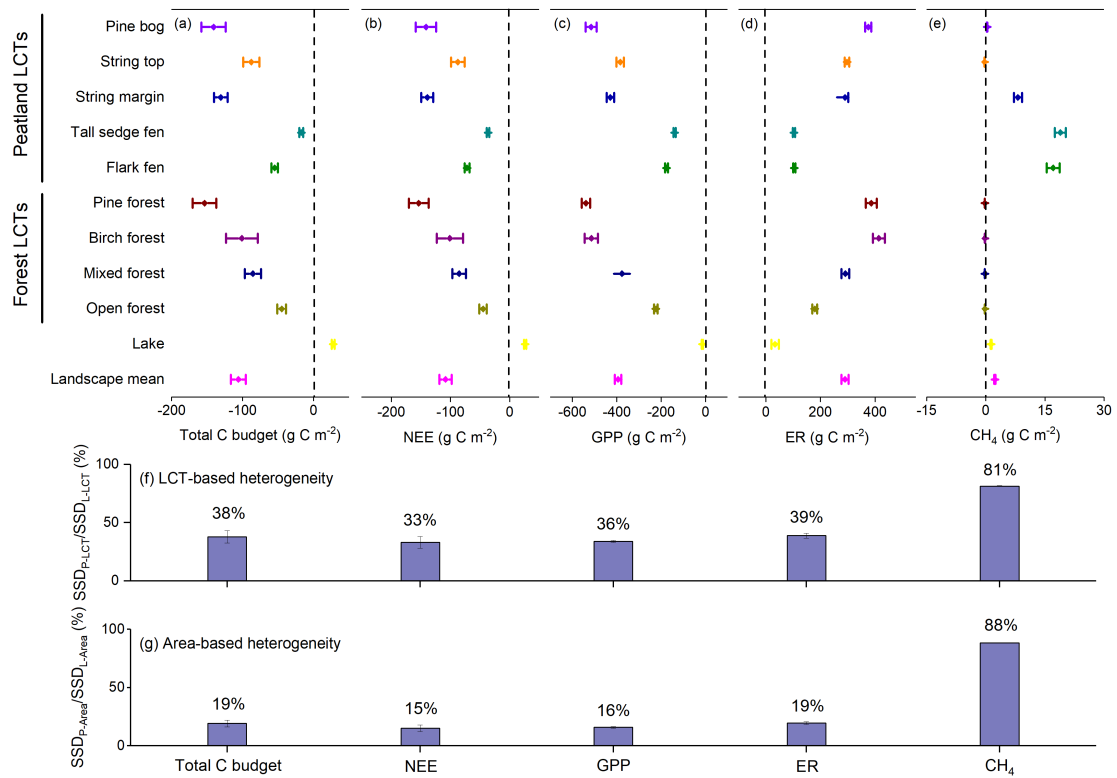


Figure 2. Heterogeneity in carbon (C) budget within the Kaamanen boreal landscape during 2005-2018. (a) Net C budgets combining carbon dioxide (CO₂) and methane (CH₄) among land cover types (LCTs) and their area-weighted landscape mean; (b) CO₂ budgets (net ecosystem CO₂ exchange, NEE); (c) Gross primary productivity (GPP); (d) Ecosystem respiration (ER); (e) CH₄ budgets; (f) Ratio between the Sum of Squared Deviations (SSD) from the arithmetic mean C budget among peatland LCTs (SSD_{P-LCT}) and that among all landscape LCTs (SSD_{L-LCT}); (g) Ratio between the SSD from the area-weighted landscape mean among peatland LCTs (SSD_{P-Area}) and that among all landscape LCTs (SSD_{L-Area}). In panels (a)-(e), a positive value means output from the ecosystem being a C output. The diamond symbol in panels (a)-(e) and the bar and number in panels (f)-(g) indicate the mean annual value, and the error bar in all panels denotes the 95% confidence interval.

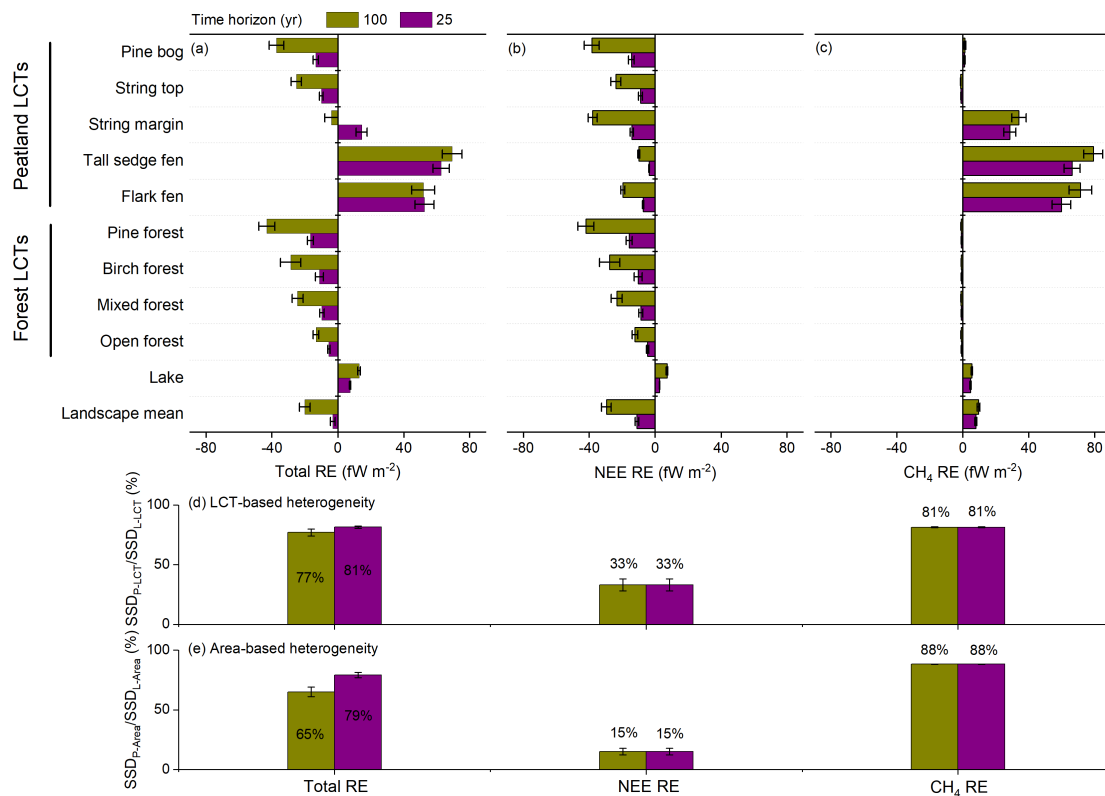


Figure 3. Heterogeneity in radiative effect (RE) of present carbon (C) budget within the Kaamanen boreal landscape. (a) Total RE due to carbon dioxide (CO₂) and methane (CH₄) exchange of different land cover types (LCTs) and their area-weighted landscape mean; (b) RE due to CO₂ exchange; (c) RE due to CH₄ exchange; (d) Ratio between the Sum of Squared Deviations (SSD) from the arithmetic mean RE among peatland LCTs (SSD_{P-LCT}) and that among all landscape LCTs (SSD_{L-LCT}); (e) Ratio between the SSD from the area-weighted landscape mean among peatland LCTs (SSD_{P-Area}) and that among all landscape LCTs (SSD_{L-Area}). The RE represents the cumulative RE due to an annual emission or uptake pulse over time horizons of 25 and 100 yr, calculated based on C flux densities (g m⁻² yr⁻¹, i.e., flux per m² of each LCT) during 2005-2018 and assuming the RCP4.5 scenario. The diamond symbol in panels (a)-(c) and the bar and number in panels (d)-(e) indicate the mean annual value, and the error bar in all panels denotes the 95% confidence interval. 1fW = 10⁻¹⁵ W.

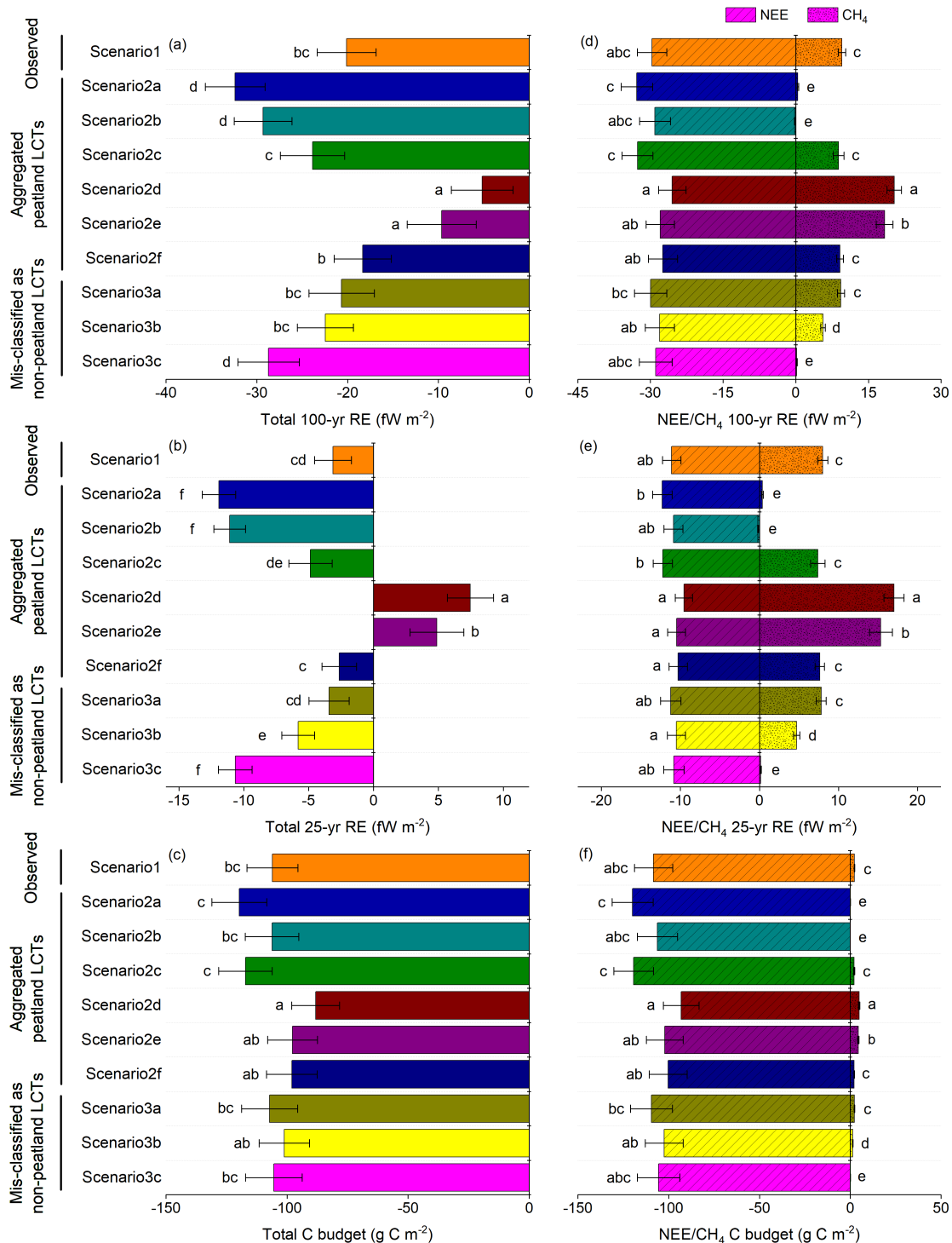


Figure 4. Uncertainty in radiative effect (RE) of landscape-scale carbon (C) budget due to aggregation or misclassification of peatlands. RE is calculated based on the C budget during 2005-2018 assuming the RCP4.5 scenario. (a-b) Total RE calculated based on landscape-scale total C budget with 100-yr and 25-yr time horizons; (c) Landscape-scale total C budget during 2005-2018; (d-e) RE calculated based on

1001 landscape-scale CO₂ and CH₄ budgets with 100-yr and 25-yr time horizons; (f)
 1002 Landscape-scale CO₂ and CH₄ budgets. RCP4.5 scenario is assumed for RE. Scenario
 1003 1 is based on the observed land cover type (LCT) data described in [Table 2](#). In scenario
 1004 2, peatlands are not distinguished but assumed to consist of a single type (in 2a-2e, pine
 1005 bog, string top, string margin, tall sedge fen, and flark fen, respectively). In scenario 2f,
 1006 all dry peatlands are allocated to string top and all water-logged peatlands are classified
 1007 as tall sedge fen. In scenario 3, peatlands are mis-classified as non-peatland LCTs: (3a)
 1008 forested peatlands (pine bog and birch swamp) as corresponding forests (pine and birch
 1009 forest, respectively), (3b) the open water-logged peatland with low vegetation cover
 1010 (flark fen) as lake, and (3c) the simultaneous occurrence of scenarios 3a and 3b and a
 1011 misclassification of all other open peatlands (string top, string margin, and tall sedge
 1012 fen) as open dry peatland (represented by string top). The bar and error bar in the plot
 1013 represent the mean value and its 95% confidence interval, respectively, and the letters
 1014 denote the statistical difference among different scenarios. 1fW = 10⁻¹⁵ W.

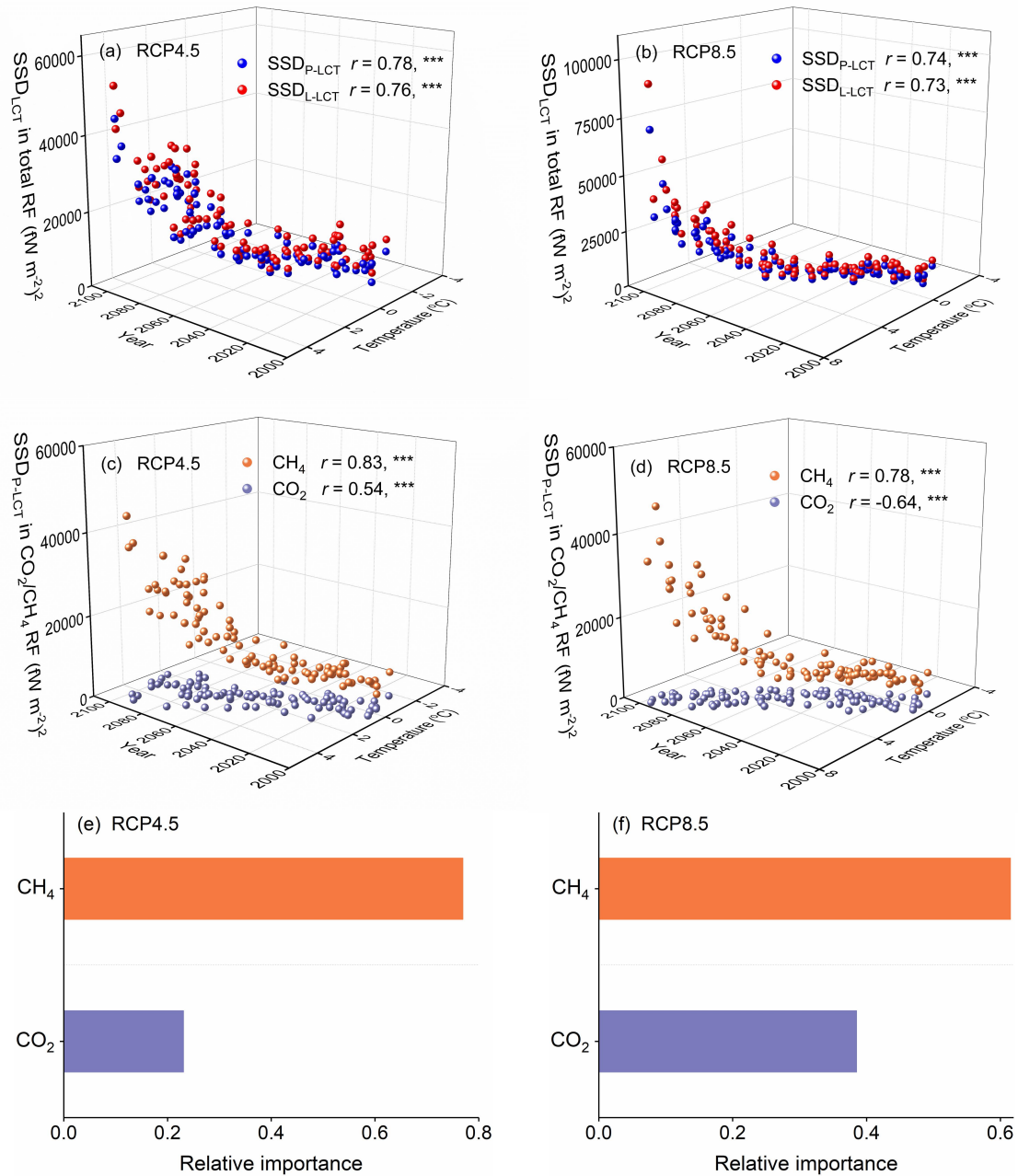


Figure 5. Potential trajectory of heterogeneity in radiative effect (RE) among different land cover types (LCTs) under future warming scenarios (RCP4.5 and RCP8.5). RE represents the cumulative RE due to an annual emission or uptake pulse over the 100-yr time horizon, calculated based on flux densities ($\text{g m}^{-2} \text{yr}^{-1}$, i.e., flux per m^2 of each LCT) of CO₂ and methane CH₄ during 2005-2099. (a)-(b) Sum of Squared Deviations (SSD) from the mean total RE among peatland LCTs (SSD_{P-LCT}) and that among all landscape LCTs (SSD_{L-LCT}); (c)-(d) SSD_{P-LCT} of the CO₂- and CH₄-induced

1023 RE; (e)-(f) Relative importance of CO₂ and CH₄ in explaining the trend in total RE
1024 heterogeneity among peatlands. *** denotes $p < 0.001$. In all panels, r denotes the
1025 correlation coefficient between SSD and temperature. To reflect warming effects,
1026 biogeochemical models were driven with variable temperature while other input data
1027 were kept constant (2005-2018 averages). $1\text{fW} = 10^{-15} \text{ W}$.

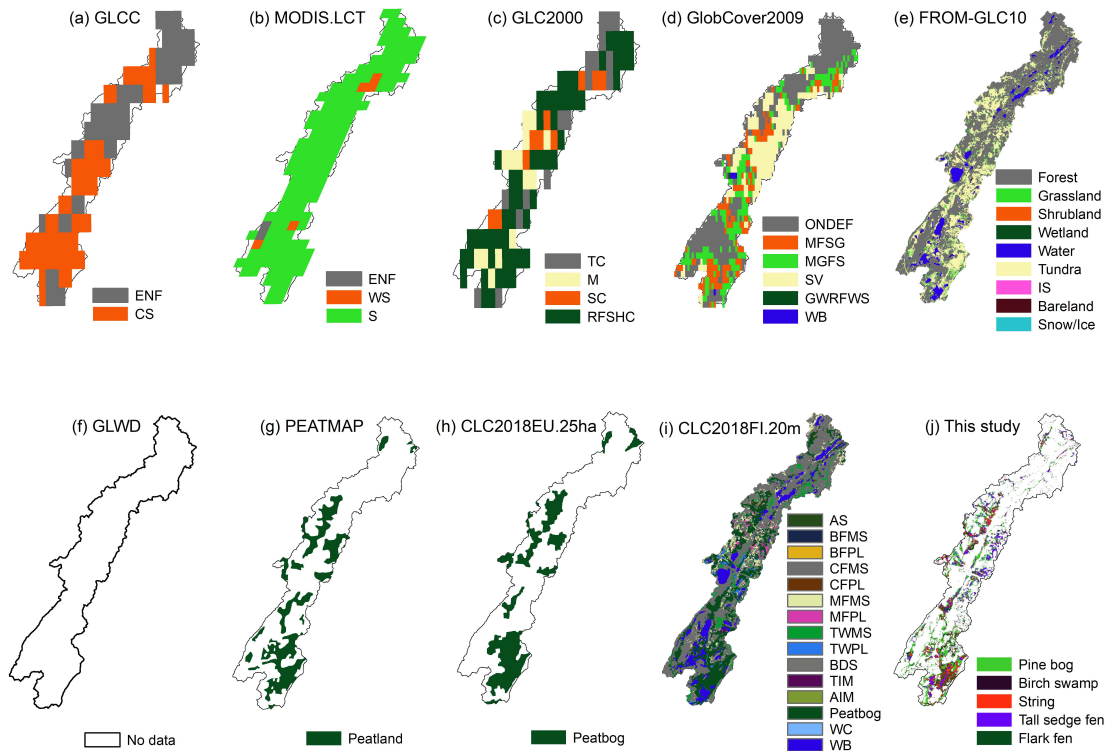


Figure 6. Land cover of the Kaamanen boreal landscape classified by global (a-g), continental (h), and national (i) land cover products and this study (j). (a) GLCC; (b) MODIS.LCT; (c) GLC2000; (d) GlobCover2009; (e) FROM-GLC10; (f) GLWD; (g) PEATMAP; (h) CLC2018EU.25ha; (i) CLC2018FI.20m; (j) Peatland types revealed by this study. For GLCC, ENF = *Evergreen Needleleaf Forest* and CS = *Closed Shrublands*, respectively; for MODIS.LCT, ENF = *Evergreen Needleleaf Forests*, WS = *Woody Savannas*, and S = *Savannas*, respectively; for GLC2000, TC = *Tree Cover (needle-leaved, evergreen)*, M = *Mosaic (Tree cover / Other natural vegetation)*, SC = *Shrub Cover (closed-open, deciduous (with or without sparse tree layer))*, and RFSHC = *Regularly flooded shrub and/or herbaceous cover*, respectively; for GlobCover2009, ONDEF = *Open (15-40%) needleleaved deciduous or evergreen forest (>5m)*, MFSG = *Mosaic forest or shrubland (50-70%) / grassland (20-50%)*, MGFS = *Mosaic grassland (50-70%) / forest or shrubland (20-50%)*, SV = *Sparse (<15%) vegetation*, GWRFWS = *Closed to open (>15%) grassland or woody*

1043 *vegetation on regularly flooded or waterlogged soil - Fresh, brackish or saline water,*
1044 *and WB = Water bodies, respectively; for FROM-GLC10, IS = Impervious surface; for*
1045 *CLC2018EU.25ha, there are three classes within the Kaamanen landscape (Coniferous*
1046 *forest, Peatbog, Water body) and only Peatbog is shown here; for CLC2018FI.20m,*
1047 *AS = Artificial surface, BFMS = Broad-leaved forest on mineral soil, BFPL = Broad-*
1048 *leaved forest on peatland, CFMS = Coniferous forest on mineral soil, CFPL =*
1049 *Coniferous forest on peatland, MFMS = Mixed forest on mineral soil, MFPL = Mixed*
1050 *forest on peatland, TWMS = Transitional woodland/shrub on mineral soil, TWPL =*
1051 *Transitional woodland/shrub on peatland, BDS = Beach, dune, and sand plain, TIM =*
1052 *Terrestrial inland marsh, AIM = Aquatic inland marsh, WC = Water course, and WB*
1053 *= Water body, respectively; for our classification, only peatland classes are shown here.*
1054 More information about the land cover products is presented in [Table 3](#).