



PeatCover: Towards a peat mapping at 90 m using satellite remote sensing and a priori inventories

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Abstract. Peatlands cover just 3-4% of Earth's land surface, yet store an estimated 600-700 Pg carbon (PgC), approximately one-third of Earth's soil carbon, making them critical regulators of the global carbon cycle. However, their spatial extent remains highly uncertain, particularly at fine spatial scales and in data-sparse regions. Existing global peatland datasets rely on inventories and regional products of heterogeneous quality, leading to inconsistencies and uncertainties in both estimated peat area and its spatial distribution. These limitations hinder accurate assessments of peatland-climate feedbacks, carbon budgets, policy development and restoration efforts. Here we propose a machine learning framework to map Northern peatland (boreal and subarctic) at a spatial resolution of 90 m that combines a priori information from existing peat databases (PEATMAP, Global Peatland Database, and CORINE Land Cover) with satellite observations (Landsat optical indices, topographic and hydrological data). The model first generates a continuous Peatland Index (PI) at 3 arc-second (~90 m) resolution, that can be combined with user-defined thresholds to obtain a binary peat classification. In regions with reliable coarse resolution peat cover information, the PI is used to downscale this peat fraction and obtain a high resolution classification. Our peatland map at 90 m was evaluated through both quantitative and qualitative approaches. Fully independent validation using the PeatDBase field dataset (over 180,000 peat and non-peat observations) demonstrates an overall accuracy of 69.0% and an F1-score of 0.81. Regional comparisons with published maps shows an overall accuracy of 69.9% (F1=0.82) in Eurasia and of 63.9% (F1=0.74) in North America. Qualitative spatial evaluation against Google Earth map across multiple case-study regions reveals that our map successfully captures fine-scale spatial details absent in existing inventories, including explicit delineation of open water bodies, river networks, and topographic constraints on peatland distribution. This work provides a spatially coherent, high-resolution peatland dataset spanning the Northern Hemisphere, offering improved capabilities for carbon stock estimation, hydrological modeling, and monitoring peatland degradation. The PeatCover dataset is available at <https://doi.org/10.5281/zenodo.21031869> (Chen et al., 2026).



1 Introduction

Peatlands are an important component of the terrestrial biosphere. These ecosystems are the most efficient long-term carbon sink but can switch to carbon source from land use change and climate change (Hugelius et al., 2020a; Loisel et al., 2021). Peatlands only account for about 3–4% of the terrestrial surface (Dargie et al., 2017; Minasny et al., 2024), but they store 600 to 700 Pg C of organic carbon (Mander et al., 2025; Leifeld and Menichetti, 2018; Hugelius et al., 2020a). This is one-third of the global soil organic carbon stock and more than double the carbon stored in global forest biomass (Loisel et al., 2021; Kopansky et al., 2022). The build up of this massive carbon stock is the result of millennia of carbon accumulation under anaerobic conditions, where the rate of net primary productivity has consistently exceeded microbial decomposition since the early Holocene (Frolking et al., 2011). Beyond their role in the carbon cycle, peatlands regulate regional hydrological cycles by mitigating peak and minimum flows and purifying water, while providing essential habitats for specialized biodiversity (Austin et al., 2025). Peatlands are increasingly vulnerable to anthropogenic and climate-driven disturbances including drainage, land-use conversion, permafrost thaw, and wildfire, which can rapidly transform them from long-term carbon sinks into large sources of greenhouse gas (GHG) emissions (Loisel et al., 2021; Canadell et al., 2021).

The vast majority of the global peatland area is concentrated in the Northern Hemisphere, accounting for more than 80% of the total extent (Xu et al., 2018; Kopansky et al., 2022; Wilkinson et al., 2023), mainly in the boreal and subarctic domains of Eurasia and North America. These high-latitude regions are currently warming at two to three times the global average rate (Rantanen et al., 2022; Masson-Delmotte et al., 2021). This rapid thermal forcing, coupled with anthropogenic disturbances such as drainage for forestry and agriculture in some regions, threatens to destabilize these ancient carbon reservoirs (Fluet-Chouinard et al., 2023). In permafrost-affected peatlands, which host nearly half of the northern peat area and carbon stock (Hugelius et al., 2020a), rapid thaw can trigger thermokarst formation and ground ice collapse (Turetsky et al., 2020), potentially shifting these long-term carbon sinks toward significant sources of methane (CH_4) and carbon dioxide (CO_2).

A fundamental barrier to accurate carbon-climate feedback projections and assessments of the role of peat in the carbon cycle and greenhouse gas budgets is the high level of spatial uncertainty in existing peatland inventories (Minasny et al., 2024). Peatland mapping efforts (Table 1) can be broadly grouped into compilation-based strategies (predominantly bottom-up) and Earth Observation (EO) modeling (predominantly top-down) (Minasny et al., 2024). Compilation-based approaches derive the extent of the peat from peat surveys, soil inventories, and expert interpretation of aerial photography (Xu et al., 2018; Kopansky et al., 2022). Products such as PEATMAP (Xu et al., 2018) and the Global Peatland Database (GPD) (Kopansky et al., 2022) represent the most comprehensive available global syntheses of a priori knowledge, as they incorporate field investigations that are reliable in data-rich regions. A related strategy derives peatland extent directly from harmonized soil taxonomy databases, identifying organic soils through their classification as Histosols and Histels. Hugelius et al. (2020a) used this approach by combining SoilGrids250m (Hengl et al., 2017) with national soil inventories maps to produce a fractional peatland coverage map at 10 km resolution in the Northern Hemisphere ($> 23^\circ$ latitude). Such soil-based approaches provide spatially consistent estimates of organic soil occurrence across large domains and are particularly useful for constraining peat carbon stocks.



Table 1. Summary of some peatland datasets and ML-based peatland mapping products. The datasets used in this study are listed in blue.

Dataset	Method	Area	Time	Resolution	Data Source/ Target	Mapped Peat Characteristics	Char- Covariates/ Input	Model	Result	Reference
PEATMAP	Inventory	Global	2018	Polygon	Integrated inventories	Peat/Non-peat, fraction	Peat —	Meta-analysis	—	(Xu et al., 2018)
GPD	Inventory (bottom-up)	Global (268 countries)	2022/2024	1 km	>200 datasets	Peat/Non-Peat (1=peat dominated, 2=peat in soil mosaic)	—	—	—	(Kopansky et al., 2022)
ESA CCI Land Cover	Remote sensing	Global	2022	300 m	Multi-sensor satellite data (AVHRR, MERIS, SPOT-VGT, PROBA-V, Sentinel-3)	wetlands, grasslands, forests, etc. (without a specific peat class)	—	Automated supervised classification	—	(ESA, 2017)
CORINE land cover	RS + Visual interpretation	Europe	2018	100 m/polygon	RS imagery + Expert interpretation	Peat bogs (412)	—	—	—	European Environment Agency (2018)
Peat-DBase	In situ	Global	—	Point	Peat(Extracted from multiple publications); Nonpeat (WoSIS)	Peat depth	—	—	—	(Skye et al., 2025)
O-horizon	In situ	Global	—	Point	Extracted from several publications	Peat depth	—	—	—	Unpublished from Hugelius et al.
Harmonized soil type coverage soil profile databases	inventory-based and estimates	North of 23° N	—	10 km	Integrated from national soil databases and Grids250m (Hengl et al., 2017)	Histosols and Histels percentage	—	—	peatland extent, depth, carbon storage and nitrogen storage	(Hugelius et al., 2020b)
Wet Horizons	Aggregation	Europe	1991–2024	Polygon	Integration (Multiple land inventories)	wet- Peatland	—	—	—	Wet Horizons DB (unpublished)
Peat-ML	ML	Global	2022	5' km	(~9 Peat fraction	Peat fractional cover age	Climate, soil, topography, vegetation	LightGBM	Global peat fraction map	(Melton et al., 2022)
ABoVE	ML	Alaska and part of Canada	1984–2014	30 m		15-class (11-fen, 12-bog)/10-class (7-fen, 8-bog)		RF	31-year LC series	Wang et al. (2019)
CWIM3 (Canada Wetland Map)	ML	Canada	2021	10m	8804 wetland + 15691 non-wetland polygons (about 1–100 ha)	bog, fen, swamp, wetland	DEM, lights, climate, water S1/S2, ALOS	Object-based RF	OA 90.53%	(Mahdianpari et al., 2021)
HCF	ML	Canadian boreal forest	2024	30 m	Publications + unpublished data; 17,000 points (3456 peat)	Bog, rich/poor land, water...	S1/S2, GEDI, DEM, RF + SHAP		OA 86.5–93.3%	(Pontone et al., 2024)
Treed Peatlands	ML	Canada	2011	250 m	Canada NFI (450 plots)	Treed peatland	Forest structure, climate, topography	BRT/ Logistic Reg.	OA 87–88%	(Thompson et al., 2016)
BAWLD	ML	Boreal–Arctic	2022	0.5° grid	29 expert-assessed wetland fractions	five wetland, lake, three river, four other classes	53 variables from 15 datasets	RF		(Olefelt et al., 2021)
Alaska Peatland Map	ML	Alaska	2019–2021	20 m	Peat presence (>40 cm organic layer)	Wet peat, Moist peat	Sentinel-2, Sentinel-1, ArcticDEM, droSHEDS	SVM (RBF kernel), ecoregion-specific models	OA 85%	(Lara et al., 2025)



Despite these strengths, compilation-based inventories are constrained by the quality and spatial extent of localized primary
 55 surveys (Melton et al., 2022). In particular, differences in peatland definitions (based on organic soil criteria or minimum
 depth thresholds) and resolution to display “geopolitical discontinuities”. Moreover, inventories are rarely wall-to-wall products,
 which may cause inconsistent quality for different spatial regions. As a consequence, they lack the ability for repeatable
 temporal dynamic monitoring required to track peatland degradation, drainage, or restoration over time.

In parallel, EO-based modeling has emerged to provide repeatable assessments in large areas. Currently, EO peatland prod-
 60 ucts are provided in two primary representational forms: fractional coverage grids and categorical location maps. Fractional
 products, such as Peat-ML (Melton et al., 2022), which provides continuous percentages of peat coverage within coarse-
 resolution pixels (e.g., 9 km). Although well-suited for Earth system modeling applications that require area-weighted fluxes,
 these representations do not resolve the spatial configuration of peat bodies within the landscape and therefore cannot indi-
 cate their precise location (Minasny et al., 2024; Olefeldt et al., 2021). Categorical products provide explicit peatland extent
 65 but remain largely confined to national or regional domains. High-resolution products, such as the 10 m Canadian Wetland
 Inventory Map (CWIM3) (Mahdianpari et al., 2021) and the 20 m map of Alaska (Lara et al., 2025), demonstrate localized
 improvements, yet remain within national boundaries. To our knowledge, a spatially coherent, high-resolution, categorical,
 northern peatland map does not exist yet.

In EO-based mapping, multi-spectral optical data are effective for capturing characteristic surface expressions of peatlands
 70 (Burdun et al., 2023; Ball et al., 2023; Abdelmajeed and Juszczak, 2024; Ghazaryan et al., 2024) associated with peat-forming
 plant functional types such as Sphagnum mosses, sedges, and shrubs, often in combination with water table at or near the peat
 surface. (Reynolds et al., 2025). These expressions arise from reflectance patterns in the near-infrared (NIR) and shortwave
 infrared (SWIR) regions that are sensitive to vegetation water content and chlorophyll-related absorption features, allowing
 optical observations to characterize the moist surface conditions typical of undrained mire ecosystems (Kolari et al., 2022;
 75 Isoaho et al., 2024). Nevertheless, the diagnostic utility of optical spectral information is often compromised in tree covered
 peatlands, when surface signals from peat-forming vegetation are obscured by upper vegetation. To address these ambiguities,
 the integration of hydro-geomorphological drivers is essential, as peatland formation and persistence are primarily governed
 by hydrological conditions (Price et al., 2023; McCarter et al., 2024), with topography exerting a first-order control through its
 regulation of water ponding and local water table depth (Sun et al., 2023). Terrain-derived indices such as the Height Above
 80 Nearest Drainage (HAND) (Rennó et al., 2008; Yamazaki et al., 2019) therefore provide physically meaningful proxies for
 hydrological connectivity and environmental suitability for peat accumulation.

In this study, we introduce PeatCover, a hybrid framework designed to retrieve a spatially coherent 3 arc-second (~90 m)
 resolution peatland map across the northern peatland domain, encompassing Europe, Russia, Canada, and Alaska (to be com-
 85 plemented in the future). Within this framework, peatlands are defined as organic soils with peat thickness exceeding 30 cm,
 consistent with commonly used definitions in global peatland inventories and with the validation dataset used in this study.
 Although individual inventories may adopt slightly different criteria, the 30 cm threshold provides a broadly comparable def-
 inition across datasets. Our approach downscales information from existing databases (PEATMAP, GPD, and CORINE Land
 Cover) with multi-source satellite observations. Using a neural network model informed by optical, topographic, and hydrolog-



ical information, PeatCover first generates a continuous Peatland Index (PI) to map the likelihood of the presence of peatland.

90 The PI is then constrained using existing peatland inventories to downscale coarse peatland information, enabling the genera-
 tion of a high-resolution categorical peatland map that preserves spatial heterogeneity while remaining quantitatively consistent
 with established regional peatland extents. By explicitly bridging inventory-based peatland maps and EO-driven spatial infor-
 mation, PeatCover provides a consistent wall-to-wall peatland map for the Northern Hemisphere. This framework is intended
 to support improved carbon stock estimation, hydrological modeling, and monitoring of peatland degradation and restoration
 95 at spatial scales relevant to both scientific analysis and policy implementation.

2 Datasets

All of the following databases have been split into $5^\circ \times 5^\circ$ tiles and projected/rasterized at 3 arc-seconds (approximately 90 m
 at the equator). The characteristics of the peat databases are gathered in Table 1 that provides the main characteristics of some
 available peatland databases. Fig. 1 displays a sample $5^\circ \times 5^\circ$ tile ($65\text{--}70^\circ\text{N}$, $27\text{--}32^\circ\text{E}$) located at the border between eastern
 100 Finland and Northwest Russia, illustrating the datasets used in this study. Panels (a-c) represent the three peat databases that
 are used in this study as a priori information. They show also some of the inputs to the model that will be developed in the
 following section. Satellite data are surface reflectances (d) from the Landsat instrument. Auxiliary data (e-h) are topographic
 information from the MERIT database (Yamazaki et al., 2017, 2019). The model also uses the Water Table Depth (WTD) from
 Fan et al. (2013) (i). In the top row, the inconsistent resolution of PEATMAP and GPD data (east and west) is apparent. In
 105 contrast, other model inputs in the following rows show a continuous east/west pattern.

2.1 Model peat labels

2.1.1 PEATMAP

PEATMAP is a globally and openly available peatland distribution dataset (Xu et al., 2018). It was constructed by combining
 many existing datasets at national, regional, and global levels. The primary sources are national inventories, including official
 110 soil surveys, geological surveys, and wetland inventories from individual countries. These cover, for example, Finland, Sweden,
 Ireland, the United Kingdom, Canada, the United States, Indonesia, Malaysia, Australia, Tasmania, and New Zealand. In
 regions where national data were not available, PEATMAP relied on broader regional or global products, such as the European
 Soil Database (Hiederer et al., 2013); the Russia Wetland Database (Stolbovoi et al., 2002); the Northern Circumpolar Soil Map
 (Tarnocai et al., 2002); and the Harmonized World Soil Database (HWSD) (Nachtergaele et al., 2010). In addition, some areas
 115 include research-based products, such as China, the Congo basin, and other areas of tropical peatlands. The combined product
 was harmonized into a GIS shapefile database in the World Cylindrical Equal Area projection. It includes different formats
 and spatial resolutions, some input data represented peat as binary presence or absence, while others, like Canada, represented
 it as fractional coverage over complex hand-drawn polygons of various size. PEATMAP has been widely used in studies of
 peatlands and carbon stocks (Noon et al., 2022; Sasmito et al., 2025; Xi et al., 2021). However, this database is not harmonized

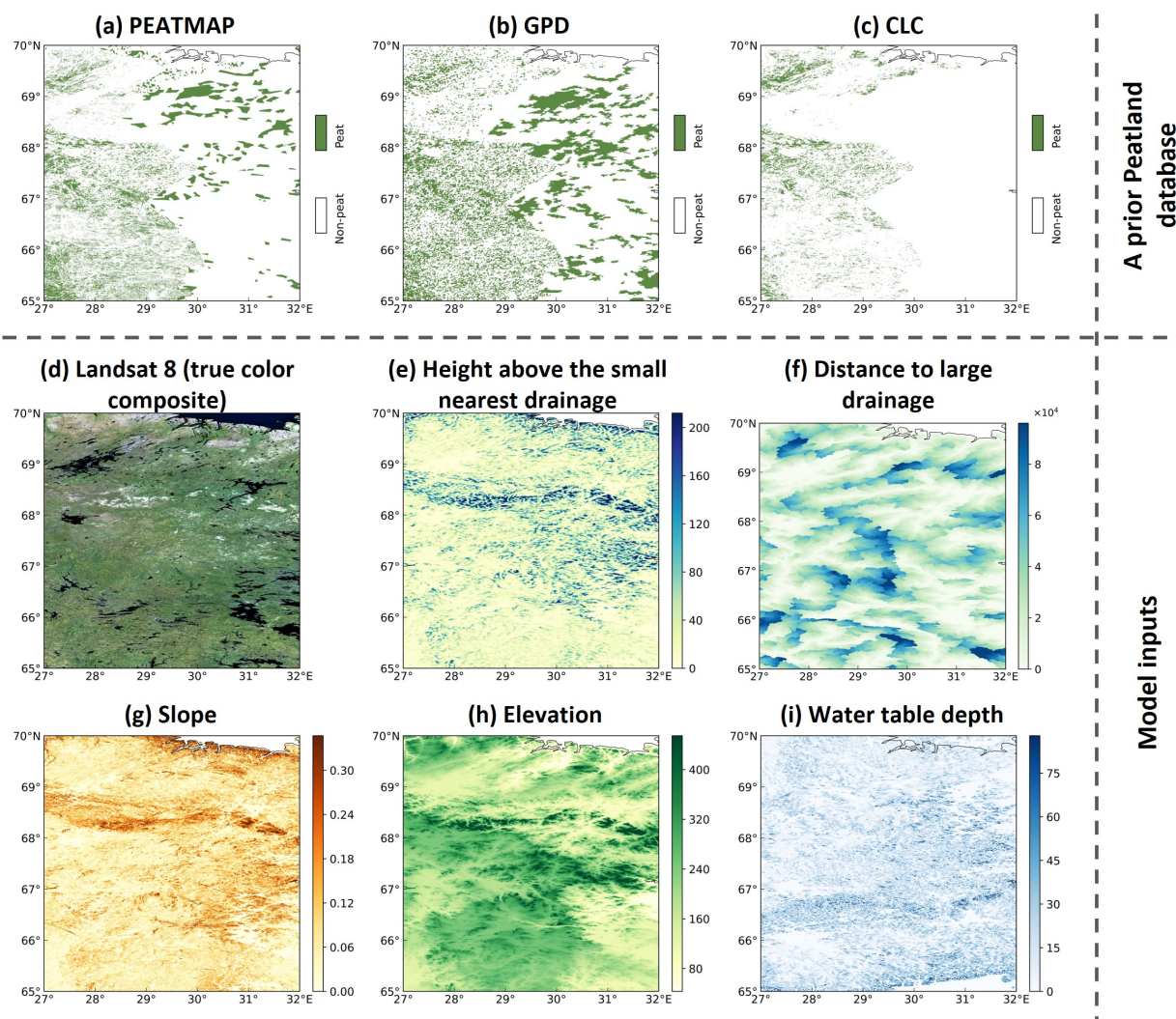


Figure 1. Example of a $5^{\circ} \times 5^{\circ}$ tile illustrating the input datasets used in this study. (a–c) Peat a priori information from three peatland databases: PEATMAP, GPD, and CLC. (d) Landsat 8 true-colour composite derived from surface reflectance data. (e–h) Topographic and hydrological variables derived from the MERIT DEM and MERIT Hydro datasets, including height above the nearest drainage, distance to drainage, slope, and elevation. (i) WTD from Fan et al. (2013). The upper row illustrates structural differences among peat inventories within the same tile, while the lower panels show the continuous environmental variables used as model inputs.

120 and its spatial resolution varies across regions and countries. In some areas, the spatial resolution remains too coarse for some applications. The quality of the database depends entirely on the data sources (national inventories): in some areas, quality is lower, e.g. the data is very incomplete over Russia.



In this study, we used PEATMAP in two different ways to maximize data fidelity. For most global regions, we employ the binary presence/absence data provided by PEATMAP to support our classification approach. However, for the Canadian region, we used the fractional coverage data to perform a continuous regression analysis. The Canadian component of PEATMAP is derived from the Peatlands of Canada Database (Tarnocai et al., 2011), which consists of polygons based on official soil surveys and air photo interpretation. Unlike other regions, this database provides bog, fen, and bog-fen features with peat coverage $\geq 1\%$ within each of the database polygons. PEATMAP aggregates these peat-related classes and retains polygons with a total peat fraction exceeding 5%. By using these continuous fractions rather than simplified categorical labels used in GPD (see Sect. 2.1.2), we avoid the information loss inherent in categorical datasets and the potential overestimation of peat area..

2.1.2 Global Peatland Database (GPD)

GPD is a bottom-up inventory of the world's peatlands, initially compiled to support the United Nations Environment Programme (UNEP) Global Peatlands Assessment (GPA) (Kopansky et al., 2022). The database has since evolved into the Global Peatland Map 2.0, which was further developed and updated by the Greifswald Mire Centre (Global Peatland Database / Greifswald Mire Centre, 2024). In this study, we refer to this spatial dataset as GPD, specifically utilizing the version 2.0 product.

The GPD database was compiled from more than 200 sources, including field mapping campaigns to fill some important data gaps. It represents peatlands on a global $1\text{ km} \times 1\text{ km}$ grid. Each grid-cell has two possible categories: 1 = peat-dominated, and 2 = peat in soil mosaic; the latter based on expert judgment about where peat occurs as part of a soil complex. GPD is a relatively recent global peatland map. It is built using different classification systems and information sources that influence the consistency and accuracy of the product. As a result, the reliability of the map is not uniform, and its level of accuracy differs between regions (UNEP, 2022). The developers note that, for instance, the extent of the peat may be overestimated in Indonesia and Malaysia. Compared to PEATMAP, GPD shows a larger area of peat in eastern Russia and the United States.

Notably, for the Canadian region, GPD incorporates the same underlying data sources as PEATMAP (Tarnocai et al., 2011). However, our analysis suggests that GPD simplifies these source polygons into discrete categories by applying specific thresholds: approximately 50% and 20% peat fraction to define Class 1 and Class 2, respectively. This conversion results in a significant loss of fine-scale spatial information. For example, a polygon with 50% peat coverage is uniformly classified as “peat-dominate” (Class 1) in GPD, creating a “50% to 100% jump” in represented area. This approach inherently overestimates peat presence and fails to identify the precise locations of peat within the landscape.

2.1.3 CORINE Land Cover (CLC)

The CLC database are European maps created as part of the Copernicus Land Monitoring Service (European Environment Agency, 2018). The main goal of this database is to describe how land is used across Europe, in a consistent way. It covers all EU member states and several neighboring countries, including Norway, Switzerland, the United Kingdom, and the Western Balkan countries. CLC is updated every six years, with land cover maps released for the years 1990, 2000, 2006, 2012, 2018, and 2023. The CLC maps are obtained using satellite images in the visible spectrum such as Landsat, SPOT, and Sentinel-2.



The classification process combines automated pre-classification and manual visual interpretation by national experts. It is provided in vector and raster formats (100 m resolution), with a minimum mapping unit of 25 ha. CLC uses a three-level classification system. In total, there are 44 types of land-cover. Each type describes a different surface, such as forests, crops, wetlands, water, or cities. Among these types, there is a class for “peat bog” (class 412). This class includes areas where
 160 peat soil is deeper than 30 cm and the surface is usually wet or waterlogged. It includes several peatland sub-types such as valley bogs, raised bogs, blanket bogs, and quaking or floating bogs. The surface of these areas can be covered by mosses (e.g. sphagnum), sedges, or grasses, but sometimes it has little or no vegetation. The peat bog class (412) focuses on the presence of peat soil, not the type of vegetation on top. However, in many regions, peatlands are not always visible in optical images, especially when the surface is heavily vegetated or forested. When peatlands are covered by grasslands, shrubs, or forests,
 165 they are often classified as other CLC categories such as natural grasslands (class 321), moors and heathland (class 322), or transitional woodland–shrub (class 423). Because of this, the CLC dataset may underestimate the true extent of peatlands in Europe. In this study, we used the 2018 vector version of the CORINE dataset, provided in the ETRS89-LAEA projection. We extracted the peat bog class (412), reprojected it to WGS84, and saved the output as a GeoPackage file.

2.1.4 ESA CCI-Water bodies

170 The European Space Agency’s Climate Change Initiative (ESA CCI) Land Cover product (ESA, 2017; Copernicus Climate Change Service (C3S), 2019) provides an annual global land cover time series derived from multiple satellite sensors, including MERIS, ASAR and AVHRR. For this study, we used the 2022 global map, provided at a native spatial resolution of 300 m and classified into a hierarchical system of 6 main classes and 36 sub-classes. Peatlands are not explicitly represented in this dataset. We specifically used the Water Bodies class (code 210) as an ancillary mask. This layer is essential for mitigating
 175 systematic errors present in coarse-resolution peatland inventories such as GPD and PEATMAP, particularly in regions with extensive lakes and water-filled depressions (e.g., Siberia and northern North America). These inventories, due to their limited effective resolution, frequently misclassify open water bodies (e.g., lakes, ponds, or water-filled depressions) located within large peatland complexes as part of the surrounding peatland matrix. This leads to localized overestimation of peatland extent and introduces significant noise into the training labels, confounding the spectral distinction between peat soils and water. The
 180 ESA CCI Water Bodies class was therefore incorporated into the training data construction to identify and exclude permanent water pixels. These pixels were assigned to the non-peat class, reducing confusion between peat soils and open water and improving the reliability of the non-peat training labels.

2.2 Model inputs variables

The characteristics of each input is summarized in Table 2.



Table 2. Input variables for Peatland Index (PI) model

Variable	Source	Description	Unit
Coastal Aerosol	Landsat 8 OLI	Coastal/Aerosol (0.43–0.45 μm)	-
Blue	Landsat 8 OLI	Blue (0.45–0.51 μm)	-
Green	Landsat 8 OLI	Green (0.53–0.59 μm)	-
Red	Landsat 8 OLI	Red (0.64–0.67 μm)	-
NIR	Landsat 8 OLI	NIR (0.85–0.88 μm)	-
SWIR 1	Landsat 8 OLI	SWIR-1 (1.57–1.65 μm)	-
SWIR 2	Landsat 8 OLI	SWIR-2 (2.11–2.29 μm)	-
NDVI	Calculated	$(Band_5 - Band_4) / (Band_5 + Band_4)$	-
dist0005	MERIT Hydro	Distance to small drainage ($\geq 0.05 \text{ km}^2$)	km
dist0100	MERIT Hydro	Distance to medium drainage ($\geq 100 \text{ km}^2$)	km
dist1000	MERIT Hydro	Distance to large drainage ($\geq 1000 \text{ km}^2$)	km
hand0005	MERIT Hydro	Height above small drainage	m
hand0100	MERIT Hydro	Height above medium drainage	m
hand1000	MERIT Hydro	Height above large drainage	m
slope	MERIT DEM	Terrain slope	
elevation	MERIT DEM	Terrain elevation	m
WTD	Fan et al. (2013)	Water table depth	m

185 2.2.1 Landsat 8 reflectances

The optical imagery dataset used in this study was derived from the Landsat 8 Collection 2 Level-2 surface reflectance products. Landsat 8, launched in February 2013, carries the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). The C2 L2 data products feature atmospherically corrected surface reflectance, making them particularly suitable for time-series analysis and multi-temporal studies of land cover.

190 Data acquisition was performed using Google Earth Engine (GEE), where we explored the availability of Landsat 8 data that span from 2013 to 2023 for each month of the year. To ensure high data quality, we implemented rigorous filtering by masking out clouds, cloud shadows, and snow/ice using the QA_PIXEL quality assessment band. Landsat 8 data were restricted to July acquisitions to maximize vegetation signal while avoiding snow cover prevalent in high-latitude winter months¹. Preliminary tests using additional months (June, August, and September) yielded similar model performance, confirming that July alone
 195 provides sufficient spectral information for peatland characterization.

The optical bands (Bands 1–7) were obtained. The Normalized Difference Vegetation Index (NDVI) was calculated using $NDVI = \frac{NIR - Red}{NIR + Red}$, where NIR represents Band 5 and Red represents Band 4 of Landsat 8. The inclusion of NDVI helps in identifying vegetation health and coverage over peatland areas.

¹ After analyzing the temporal coverage patterns, we determined that the months from June to September consistently provided sufficient data coverage across our study area, while other months exhibited significant data gaps due to cloud cover and seasonal limitations.



2.2.2 MERIT topography and hydrography

200 The MERIT Hydro database (Yamazaki et al., 2017, 2019) provides globally consistent topographic and hydrographic information at 3 arc-second resolution (~ 90 m). We extracted eight variables characterizing drainage network proximity and terrain position. Distance to drainage variables (dist0005, dist0100, dist1000) quantify lateral proximity to streams of different sizes, while height above nearest drainage variables (hand0005, hand0100, hand1000) characterize vertical position relative to the drainage network. These multi-scale descriptors capture the spectrum from local to regional hydrological connectivity, which is
 205 important for peatland formation and persistence. Elevation and slope were derived from the MERIT DEM after hydrological correction.

2.2.3 Water table depth (WTD)

A continuous global map of WTD was constructed by Fan et al. (2013) on a $30''$ grid. The groundwater model compiled 1,603,781 direct well measurements collected from government archives and published studies. Observation density is higher
 210 in North America and Europe, while data coverage is sparse in parts of Asia and Africa. To interpolate the WTD over a global grid, the model was driven by sea level, terrain, and present-day climate. Note that this study focuses primarily on broad-scale and natural patterns, neglecting human influences like pumping and drainage. A potential limitation of this dataset is that it does not account for the impact of the permafrost table on WTD, as exemplified by the deep water tables (>2.5 m) predicted across much of the permafrost-affected Boreal forest and tundra domain (Fan et al., 2013). Despite this limitation,
 215 the dataset still provides a reasonable representation of large-scale groundwater patterns relevant to peatland occurrence and therefore remains a valuable predictor, as it effectively captures the regional topographic and climatic gradients that govern environmental suitability for peatland formation.

2.3 Peat-DBase in situ dataset

Independent field observations were obtained from Peat-DBase (version 1.0), a harmonized global compilation of basal peat
 220 depth measurements (Skye et al., 2025), used exclusively for evaluation purposes and withheld from all stages of model training and calibration. The database comprises 204,902 records collected from 29 distinct sources and spans a wide range of climatic and physiographic settings. To ensure adequate representation of non-peat conditions, the peat observations are complemented by 94,615 mineral soil measurements derived from the World Soil Information Service (WoSIS) (Batjes et al., 2017). For evaluation purposes, only observations located within the study area were retained. Following the quality control protocols recommended by Skye et al., records flagged as erroneous (`error_found = True`) were excluded. Furthermore, potential dupli-
 225 cates were filtered using the accompanying duplication indicators, retaining only those with `sample_duplication_flag` values of 1, 2, 3, 4, or 5. In accordance with the most widely adopted soil classification threshold, only observations with a recorded peat depth ≥ 30 cm were classified as peatland for evaluation.



3 Methodology and processing framework

Our methodology employs a two-stage and regionally stratified framework to generate a consistent high-resolution peatland map across boreal and subarctic region. The workflow (Fig. 2) integrates prior knowledge of peatland extent at coarse-resolution, with fine-scale environmental information extracted from multi-source remote sensing and ancillary datasets. The two stages are: (1) generating a continuous Peatland Index (PI) at 3 arc-second resolution using regionalized neural networks; and (2) applying a threshold-based down-scaling procedure to constrain the PI to match coarser resolution prior peatland area estimates. This idea is similar to the use of a floodability index (Nguyen and Aires, 2023) to downscale surface waters (Nguyen and Aires, 2024).

The methodology distinguishes two region-specific approaches driven by differences in reference data characteristics: a regression model for Canada, where PEATMAP provides continuous fractional labels; and a classification model for the Eurasia/US domain, which relies on binary presence/absence labels. Regardless of the training approach, both models output a continuous PI ranging between 0 and 100, representing the pixel-level likelihood of peatland presence.

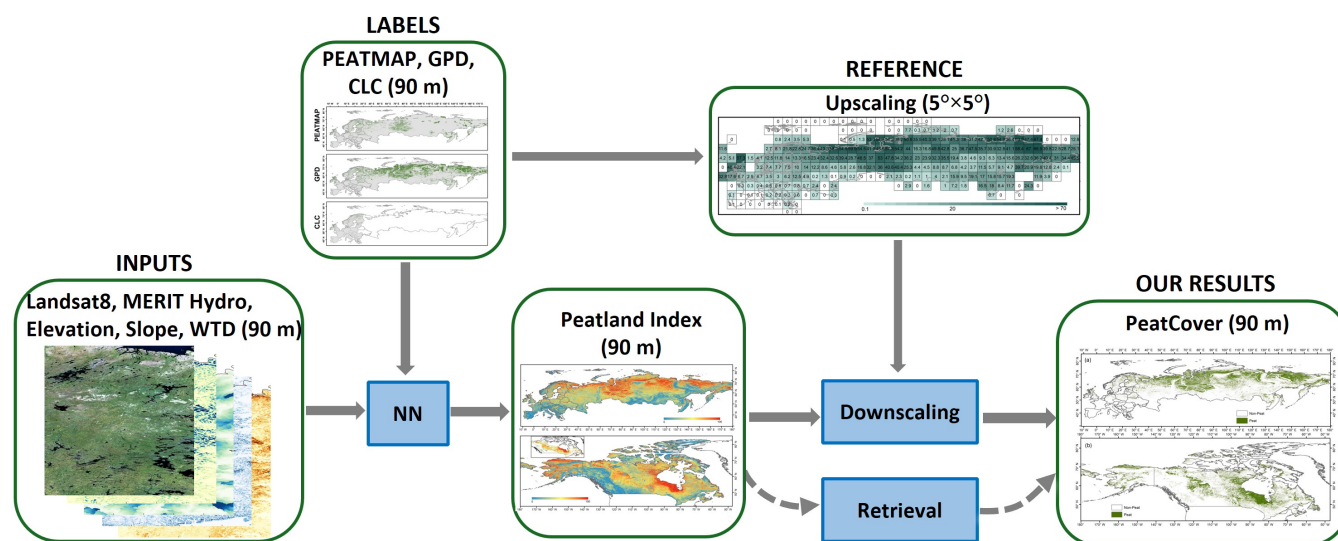


Figure 2. Overview of the PeatCover framework. High-resolution environmental inputs (90 m) and multiple peatland reference datasets (PEATMAP, GPD, CORINE) are used to train a neural network to produce a Peatland Index (PI) at 90 m. The PI is then constrained by reference peat fractions at the 5°×5° tile scale (a priori information) to perform downscaling and generate the final 90 m peatland map (PeatCover). In areas where the reliability of the reference datasets is limited, a direct retrieval (thresholding) approach is employed.



3.1 Peatland Index model

3.1.1 Training database

We constructed two distinct training datasets corresponding to the two modeling approaches, reflecting the continuous and binary nature of the reference data. Both models used the 17 predictors of Table 2 as inputs. These inputs to the PI model have
 245 been selected based on their link with peatland hydrology, topography, and vegetation characteristics.

Canadian Regression dataset: As detailed in 2.1.1 and 2.1.2, the training labels for Canada are derived directly from the fractional peat coverage provided by the PEATMAP. To ensure balanced representation across the peatland percentage spectrum, we implemented an equiprobability sampling. The percentage range [0-100%] was divided into ten equal bins (0-10%, ..., 90-100%), with equal numbers of samples in each bin. This sampling strategy ensures adequate representation of extreme
 250 cases (0% and 100%) alongside intermediate values, preventing the model from being biased toward the numerically dominant intermediate percentages.

Binary Classification Dataset (Other Regions): For Europe, Russia, and the USA, we derived training labels from the spatial agreement of three peatland reference datasets: PEATMAP, GPD, and CLC. To maximize label reliability while acknowledging these limitations, we applied a multi-source agreement rule. In CORINE-covered regions of Western and Central Europe where
 255 all three datasets overlap, pixels were labeled as peat (class = 1) only where the three datasets agreed on peat presence; and as non-peat (class = 0) only where all three indicated absence. Pixels with partial agreement (one or two datasets indicating peatland) were excluded from the training stage (class = -1). In regions covered by only PEATMAP and GPD over Russia or Alaska, a two-way agreement rule was applied, with disagreement cases excluded. This conservative labeling strategy prioritizes label accuracy over sample size.

260 Small surface-water bodies represented a particular source of error in coarse-resolution peatland datasets. In many regions, the polygons provided by PEATMAP and GPD encompass water-filled depressions that are misclassified as peatland due to the limited spatial resolution of the original inventories. To reduce this source of mis-classification, the ESA CCI - water class (210) was used to identify such features; these pixels were then reclassified as non-peatland (0) within the training labels, thereby minimizing confusion between peatlands and open-water areas.

265 The final training dataset comprises 10 million pixels (5 million peatland and 5 million non-peatland). Recognizing the higher mapping accuracy and better inter-dataset agreement of CORINE over Europe, we allocated 50% of training samples to this region, the remaining 50% distributed across Russia and USA. Within each geographic stratum, sample allocation across tiles was proportional to peatland pixel counts to ensure adequate representation of peatland-rich areas. The dataset was randomly partitioned into training (70%), validation (15%) and testing (15%) subsets.

270 3.1.2 Neural network PI model

We employed a feedforward neural network (NN) with a single hidden layer (Bishop, 1995) to obtain our PI model. The architecture consists of 17 input neurons, 10 hidden neurons, and region-specific outputs: two neurons with one-hot encoding for binary classification (Europe, Russia, USA) and a single neuron for regression (Canada). Binary classification used scaled



conjugate gradient optimization (trainscg) with cross-entropy loss, while regression used Levenberg-Marquardt optimization
 275 (trainlm) with mean squared error. Training incorporated early stopping based on validation performance to prevent overfitting.
 Input variables were normalized to [0, 1] using min-max normalization after removing constant features. The NN output is a
 “Peatland Inde” (PI), with a value for each high resolution (HR) pixel ranging from 0 to 100, where 0 means a confident
 absence of peat, and 100 a confident peat presence. The PI for northern regions is shown in Fig. 3.

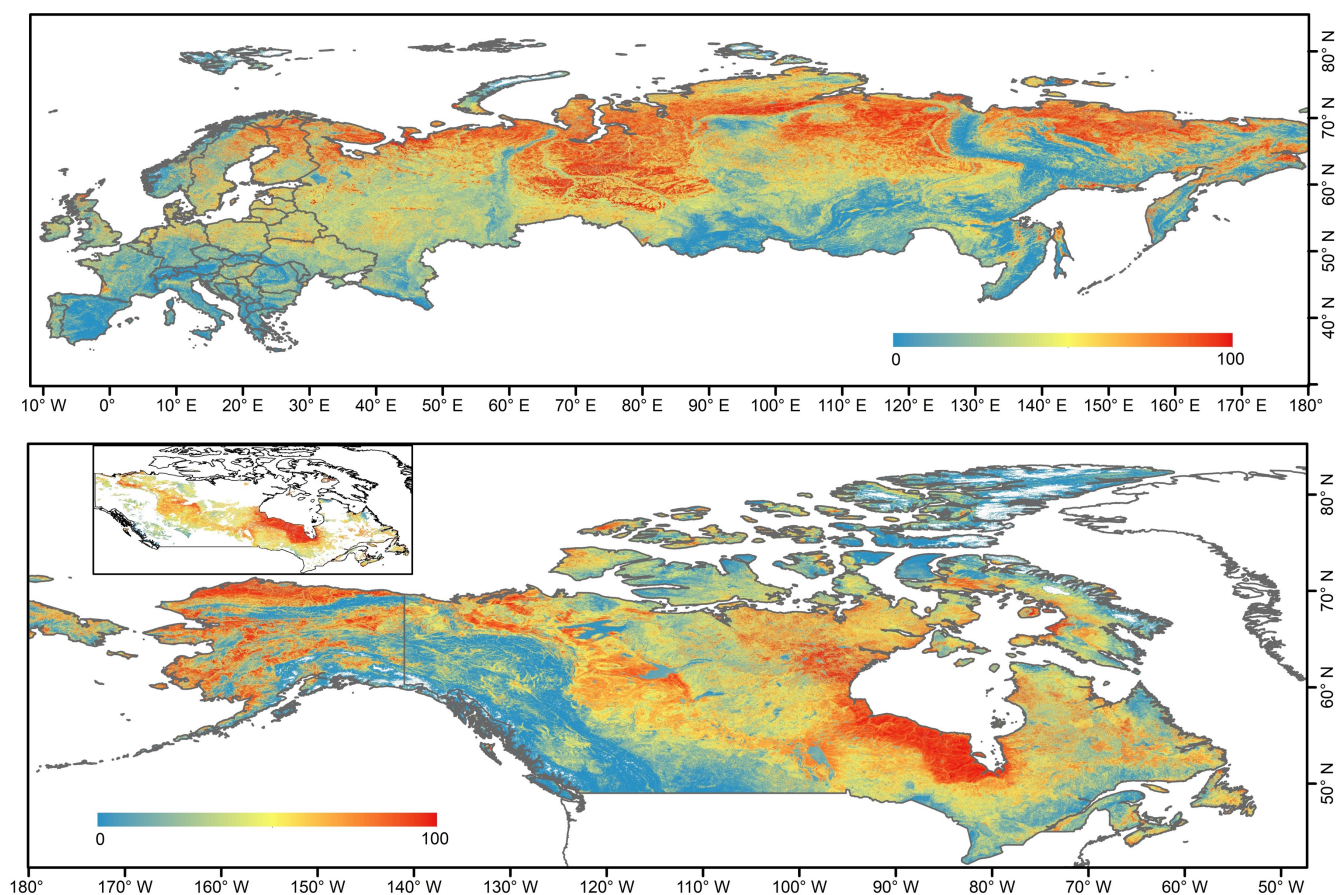


Figure 3. Spatial distribution of the PI across northern high-latitude regions. The upper panel shows PI over Eurasia, derived from the classification-based PI model trained using binary peatland reference data; The lower panel presents PI over North America. The inset highlights Canada, where PI was generated using a regression model. Outside Canada, PI values were produced using a classification-based model consistent with the Eurasian domain. The PI values range from 0 to 100, with higher values indicating a greater likelihood of peatland presence.



3.2 High-resolution downscaling

280 The PI map in Fig 3 provides spatially detailed information about the likelihood of peatland based on environmental conditions. However, direct conversion of PI to binary peatland maps using a single global threshold produces systematic regional biases. These biases arise from multiple reasons: (1) geographic variations in peatland types and their corresponding environmental signatures across different bioclimatic gradients (e.g., maritime vs. continental peatland systems); (2) differences in training sample density and quality across regions; (3) regional variations in the agreement between reference datasets.

285 To address these challenges while preserving the fine-scale spatial detail provided by the PI, we developed a thresholding framework. The key principle is that, within defined spatial units (polygons for Canada, tiles for other regions), the total peatland area derived from the PI thresholding should match the peatland area of the reference datasets; while the specific spatial distribution of peatland within each tile is determined by the PI value. This approach can be conceptualized as a constrained down-scaling procedure. Therefore, our framework integrates two complementary sources of information: (1) prior
 290 knowledge of peatland extent from the coarser resolution peatland datasets; and (2) high-resolution environmental information captured by the PI model that derives from satellite observations. The result is a peatland map that is both spatially detailed and quantitatively consistent with existing a priori knowledge.

3.2.1 Reference peat area at coarse resolution

The determination of the reference peat area differs by domain. For Canada, the reference polygons from PEATMAP directly
 295 provide peatland fractions ranging from 5 to 100%. This is the chosen reference peat area for Canada.

For other regions with binary reference data, the downscaling procedure is more complex due to the need to integrate multiple datasets and compute spatially varying thresholds. For each $5^\circ \times 5^\circ$ tile, the peatland fraction was computed using the available datasets (PEATMAP, GPD, and CLC). The spatial distribution and tile-level peatland fractions of each dataset are illustrated in Fig. B1. Tiles contain three- or two-source coverage areas. Directly averaging the peat fractions from each dataset would
 300 introduce mistake between these regions, so a pixel-level averaging approach was applied to the tiles highlighted in green in Fig. B1 “Averaging tile”.

At each pixel x , peat presence from dataset k is represented by $p_k(x) \in \{0, 1\}$, where $p_k(x) = 1$ if dataset k classifies the pixel as peatland and 0 otherwise. The number of datasets covering pixel x , $d = 3$ in CLC-covered areas and $d = 2$ elsewhere for PEATMAT and GPD. The pixel-level “peat” value (i.e., a local fraction) is defined as:

$$305 \quad f(x) = \frac{1}{d} \sum_{k=1}^d p_k(x). \quad (1)$$

The reference peat fraction for the tile is the mean of these “peat” values:

$$F_{\text{ref}} = \frac{1}{N_{\text{valid}}} \sum_{x=1}^{N_{\text{valid}}} f(x) \times 100\%, \quad (2)$$

where the summation is over all valid pixels x within the tile, with N_{valid} the number of valid pixels (excluding ocean).



Some tiles in Russia required additional correction because PEATMAP provides little or no peat information in this region, while GPD identifies substantially more peatland. Visual interpretation using Google Earth Pro indicated that PEATMAP substantially underestimates peatland extent, whereas GPD maps the spatial distribution more accurately, though it may overestimate total area due to its coarser effective resolution.

To correct for missing PEATMAP information, we computed the ratio between PEATMAP and GPD peat fractions:

$$R = \frac{F_{\text{PEATMAP}}}{F_{\text{GPD}}}, \quad (3)$$

for each tile in regions where both datasets are reliable. These ratio values were then interpolated across eastern Russia to form a spatially continuous field $R(I, J)$. For tiles where PEATMAP was incomplete, a corrected PEATMAP fraction was estimated as:

$$F_{\text{PEATMAP,corrected}}(I, J) = R(I, J) \cdot F_{\text{GPD}}(I, J), \quad (4)$$

and the final reference peat fraction was computed as the average of the corrected-PEATMAP and GPD fractions: $F_{\text{ref,Russia}} = \frac{1}{2}(F_{\text{GPD}} + F_{\text{PEATMAP,corrected}})$.

3.2.2 Downscaling using PI thresholding

Within one low resolution spatial unit (polygons over Canada, tiles everywhere else), all high-resolution pixels are ranked by their PI values. The optimal local PI-threshold θ_{opt} is defined as the PI-value that ensures the fraction of pixels exceeding it is exactly equal to the target reference fraction F_{ref} :

$$\Theta_{\text{opt}} = H, \text{ such that } \frac{\sum_{x=1}^{N_{\text{valid}}} \mathbb{1}_{\{PI(x) \geq H\}}}{N_{\text{valid}}} = F_{\text{ref}} \quad (5)$$

This straightforward procedure to choose the optimal PI threshold ensures that the downscaled binary map preserves the reference peat fraction at coarse resolution within each Polygon or Tile, while distributing peatland spatially according to environmental suitability captured by our PI.

However, directly applying a uniform Θ_{opt} across the spatial unit ($5^\circ \times 5^\circ$ tile or polygon) would introduce artificial discontinuities between spatial units. Instead, the tile-center θ_{opt} values were interpolated to the 3 arc-second resolution using bilinear interpolation. Bilinear interpolation was chosen for its computational efficiency and its ability to smoothly transition the threshold values between adjacent tiles. This interpolated, high-resolution threshold surface $\theta_{\text{int}}(i, j)$ imposes a smoothing in the thresholding to obtain binary peat presence pixels at HR.

The final classification of peatland cover was calculated by comparing the $pi(i, j)$ values with the interpolated threshold surface $\theta(i, j)$:

$$peat(i, j) = \begin{cases} 1, & \text{if } pi(i, j) \geq \theta_{\text{int}}(i, j) \text{ (peat),} \\ 0, & \text{otherwise (non peat).} \end{cases} \quad (6)$$



3.2.3 Regional implementation

The downscaling framework is applied in a regionally stratified manner depending on the availability and format of prior peat information. In Europe, Russia, and Alaska, where only binary inventories are available, peat fractions are harmonized at the
 340 $5^{\circ} \times 5^{\circ}$ tile level and downscaled using a classification-based PI model constrained to preserve tile-level peat extent. In Canada, where polygon-level fractional peat information is available, a regression-based PI model is applied to rank pixels within each inventory polygon while conserving total peat area. In high-latitude northern Canada where reliable training targets are absent, peat occurrence is inferred using a transfer learning strategy based on the Eurasian classification model. Detailed harmonization procedures and area calculation methods are provided in Appendix B. The resulting spatial distribution of northern peatlands
 345 is presented in Fig. 4.

4 Results

4.1 PeatCover: Northern peatland map

The spatial distribution of northern peatlands is shown in Fig. 4. At 90 m resolution, peatland boundaries follow local topographic and hydrological gradients, enabling explicit separation of peat bodies from open water and non-peat mineral soils.
 350 Overall, peatlands are unevenly distributed, with the largest peatland systems located in West Siberian Lowlands (WSL) and Hudson Bay Lowlands (HBL). This large-scale pattern is consistent with long-standing understanding that sustained water saturation, coupled with cool conditions that suppress decomposition, that favors long-term peat accumulation (Limpens et al., 2008). In addition, northern peatlands are closely associated with postglacial landscape evolution, where flat lowlands and poor drainage promote extensive wetland formation (Yu et al., 2010).

355 PeatCover estimates a total peatland area of 5.94 million km^2 across the study domain. For comparison, PEATMAP reports 2.94 million km^2 , while GPD reports 7.19 million km^2 (sum of class 1 and class 2) over the same region. At the country level, the largest peatland areas are consistently identified in Russia, with PeatCover estimating 3.75 million km^2 , compared to 4.53 million km^2 in GPD and 1.44 million km^2 in PEATMAP, reflecting the more limited coverage of peatlands in PEATMAP for this region. Canada follows, with estimated peatland areas of 1.73 million km^2 (PeatCover), 2.03 million km^2 (GPD), and
 360 1.13 million km^2 (PEATMAP). In Alaska (USA), peatland areas are estimated at 0.20 million km^2 (PeatCover), 0.26 million km^2 (GPD), and 0.08 million km^2 (PEATMAP).

4.2 Eurasian peatland distribution

Eurasia holds approximately 40% of the global peatland area (Xu et al., 2018; Kopansky et al., 2022). Peatland extent exhibits a sharp latitudinal peak between 50° N and 70° . The most extensive peatland complexes occur in West Siberian Lowlands
 365 (WSL), widely recognized as one of the world's largest high-latitude wetland regions (Kremenetski et al., 2003; Yu et al., 2010). Outside this core region, substantial peatland coverage is also identified in Finland, Sweden, and the United Kingdom, Europe (10° W and 30° E) where PeatCover, PEATMAP, and GPD show broadly consistent longitudinal area distributions.

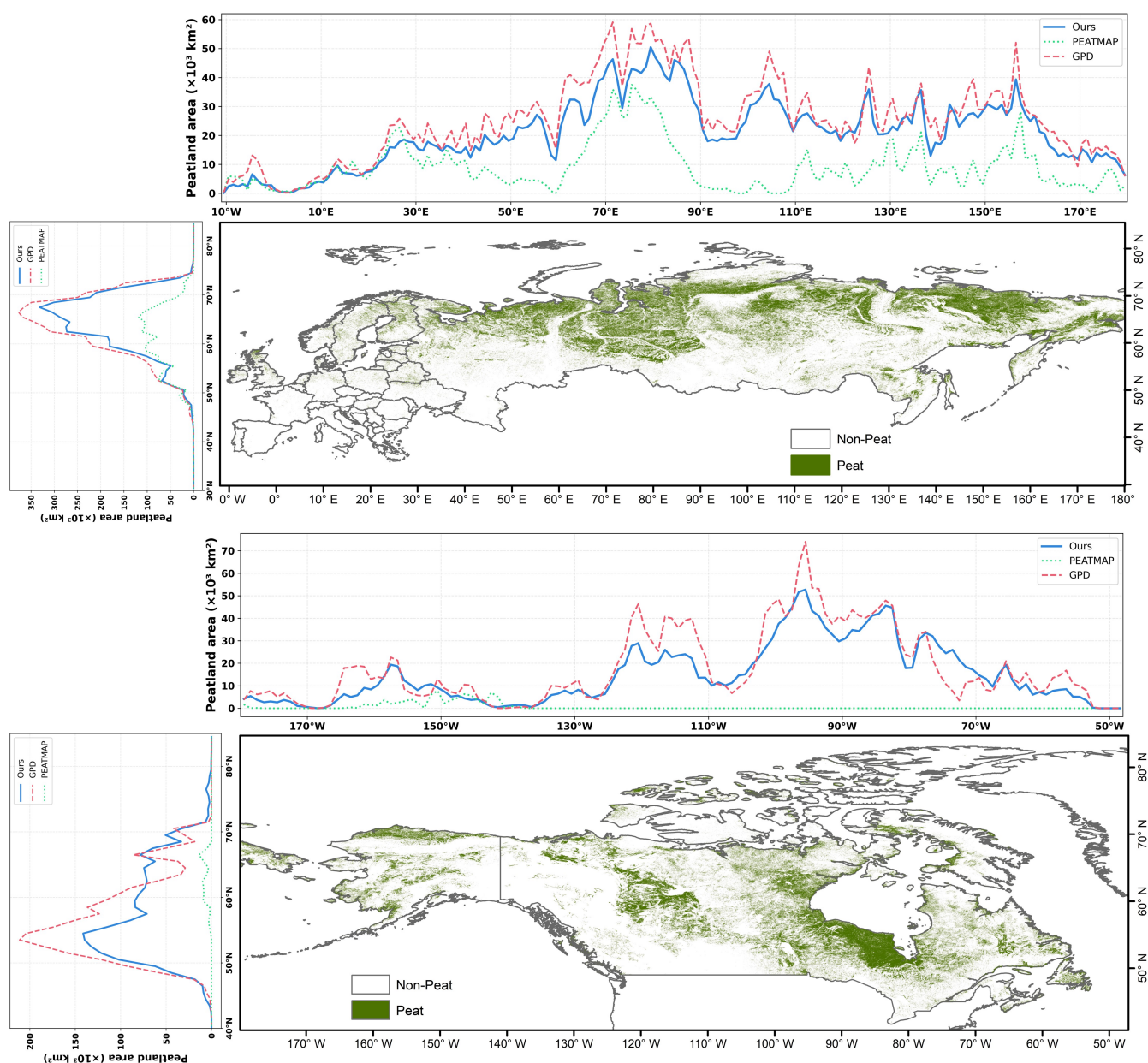


Figure 4. Spatial distribution of peatlands and zonal area comparison across Eurasia (top) and North America (bottom). Peat areas derived from PeatCover are shown in green. Peatland area aggregated by longitude (top panels) and latitude (left panels) ($\times 10^3 \text{ km}^2$) is compared with PEATMAP and GPD. Blue solid lines represent PeatCover, green dotted lines PEATMAP, and red dashed lines GPD.



In contrast, eastern Russia, particularly the Sakha Republic (Yakutia) and adjacent lowlands between approximately 130° E and 170° E, exhibits the largest inter-inventory discrepancies. PEATMAP substantially underestimates peatland extent in these regions due to incomplete source data, while GPD reports substantially larger areas. PeatCover provides an intermediate estimate, capturing thermokarst landscapes and seasonally saturated lowlands more consistently than PEATMAP while avoiding the overestimation tendencies of GPD. This reduction relative to GPD primarily reflects PeatCover's explicit delineation of river networks and open water bodies, which are frequently amalgamated into peatland pixels in coarser inventories.

These patterns are further illustrated by representative case studies across six Eurasian regions (Fig. 5). In Scotland (Fig. 5 a), peatlands (blanket bogs) are correctly confined to upland and gently sloping terrain, with PeatCover showing spatial patterns similar to CLC and improved topographic coherence relative to PEATMAP and GPD. In Finland (Fig. 5 b), PeatCover captures an intermediate spatial extent between the conservative PEATMAP and the broader GPD, preserving internal heterogeneity consistent with visual interpretation. In Estonia–Latvia (Fig. 5 c), illustrates a sparse peatland setting, peatland patches appear fragmented and locally constrained, closer to CLC than to the schematic polygons of PEATMAP. Across the three Russian panels (Fig. 5 d–f), the improvement is most pronounced: PeatCover explicitly resolves river networks, open water, and internal drainage structure that neither PEATMAP nor GPD capture at fine scale, with spatial patterns that closely match high-resolution Google Earth imagery. In North Siberia (Fig. 5 e), independent Peat-DBase field points confirm peat presence in areas where PEATMAP shows no coverage, supporting PeatCover's intermediate representation.

4.3 North American peatland distribution

In North America, peatlands are primarily concentrated in Canada and Alaska, displaying strong spatial heterogeneity (Fig. 4). The largest peatland complex occurs in the HBL (centered around 84° W), which dominates the continental peatland signal and forms a pronounced peak in both latitudinal and longitudinal distributions. This region is characterized by low topographic gradients and widespread waterlogged conditions, favoring extensive peat accumulation. Another prominent longitudinal peak is observed between 90° W and 100° W, corresponding to peat-rich regions in the Mackenzie River Valley. Although peatlands in this zone are more spatially fragmented than in the HBL, their cumulative area remains substantial, particularly including the peatland extents at higher latitudes in northern Canada that are largely omitted in PEATMAP and GPD (Fig. B3). Alaska also contains substantial peatland coverage, particularly across coastal lowlands and interior river valleys. Notably, since PEATMAP represents peatland as fractional coverage within irregular polygons over Canada, it is not possible to accurately aggregate its area into discrete 1° bins for direct comparison.

These spatial patterns and qualitative evaluation are further examined through six representative case studies (Fig. 6).

In Alaska, a subregion where both inventories report peat presence was selected (Fig. 6 a). Even within this overlapping area, the two inventories exhibit considerable disagreement in spatial extent and internal structure. PeatCover reproduces the large-scale spatial organization indicated by GPD, while providing a more detailed and heterogeneous representation that is consistent with landscape patterns visible in Google Earth imagery.

Panels (b) and (c) in Fig. 6 show peatland-rich regions in southern Canada, where both PEATMAP and GPD provide coverage but neither explicitly resolves peat spatial distribution at the pixel level. PeatCover addresses this by identifying

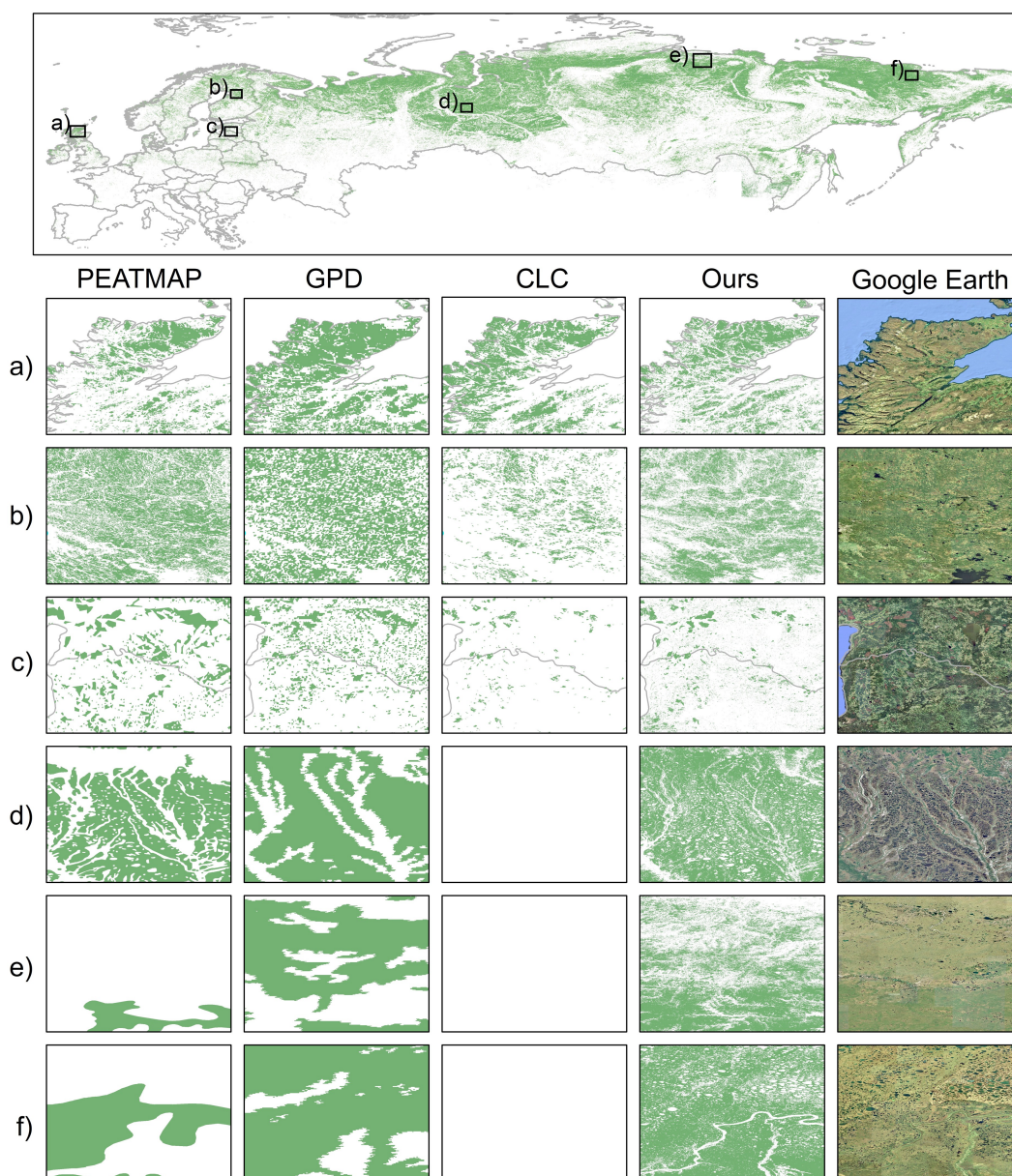


Figure 5. Regional comparison of peatland distributions across selected Eurasian case-study areas. Six representative regions are shown: (a) Scotland, (b) Finland, (c) Estonia/Latvia, (d) West Siberia, (e) North Siberia, and (f) Eastern Russia. For each region, peatland distributions from PEATMAP, GPD, CLC and the proposed peatland map (Ours) are compared, with high-resolution Google Earth imagery shown as a visual reference. Imagery © 2026 NASA, Map data © 2026 Google.

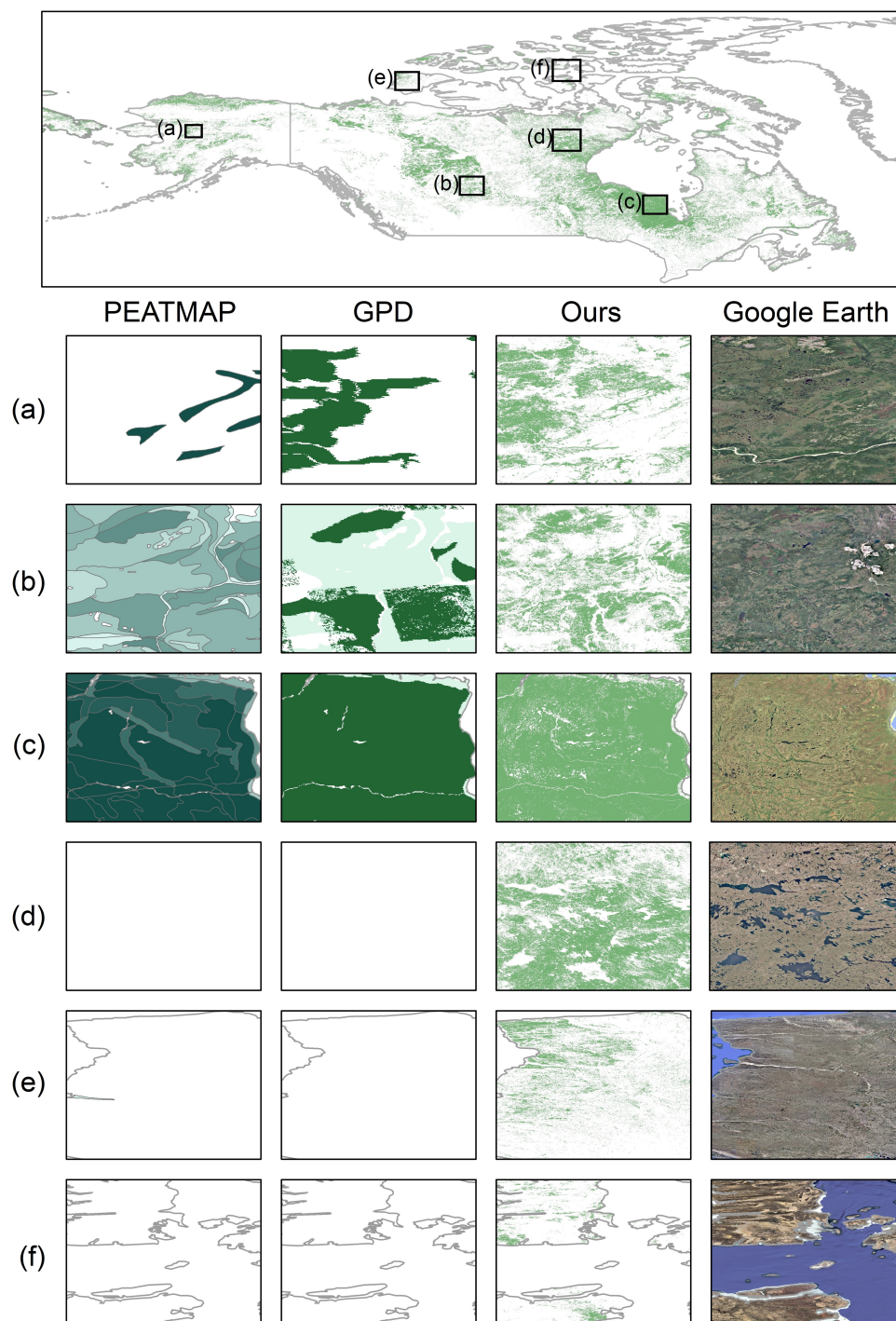


Figure 6. Regional comparison of peatland distributions across selected North American case-study areas. Six representative regions are shown: (a) Alaska, (b–f) peatland-rich regions across Canada. For each region, peatland distributions from PEATMAP, GPD, and the proposed peatland map are compared, with high-resolution Google Earth imagery provided as a visual reference. Imagery © 2026 NASA, Map data © 2026 Google.



peat occurrence at pixel scale and explicitly separating peatland from open water and drainage features. This is particularly clear in panel (c), located in the HBL, where inventory products suggest near-complete peat coverage, but PeatCover reveals a heterogeneous mosaic consistent with high-resolution Google Earth imagery.

405 Panels (d–f) focus on northern Canada, a region characterized by permafrost, thermokarst features, and poorly drained lowlands. Although existing inventories show extensive gaps in these high-latitude environments, independent field observations from Peat-DBase and studies Merchant et al. (2023) confirm peat accumulation across these permafrost-affected landscapes. PeatCover identifies extensive peatland presence in these regions, reproducing spatial patterns including thermokarst depressions and saturated lowland complexes that are consistent with observed surface characteristics. However, we acknowledge a
 410 potential risk of overclassification in these high-latitude, continental permafrost zones; despite the prevalence of surface wetness, the extremely cold climates and relatively recent deglaciation may limit peat accumulation to depths below the 30 cm threshold in some areas.

4.4 Quantitative evaluation

To establish the reliability of the PeatCover product, we conducted a two-step quantitative evaluation using the independent
 415 Peat-DBase dataset. We first examine the discriminative power of the continuous PI and then assess the classification accuracy of the final binary map.

4.4.1 Distributional evaluation of the PI

The consistency between the PI and field observations was first examined through an analysis of the PI Probability Density Functions (PDFs) constructed separately for peat and non-peat samples in Fig. 7.

420 As a reference, the analysis was conducted first using peat fraction values derived from the PEATMAP inventory at Peat-DBase locations in Canada (Fig. 7). It is clear that the comparison of PEATMAP with Peat-DBase field observation is extremely difficult because one is provided over polygons and the other on point measurements. We would expect that the peat distribution would be biased towards higher peat fractions and non-peat distribution towards lower peat fractions. However, the resulting distributions show substantial overlap : Peat sites are characterized by a mean peat fraction of 38.6% (standard deviation:
 425 31.2%), whereas non-peat sites exhibit a lower mean of 20.3% (standard deviation: 15.4%). The limited separation between the two distributions is reflected by a Kolmogorov–Smirnov (KS) statistic of 0.28, which quantifies the maximum difference between their cumulative distributions.

The distributions obtained from PI display a stronger separation (Fig. 7b). In Canada, peat observations are associated with substantially higher PI values than non-peat observations: mean values of 60.2 and 33.7, respectively. The corresponding KS
 430 statistic increases to 0.57, indicating a pronounced improvement in the distinction between peat and non-peat conditions. There are some overlapping of the two PDFs meaning that improvement could probably be achieved (see perspectives section).

Comparable behavior is observed across Eurasia. The PI distributions for peat and non-peat field observations exhibit clear separation (Fig. 7c), with mean values of 68.1 and 21.8, respectively, and a KS statistic of 0.66. Despite regional differences in peatland density and data availability, the consistent increase in distributional separability across both regions suggests that the

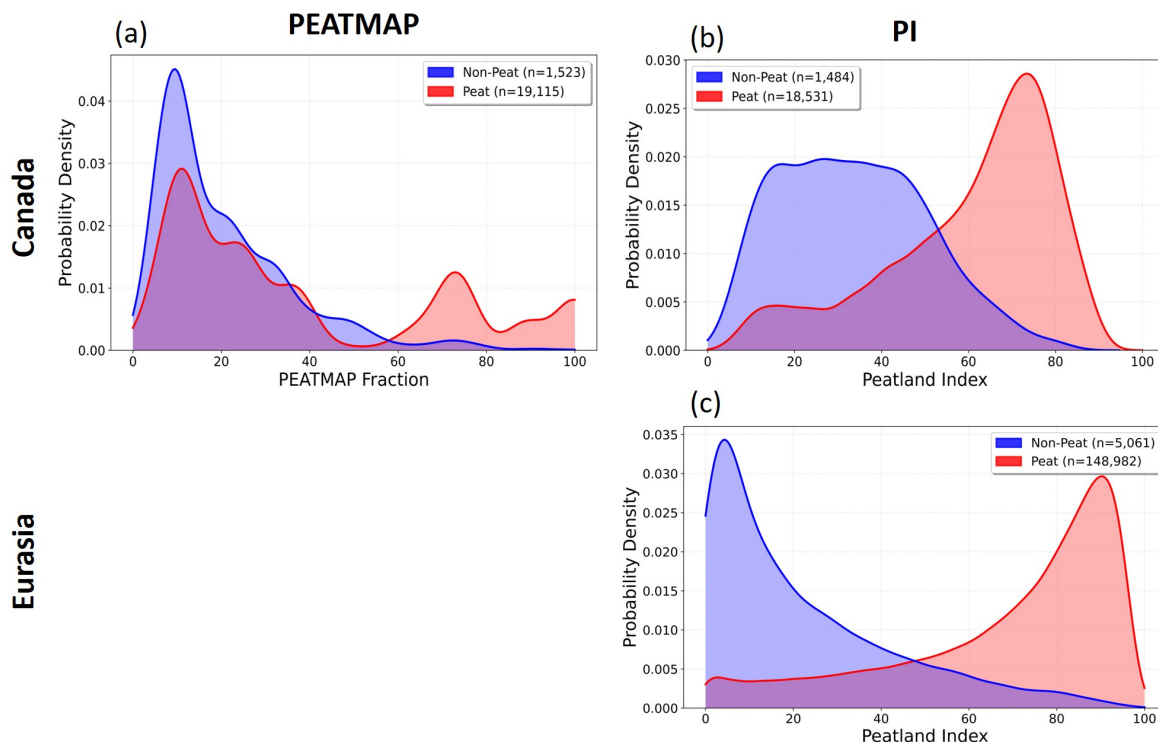


Figure 7. PDFs of peat fraction (left, for PEATMAP) and of our peatland index (right), for peat and non-peat samples from the independent field database Peat-DBase (Sect. 2.3); over Canada (top) and Eurasia (bottom). (Note that the PEATMAP fractions are not associated to a single pixel but a statistical dependency with peat presence would be expected).

435 PI captures a reliable signal of peat presence (rather than region-specific artifact). Note also that the peat detection over North America seems to be more difficult than over Eurasia, showing that some improvement could probably be made in the future.

4.4.2 Accuracy Assessment

The accuracy of our final peatland classification was assessed using independent in situ observations from Peat-DBase (using a 30 cm thickness threshold to define peat presence). Validation was conducted across the study region, Eurasia, North America, and selected peat-rich countries. A summary of the main performance metrics is provided in Table 3. The classification performance is evaluated using several standard metrics derived from the confusion matrix. Overall accuracy (OA), recall (sensitivity), specificity, precision, and the F1-score are defined as:

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$



$$\text{Recall} = \frac{TP}{TP + FN} \quad (8)$$

$$445 \quad \text{Specificity} = \frac{TN}{TN + FP} \quad (9)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (10)$$

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (11)$$

where TP , TN , FP , and FN denote true positives, true negatives, false positives, and false negatives, respectively.

Prior to this independent evaluation, the classification model was internally assessed using a conventional train–validation–test
 450 split of the available labeled data. On the held-out test set, the model achieved an overall accuracy of 82.3%, with a precision
 of 0.81, a recall of 0.84, and an F1-score of 0.83, indicating strong predictive skill under controlled sampling conditions.
 While these results demonstrate the internal consistency of the model, they remain conditional on the spatial distribution and
 representativeness of the training data.

To evaluate the robustness and real-world applicability of the final peatland map beyond the training domain, an additional
 455 validation was therefore performed using the fully independent Peat-DBase field observations. Given the pronounced class
 imbalance in the validation dataset, overall accuracy is reported for completeness but should be interpreted with caution. In
 this context, class-specific metrics associated with the presence of peat provide more informative indicators of the reliability of
 the map. Across all evaluated regions (Table 3), our peat map achieves an overall accuracy of 69.0%, and an F1-score of 0.81.

When the evaluation is restricted to Europe, the overall accuracy reaches 69.9%, with an F1-score of 0.82 for the peat
 460 class. In North America, based on an independent subset of field observations, the overall accuracy is 63.9% and the peat
 F1-score reaches 0.74. The lower scores observed in North America likely reflect the heterogeneous and fragmented nature of
 peatland–mineral soil mosaics common in parts of Canada, where peat occurs in small, discontinuous patches that are difficult
 to localize precisely at the pixel scale. For other regions, including Russia and the USA, the performance metrics remain
 consistent with the pan-boreal average, as detailed in Table 3.

465 Overall, the consistently high peat precision observed across regions confirms that the final peatland map provides a reliable
 identification of peat presence when evaluated against independent field observations. While binary classification necessarily
 simplifies the continuous nature of peat presence, these results demonstrate that the adopted classification strategy yields robust
 peatland maps suitable for large-scale applications.



Table 3. Accuracy of the final peatland classification evaluated using independent in situ observations from Peat-DBase.

Region/Country	Total samples	Peat samples	Non-peat samples	OA (%)	Recall	Specificity	Precision	F1
All regions	180,986	171,910	9076	69.0	0.68	0.94	0.99	0.81
Eurasia	154,043	148,982	5061	69.9	0.69	0.97	0.99	0.82
North America	26,943	22,928	4015	63.9	0.59	0.91	0.97	0.74
Canada	26,330	22,359	3971	64.7	0.60	0.91	0.97	0.74
United Kingdom	145,134	144,989	145	70.0	0.70	0.92	0.99	0.82
Russia	1618	1058	560	58.7	0.41	0.93	0.92	0.56
Finland	1052	1048	4	52.4	0.52	1	1	0.69

5 Discussion

5.1 Reconciling heterogeneous peat inventories with EO-driven spatial information

Existing large-scale peatland inventories have been compiled from national surveys, soil maps, and field investigations. Their direct use in high resolution spatial analyses is hindered by fundamental heterogeneity such as mapping conventions (peat fractions or binary values) or spatial resolution. As a result, these products often exhibit abrupt discontinuities across national borders and limited internal spatial detail, reducing their applicability in Earth system and land-surface modeling.

The PeatCover framework was explicitly designed to address these gaps by reconciling heterogeneous inventory information with spatially continuous EO-driven and hydro-topographic constraints. Rather than replacing existing databases, our approach redistributes their a priori peat occurrence information onto a coherent 90 m grid, guided by 1) satellite observations (visible reflectances giving information on vegetation and water presence) and 2) landscape-scale controls on peat formation and persistence. This enables a spatial representation that remains consistent with the broad peatland provinces defined by inventories while being responsive to fine-scale hydrological structure.

Compared to current peat databases, the principal improvement therefore lies not in redefining peatland extent itself, but in resolving where peat is most likely to occur within coarse polygons and mixed land cover areas, and supplement inventories on regions with missing data. This results in a product that better captures internal peatland geometry, excludes non-peat features such as river networks, open water bodies, and large artificial infrastructures (e.g., dams and reservoirs), and reduces artificial spatial fragmentation induced by inventory boundaries. In this sense, PeatCover functions as a harmonized spatial interface between compilation-based peat inventories and EO-based environmental analyses.

5.2 Independent validation and interpretation

A major strength of the evaluation is the use of independent in situ observations from Peat-DBase, filtered to represent peat presence based on peat depth (here ≥ 30 cm). This independence matters because many wetland/peatland mapping studies rely on internal cross-validation where training and testing subsets originate from the same compilation workflow, which can inflate apparent skill and conceal structural errors. Using Peat-DBase as an external benchmark therefore provides a more realistic



measure of generalization. The validation results ($OA \approx 68.4\%$) reveal high precision (0.99) but more moderate recall (0.67), suggesting a conservative model behavior. This pattern is physically consistent with the difficulty of identifying peatlands in fragmented boreal landscapes, where narrow peat patches are often embedded within mineral forest mosaics.

495 Furthermore, validation based on independent point observations represents a challenging test for gridded land-cover products. Field measurements correspond to point locations, whereas the mapped predictions represent 90 m pixels ($\approx 8,100 \text{ m}^2$) that may contain heterogeneous land-cover conditions. Even when field samples are collected from representative peat locations (Hugelius et al., 2020a), sub-pixel variability within the satellite footprint can lead to differences between a local field label and the dominant land-cover condition within the mapped pixel. In addition, positional uncertainties in field coordinates or satel-
 500 lite geolocation may introduce small spatial offsets that affect pixel–point comparisons, particularly in fragmented landscapes where peatlands occur as small patches embedded within mineral soils. These scale and positional effects are well recognized in remote sensing accuracy assessments (Foody, 2002; Olofsson et al., 2014; Stehman and Foody, 2019). Consequently, independent point-based validation often represents a conservative estimate of map performance, especially in heterogeneous boreal environments.

505 5.3 Implications for applications and inventory use

From an application perspective, the main value of a coherent 90 m peatland layer is that it reduces the scale-mismatch between peatland extent information and the typical resolution of land surface modeling, methane upscaling, and national greenhouse-gas reporting workflows. By providing a spatially explicit allocation of peat presence within coarse polygons or heterogeneous administrative units, the product can support more consistent overlays with climate, permafrost, fire, and land-use layers, and
 510 thereby reduce artifacts caused by administrative borders and inventory conventions.

5.4 Limitations

Despite its advances, PeatCover has several limitations that should be considered to guide future refinements. First, the present map provides a static representation of peatland extent. It does not capture the dynamic changes driven by anthropogenic disturbances, such as drainage for agriculture or forestry, and climate-induced degradation. This means that static extent products can
 515 be useful for locating peat-forming landscapes, but they cannot track degradation states or transitions that directly determine greenhouse gas (GHG) fluxes change and climate mitigation prioritization.

Second, PeatCover provides a binary peat/non-peat classification without distinguishing between functionally distinct peatland types. Peatlands are ecologically diverse, encompassing distinct types such as bogs, fens, and permafrost-associated palsas, each with unique hydrological regimes and carbon storage capacities. The lack of differentiation between these types limits
 520 the map’s utility for specific GHG flux modeling, which vary significantly between ombrotrophic bogs and minerotrophic fens (Zhang et al., 2021).

Our training labels are derived from the spatial consensus of existing peatland inventories. However, some of these primary records are based on historical soil surveys and aerial photography that may be several decades old. This introduces a potential



“legacy error”, where areas that have since been drained or converted—and thus no longer function as active peatlands—are
 525 still labeled as peat in the training regime, potentially confounding the neural network’s spectral learning.

Finally, the current framework applied a regionally stratified but not environmental stratification (e.g., eco-regions, ecological land units) approach. Peatlands develop under distinct combinations of climate, hydrology, vegetation, and permafrost conditions across bio-climatic zones (Gallego-Sala et al., 2010; Fewster et al., 2022), and a single model may not optimally capture the environmental signatures of all peatland types across the pan-boreal domain. Studies have shown that regionalized
 530 classification models using region-specific training data can substantially outperform global models (Karlson and Bastviken, 2023).

5.5 Perspectives

Several directions emerge for further development of the PeatCover framework.

Future versions should move beyond regionally stratified modeling toward environmentally stratified modeling. We plan to
 535 incorporate a wider array of environmental variables, e.g., precipitation, temperature, soil moisture, permafrost Active Layer Thickness (ALT) and so on. Our current framework relies primarily on optical satellite data, integrating active microwave data should substantially extend the observational capacity of the system, as SAR sensors provide complementary information on surface moisture and vegetation structure under all-weather, day-and-night conditions. Sentinel-1 C-band data have demonstrated sensitivity to surface moisture of peatlands and the dynamics of the water table (Merchant et al., 2023; Lees et al.,
 540 2021); while ALOS PALSAR L-band data offer deeper canopy penetration and enhanced discrimination of forested peatlands (Zhou et al., 2019). To fully exploit the complementary strengths of optical, SAR, hydrological, and topographic data streams, multi-modal deep learning approaches (Chen et al., 2025) offer a promising path forward.

In terms of methodology, future work will test other models than the MLP used here for the PI (Sect. 3.1.2). In particular, deep learning models capable of exploiting spatial context will be investigated. While the current framework relies on
 545 a pixel-based representation, peatlands often exhibit spatial organization linked to hydrological and geomorphological processes. Approaches such as Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), or transformer-based architectures may therefore be explored. These models could potentially enhance the detection of fragmented peatlands and improve the delineation of peatland boundaries. However, their implementation requires substantially larger training datasets and increased computational resources, and their added value for large-scale peatland mapping will need to be carefully evaluated.

550 A key objective of future work is to classify peatlands based on their functional and greenhouse gas-related types, like bogs, fens, and permafrost peatland types. This is essential because the carbon sequestration potential and CH_4 emission profiles are fundamentally different across these categories; for example, fens often exhibit higher methane emissions due to their nutrient-rich, minerotrophic status compared to more acidic, isolated bogs (Turetsky et al., 2014).

In addition, moving from static extent to dynamic assessment remains an important longer-term goal, which will allow for
 555 the monitoring of peatland disturbance and restoration progress. Finally, extending the framework beyond the pan-boreal is a long-term objective. Tropical peatlands differ fundamentally from boreal systems in geomorphology, vegetation structure, and



hydrological controls, and their mapping requires adapted feature design, sensor selection, and training strategies. PeatCover provides a methodological basis that can be developed toward a globally consistent, high-resolution peatland dataset.

6 Conclusions

560 This study presents PeatCover, a first spatially coherent peatland dataset at 90 m resolution for the boreal and subarctic regions. By combining existing peat inventories with high-resolution satellite, topographic, and hydrological information, the framework reconciles spatially heterogeneous peat databases into a consistent gridded product. The resulting map resolves fine-scale landscape features, such as river networks and open water bodies, that are often embedded within coarse inventory polygons.

PeatCover estimates a total peatland area of 5.94 million km² across the study domain. Independent validation using depth-
565 based field observations yields an overall accuracy of 68.4% and high precision in peat detection. The product also improves spatial coverage for high-latitude regions, such as Northern Canada, where detailed spatial information has previously been limited.

By providing a more precise characterization of peatland distribution and internal landscape structure, PeatCover serves as an updated spatial basis for Earth system modeling and regional carbon budget assessments. This high-resolution representation
570 contributes to more refined estimates of northern carbon stocks and their potential environmental responses. Furthermore, the methodological approach established in this work provides a scalable foundation for future dynamic monitoring and expansion to other regions globally.

Data availability. The PeatCover dataset is available at Zenodo via <https://doi.org/10.5281/zenodo.21031869> (Chen et al., 2026). The dataset is provided as a GeoTIFF file (PeatCover.tif) at 3 arc-second resolution (90 m at the equator) in WGS84 geographic coordinates
575 (EPSG:4326). It covers the boreal and subarctic peatland regions of Eurasia and North America, including Europe, Russia, Canada, and Alaska. Pixel values are encoded as 8-bit unsigned integers, where 0 indicates non-peatland and 1 indicates peatland.

Appendix A: Notations

Appendix B: Technical Details of Peat Mapping

This appendix documents implementation details of the regionally stratified downscaling, including (i) the tile-level harmoniza-
580 tion used in Eurasia and Alaska; (ii) the polygon-based regression approach in Canada; and (iii) the transfer-learning strategy in unmapped northern Canada. Our PeatCover framework is presented in more detail, and results are illustrated separately for two geographical subsets: Eurasia and North America.

In addition, all area estimates were derived using a unified calculation framework. We employed a geodesic area calculation on the WGS84 ellipsoid to account for Earth's curvature, which is particularly important at high latitudes. All datasets were
585 rasterized to a common spatial resolution and intersected with a consistent national boundary dataset to avoid discrepancies



Table A1. Notations. HR is for High-Resolution (90 m) and LR is for Low Resolution (complex polygons at several resolution over Canada or $5^\circ \times 5^\circ$ tiles elsewhere).

Variable	Description	Resolution
x	Pixel at 90 m	HR
(i,j)	Coordinates for pixels	HR
(I,J)	Coordinates for tiles or polygons	LR
D	Number of peat reference datasets	-
$p(x)$	=1 for peat and 0 for non-peat	HR
$f(x)$	Local “peat fraction”	HR
F_{ref}	Reference peat fraction	LR
r_{tile}	PEATMAP/GPD peat fraction ratio	LR
PI or pi	Peatland Index	HR
Θ_{opt}	Optimal threshold on PI	LR
Θ_{int}	Interpolated threshold on PI	LR
θ_{opt}	Local threshold on PI	HR

arising from differences in political border definitions. Minor differences between our recalculated PEATMAP area original values of the PEATMAP publication are expected. PEATMAP was originally provided in a World Cylindrical Equal Area projection, whereas our workflow involved reprojection to WGS84 followed by rasterization and resampling. These steps, combined with the use of a different national boundary dataset, inevitably introduce small numerical variations. For GPD, both the peat-dominated (Class 1) and peat-in-soil mosaic (Class 2) categories were aggregated into a single peat presence mask to ensure consistency with the binary representation used in the PeatCover product. Class 2 areas are primarily located in Canada, while only limited occurrences are reported across Eurasia, for example in Italy, Hungary, and Belgium. In many of these Eurasian locations, the Class 2 areas partially overlap with regions already identified as peat in PEATMAP. Consequently, the two classes were directly merged.

B1 Eurasia

Eurasia holds about 40% of the northern peatland area (Xu et al., 2018; Kopansky et al., 2022). Fig. B1 illustrates the sequential steps put in place to build the peat classification, showing how heterogeneous a priori datasets are reconciled across spatial scales to derive the final PeatCover product. The left panels of the first three rows display the current peatland inventories (PEATMAP, GPD, CLC), at their native resolutions, where gray shading denotes data coverage and green represents peatland presence. These datasets are upscaled to a common coarse-resolution grid using $5^\circ \times 5^\circ$ tiles (right panels), allowing tile-level peatland fractions to be compared and combined to provide the best consensus reference peat fraction.

As shown in the first three rows, the datasets show broadly consistent spatial patterns over parts of Europe, but large differences in peatland fraction values. In general, GPD reports the largest extent, followed by PEATMAP and CLC. CLC provides

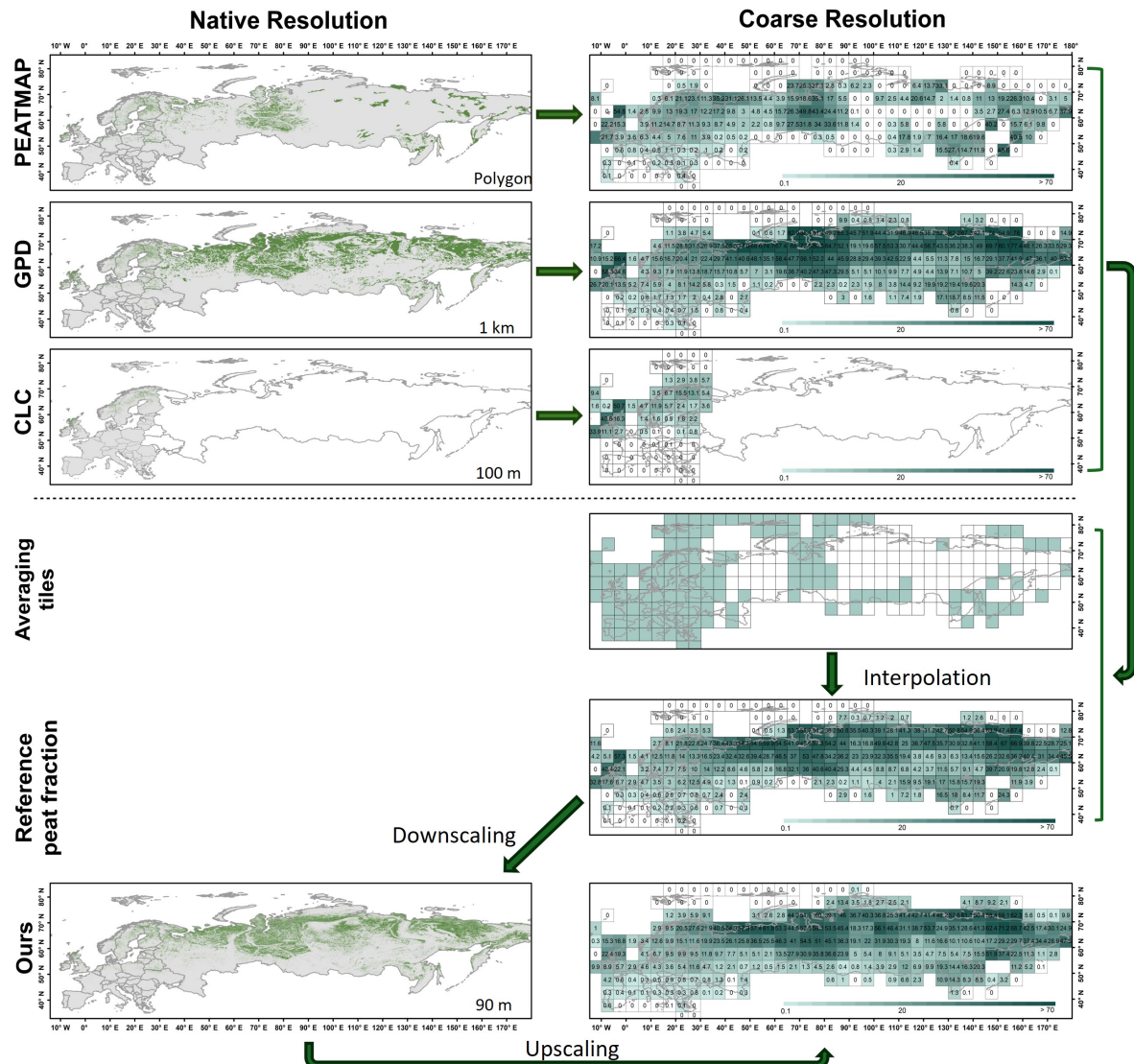


Figure B1. Illustration of the peat retrieval framework steps, over Eurasia. First 3 lines: The current datasets (PEATMAP, GPD and CLC) (on the left) are upscaled to the $5^{\circ} \times 5^{\circ}$ tiles (on the right). The corresponding peat fractions are averaged on each tile, and interpolated when missing, to obtain the reference peat fraction, that is downscaled at 90 m resolution (bottom left) using the PI of Fig 3.

relatively accurate peatland locations where available due to its higher native resolution (100 m), it systematically underestimates total area as described in Sect. 2.1.3. In contrast, GPD generally reports larger peatland extents than PEATMAP, particularly over Russia, reflecting its integration of a wider range of regional data sources and its better agreement with visual interpretation. Nevertheless, GPD exhibits spatial offsets in some regions, which have limited impact on large-scale area estimates but can introduce substantial errors when used directly at fine spatial resolution or as training data. PEATMAP is

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comparatively more conservative in several northern regions and contains data gaps, but where peatland is mapped, its spatial
 610 localization is generally reliable.

To account for these complementary strengths and limitations, a “reference peat fraction” is derived as prior information. For tiles where multiple datasets overlap, the fraction is obtained by direct averaging (shown in green in the fourth row of Fig. B1). These averaged values also serve as inputs for an interpolation scheme used in tiles where PEATMAP is missing or where large discrepancies between PEATMAP and GPD are identified (shown in white). This procedure yields a harmonized
 615 reference peat fraction at $5 \times 5^\circ$ resolution (Sect. 3.2.1).

This coarse resolution reference is then downscaled at 90 m using the PI of Sect. 3.1 and downscaling scheme of Sect. 3.2. When upscaled towards the coarse resolution (bottom right panel of Fig. B1), it can be confirmed that the downscaling process conserves well the peat fraction of the reference peat fraction map. It is worth noting that the interpolation of the optimal PI threshold (Sect. 3.2.2) inevitably introduces a degree of spatial smoothing, bringing differences with the reference peat fraction.

620 B2 North America

Peatland mapping in North America reflects the strong heterogeneity of inventory data, requiring a stratified framework adapted to the format and quality of prior information (Fig. B2). A comparison of global peatland databases (Fig. B3) highlights substantial inconsistencies, particularly in Alaska, where PEATMAP and GPD differ not only in total estimated peat area but also in spatial coverage. In Canada, both datasets originate from the same primary source (Tarnocai et al., 2011), but have
 625 undergone different processing procedures (see Sect. 2.1.1 and 2.1.2). Moreover, large parts of northern Canada lack detailed inventory coverage, further increasing uncertainty in these regions.

To address these varying levels of data availability, we implemented a three-tiered modeling strategy based on data availability. For the Canadian domain (green region in Fig. B2), a regression-based PI model was used to exploit continuous fractional labels, enabling pixel-level ranking within each inventory polygon and producing a 90 m peatland map that preserves the
 630 original total peat area. For Alaska (blue region), we applied a tile-based downscaling approach consistent with the Eurasian subset to reconcile the discrepancies between PEATMAP and GPD. Finally, for the high-latitude permafrost regions (orange region) where no reliable training targets exist, peatland distribution was inferred using a transfer learning strategy based on a classification model trained over the eco-climatically similar Eurasian domain.

Author contributions. M.C. designed the study, developed the software, and performed the investigation, data curation, validation, and visualization. P.C., G.H., and F.A. contributed to the conceptualization. M.C. developed the methodology with guidance from P.C. and F.A., and performed the formal analysis. Resources were provided by P.C., G.H., and F.A. M.C. wrote the original draft. P.C., G.H., and F.A. reviewed and edited the manuscript. P.C. and F.A. supervised the research and acquired funding. F.A. administered the project. All authors have read and approved the final manuscript.

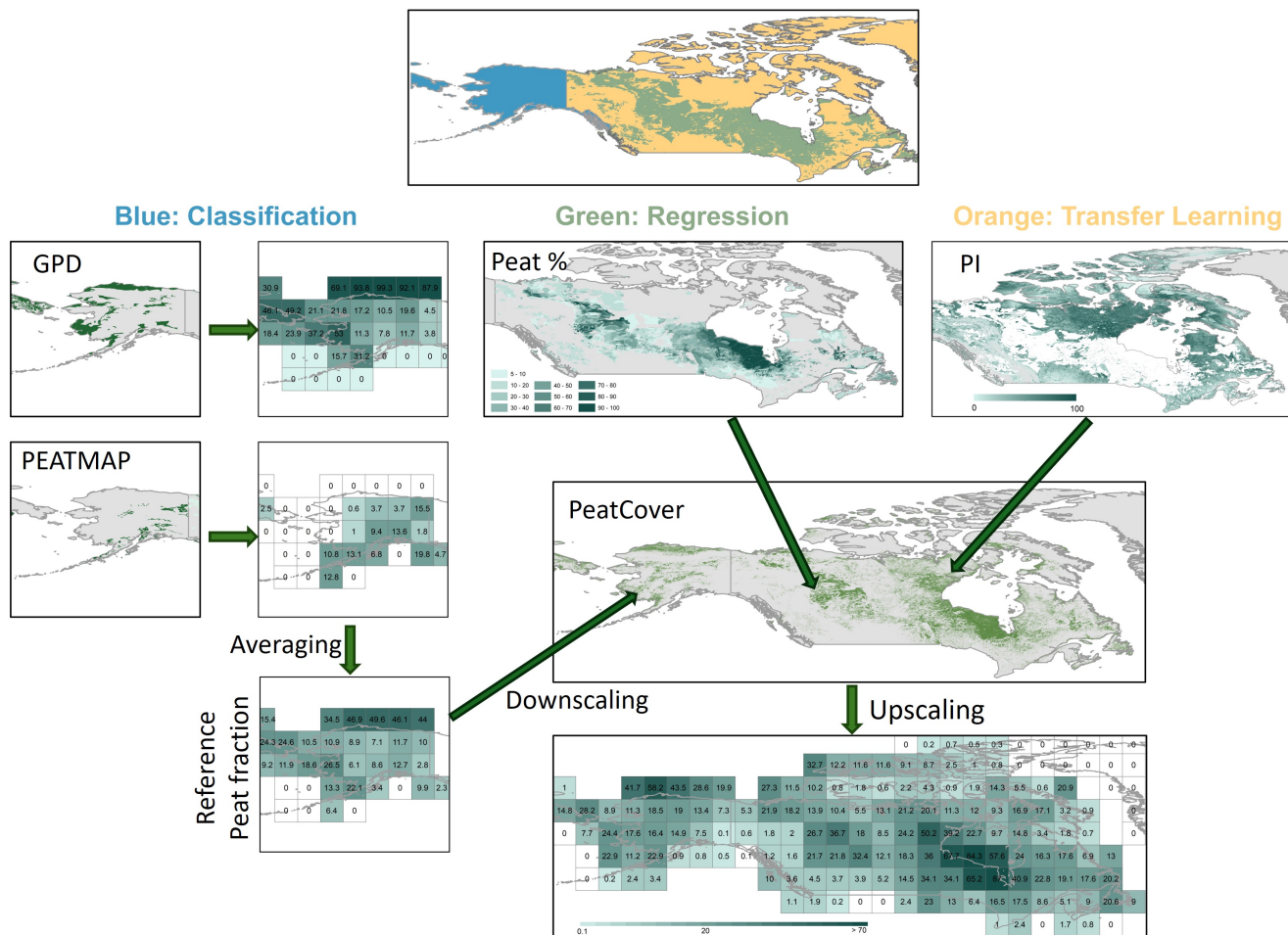


Figure B2. Illustration of the peat retrieval framework steps, over North America. The blue pixels on the top are processed in the same way as in Eurasia (Fig. B1). Over Canada (green pixels) PEATMAP is directly downscaled using our PI. Over the orange pixels, a transfer learning is chosen using a NN retrieval.

Competing interests. The authors declare that they have no conflict of interest.

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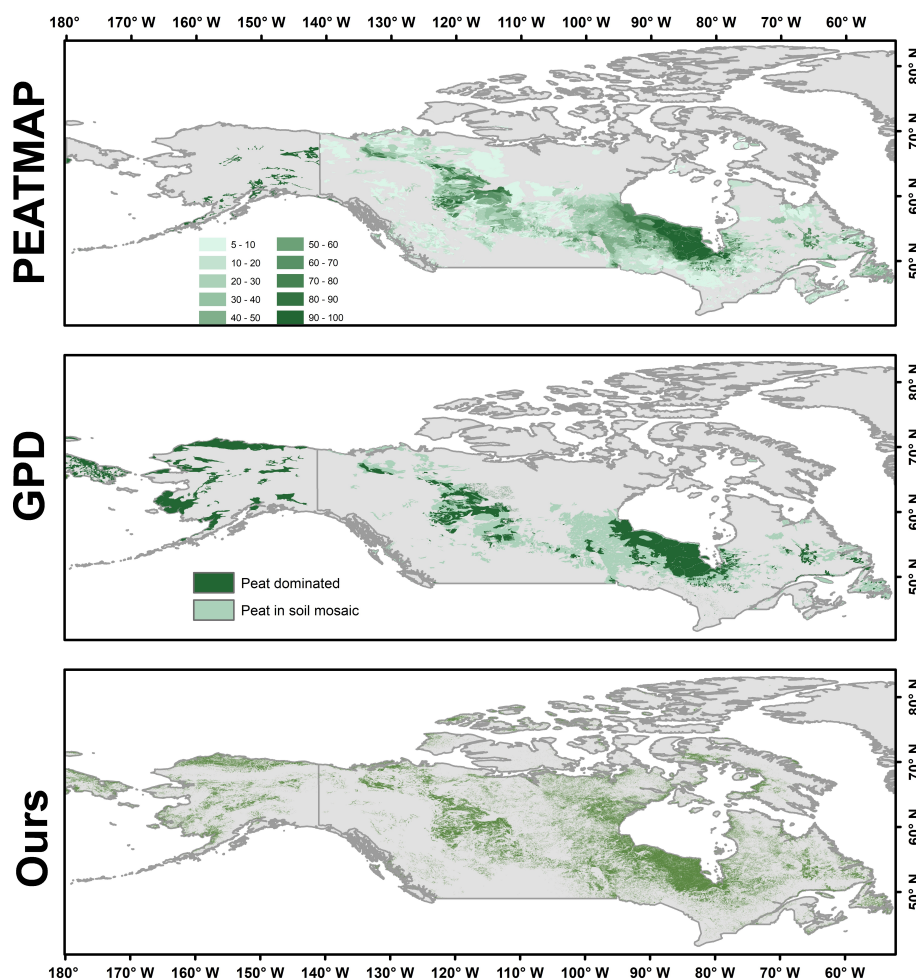


Figure B3. Comparison of peatland distributions across North America derived from three datasets: PEATMAP (top), GPD (middle), and the peatland map produced in this study (bottom). PEATMAP is shown as fractional peat coverage, GPD as categorical peat extent (peat-dominated and peat-in-soil mosaic), and our map as the final binary peatland classification.

making harmonized peat depth observations openly available, which were used for independent evaluation. We gratefully acknowledge the Jean Zay high-performance computing facility, as well as the computing infrastructure available at the authors' laboratories and institutions. We thank the members of the PhD monitoring committee for valuable feedback and guidance, including Elodie Salmon, Fabrice Jégou, and Paola Di Matteo. We also thank David Olefeldt and McKenzie Ann Kuhn for helpful discussions regarding peatland data.

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