# Data-driven modeling of carbon dioxide and methane fluxes across the Arctic-boreal region: recent achievements and future opportunities

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# Abstract

The Arctic-boreal region contains a significant portion of the global carbon reservoir, which is becoming increasingly vulnerable to atmospheric release due to climate change. Thus, it is vital to monitor and model Arctic-boreal carbon flux dynamics to understand the shifting carbon balance. Data-driven statistical and machine learning models are now commonly used to upscale carbon dioxide ($CO_2$) and methane ($CH_4$) fluxes in northern ecosystems from local to circumpolar scales. This review highlights recent progress, ongoing challenges, and new insights into data-driven Arctic-boreal carbon flux modeling. We identify five key areas for future model development: (1) developing comparable upscaling frameworks for terrestrial and freshwater ecosystems, especially for understudied systems like lakes and rivers; (2) reducing uncertainties and gaps in geospatial observations to better represent landscape heterogeneity; (3) fusing process-based with upscaling models to reduce computational demands, allowing to increase resolution and boost predictive power; (4) maximizing synergies between data-driven, process-based, and atmospheric inversion models using hybrid modeling; and (5) collaborating with field and remote sensing scientists to ingest observations in the upscaling process in near-real-time. These steps will reduce carbon budget uncertainty, advance our understanding of the carbon cycle, and support global climate policy.

# 1 Introduction

The balance of carbon fluxes, including carbon dioxide ($CO_2$) and methane ($CH_4$) from the Arctic-boreal region is changing as climate warming degrades permafrost and alters vegetation dynamics (Biskaborn et al., 2019; Meredith et al., 2019; Virkkala et al., 2025a; Watts et al., 2025). Because permafrost and Yedoma soils in the Arctic-boreal region store over 1,700 Pg of carbon, about one-third of global soil carbon (Hugelius et al., 2020, 2014; Mishra et al., 2021), these changes are creating global climate feedbacks (Natali et al., 2021; Schuur et al., 2022). There is high spatiotemporal complexity in carbon fluxes and drivers at scales ranging from local to regional/circumpolar and disentangling this complexity is necessary to understand current and expected fluxes (Euskirchen et al., 2022). The limited spatiotemporal coverage of carbon flux observations in the Arctic-boreal region requires scaling approaches to project local-scale information across larger-scale domains (See et al., 2024; Virkkala et al., 2025a). The most common techniques available for this purpose include atmospheric inverse modeling, bottom-up process modeling, and data-driven upscaling (Bruhwiler et al., 2021; Hugelius et al., 2024; Treat et al., 2024).

Atmospheric inversion models are a method for characterizing surface-atmosphere exchange across regional to global scales from the "top-down" perspective by combining measurements of atmospheric mixing ratios with atmospheric transport modeling and advanced statistics (Bruhwiler et al., 2021; Ciais et al., 2022). These approaches facilitate an atmospheric constraint of large-scale carbon fluxes between the surface and atmosphere, with relatively coarse observational footprints of hundreds of kilometers extending over regional to global extents (e.g., Houweling et al., 2017; Rödenbeck et al., 2018). Atmospheric inversions offer an independent method for estimating carbon budgets compared to bottom-up scaling approaches, such as process-based models or data-drive upscaling (e.g., Ramage et al., 2024). Inversions are commonly informed by prior flux information as a starting point, including estimates of flux magnitudes from e.g. fossil fuel inventories, land cover maps and output from process-based models. In regions that lack observational constraints, such as the Arctic-boreal (e.g., Wittig et al., 2024) inversions gravitate strongly to these existing priors, thus limiting their ability to add information on properly attributing fluxes.

Process-based models simulate ecosystem dynamics using mathematical equations of biophysical, biochemical, and ecological processes and their feedbacks (Heffernan et al., 2024; Huntzinger et al., 2020; Mevenkamp et al., 2023). Importantly, as processed-based models directly incorporate mechanisms, they may be used to predict future states outside of present-day climatic boundaries (e.g., Kleinen et al., 2021), or to experiment with how changes in specific inputs affect results (i.e., senstitivity analyses, e.g., De Vrese et al., 2023). But their predictive capacity strongly depends on accurate representation of complex underlying processes (e.g., Gier et al., 2024). The current generation of Arctic-boreal process-based models still has limitations due to missing processes, such as permafrost feedbacks, limited representation of thermal and moisture dynamics, as well as a poor representation of soil carbon stocks (Hugelius et al., 2024; Schädel et al., 2024). Consequently, they may underestimate $CO_2$ and $CH_4$ flux variability from permafrost ecosystems (Treat et al., 2024; Virkkala et al., 2025a).

Data-driven upscaling uses various statistical techniques applied to large but typically geographically biased data volumes, to analyze relationships between in-situ carbon flux measurements and explanatory variables, such as environmental conditions and ecosystem characteristics (Jung et al., 2020; Kuhn et al., 2025; Virkkala et al., 2025a; Ying et al., 2025; Yuan et al., 2024). These models are thus correlative in nature and can make full use of available data in finding relationships between target and predictor variables in ways other modeling techniques cannot. However, the strengths and directions of the relationships between target and predictor variables in regional upscaling efforts are often consistent with concepts used in other modeling studies (e.g., positive relationships between temperature or $CH_4$ fluxes and ecosystem respiration are positive; (Virkkala et al., 2021; Yuan et al., 2024). Current data-driven models are generally multivariate, meaning that several predictors - and often also their interactions - are included. Data-driven approaches can include static predictors (e.g. fundamental physical state variables such as land cover type or permafrost), and dynamic variables (e.g. temperature, soil moisture, and vegetation indices), which follow the timestep of the model. Additionally, different types of new predictors are continuously being explored, e.g. novel static geospatial layers (e.g., burned status) or parameters accounting for temporal lags (e.g., accounting for delayed transport and release of gas, Yuan et al., 2022). Although the absence of processed-based mechanisms and feedback may introduce uncertainties, the ability of data-driven models to ingest large datasets

and the much lower computing demand make them ideal for more rapidly upscaling data and modeling over larger spatial domains.

In this review, we examine the history, development, and current status of data-driven upscaling methods, emphasizing their role in understanding carbon flux dynamics in the Arctic-boreal region, the extent of which is defined here by Dinerstein et al. (2017). Our focus is on biogenic surface-atmosphere carbon fluxes; $CO_2$ fluxes, encompassing plant carbon uptake and emissions from microbial and plant respiration and $CH_4$ fluxes, including emissions driven by methanogenesis and uptake driven by methonotrophy. Different methodological approaches have been used in carbon flux upscaling studies that have been conducted for terrestrial ecosystems versus inland water ecosystems (including freshwater lakes, reservoirs, ponds, rivers, and streams; Ramage et al., 2024), and methods have also varied depending on the carbon species targeted (Johnson et al., 2022; Ramage et al., 2024; Rocher-Ros et al., 2023; Virkkala et al., 2021). These differentiations have been required since relationships with covariates and data coverage often differed between ecosystem types and/or carbon species. In the following, we will compare scaling methods, summarize data considerations of both in-situ and gridded data important for constructing and running models, and provide best practices for operating data-driven upscaling frameworks. Finally, we will discuss future directions for enhancing the quality of data-driven upscaling products.

# 2 History of Arctic-boreal Data Driven Upscaling

The first data-driven approaches to scaling carbon fluxes across Arctic-boreal ecosystems date back to the 1970s (Ehhalt, 1974). These early efforts were limited to in-situ observations from a handful of field sites, and geospatial information on landscape structure and climate, and computational resources, were limited (Oechel et al., 1993). Accordingly, assessed carbon fluxes for complex high-latitude landscapes were simplified by calculating the product of landcover area and flux intensity ("paint-by-numbers") for a few dominant landcover types to extrapolate across a large region (Figure 1). First attempts to quantify northern wetland $CH_4$ budgets were based on wetland maps and chamber-flux values from literature (Table 1; Matthews and Fung, 1987), on observations from a limited number of sites in Alaska (Sebacher et al., 1986), and a

tundra $CH_4$ budget for the Russian domain (Ehhalt, 1974). Similarly, early estimators of inland water carbon budgets were restricted to data from the North Slope of Alaska (Kling et al., 1992)and isolated regions of northern Siberia (Zimov et al., 1997).

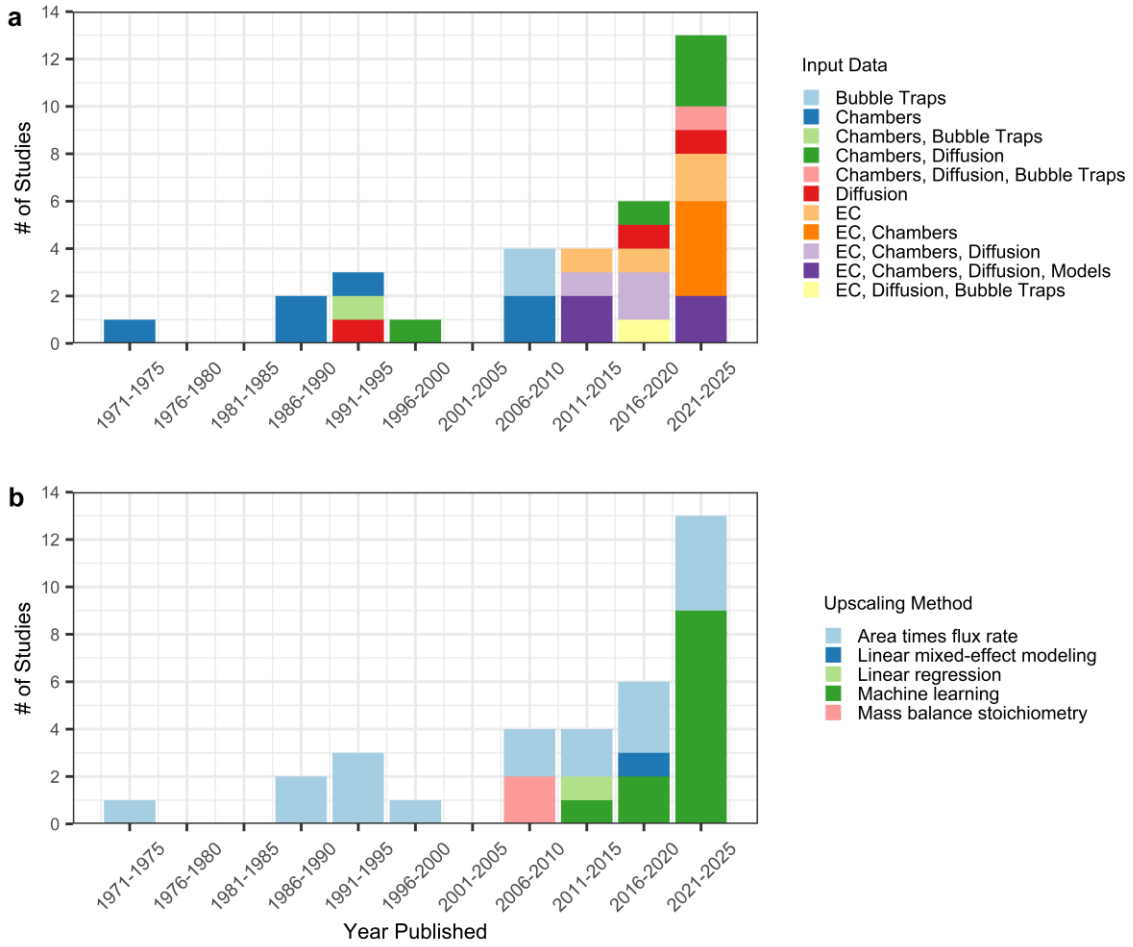


**Figure 1.** Count of carbon flux upscaling studies based on in-situ flux data using various measurement methods **(a)** and upscaling methods **(b)** for data-driven regional budget estimates from 1971 to 2025. Based on a compilation of studies as of February 2025 where the upscaling method and input data were identified through expert assessment (SI Table 1). Chambers refer to both terrestrial and inland water ecosystems and diffusion is the diffusion flux method from inland water systems. EC is eddy covariance. Models as data input use model outputs in upscaling.

Starting in the 1990s, new generations of instrumentation for field observations led to a rapid expansion of Arctic-boreal carbon flux monitoring (Belshe et al., 2013; Oechel et al., 2014;

Pallandt et al., 2022; Suni et al., 2003; Vogt et al., 2025), initially focusing on $CO_2$ measurements. The first year-round $CH_4$ measurements at a boreal site were established a few years later (Rinne et al., 2007). Progress in the availability of in-situ observations was accompanied by improvements in spatial resolution and thematic content of geospatial data layers of the explanatory variables (Ueyama et al., 2013; Wik et al., 2016). This provided the foundation for the development of more sophisticated upscaling methods that included higher levels of detail regarding the functional relationships between fluxes and explanatory variables, or the differentiation of ecosystem types within structured landscapes. A key effort has been the global upscaling framework FLUXCOM investigating e.g. how different predictor datasets and machine learning models impacted upscaled global terrestrial $CO_2$ and energy fluxes (Jung et al., 2020; Nelson & Walther et al., 2024; Tramontana et al., 2016). With the ongoing improvement of methods, information, and computational resources, a generation of advanced upscaling products has emerged, which makes it possible to resolve the Arctic-boreal domain at relatively high spatio-temporal resolution and link fluxes and controls in a high degree of detail (Figure 2, Peltola et al., 2019; Virkkala et al., 2021; Ying et al., 2025).

Recent wetland $CH_4$ budget assessments suggest wide emissions ranges based partly on the regions covered and wetland maps used (Table 1, Peltola et al., 2019; Ramage et al., 2024; Ying et al., 2025; Yuan et al., 2024). Other recent studies have started to focus on $CH_4$ uptake showing emissions may be offset partially by drier ecosystems, previously process-based and inversion models dominated $CH_4$ uptake studies (Jiang et al., 2025; Oh et al., 2020; Parmentier et al., 2024; Voigt et al., 2023). In contrast, terrestrial $CO_2$ budgets indicate a relatively strong carbon sink in the boreal region, while the tundra biome exhibits a smaller sink to near-neutral budget (Ramage et al., 2024; Virkkala et al., 2025a). Recent papers suggest a wide range in estimated lake $CO_2$ emissions (Ramage et al., 2024; Song et al., 2024) and generally higher and more variable estimates were reported for rivers (Lauerwald et al., 2023; Liu et al., 2022; Ramage et al., 2024; Song et al., 2024), where lake $CH_4$ emission estimates tend to agree more than $CO_2$ (Johnson et al., 2022; Kuhn et al., 2025; Matthews et al., 2020; Ramage et al., 2024; Sieczko et al., 2020; Wik et al., 2016); however, this agreement may be incomplete because most models potentially have issues capturing the spring ice-breakup period. River emission of $CH_4$ for the Arctic-boreal region was also substantial and was estimated to 17% of the global riverine $CH_4$ emissions (Rocher-Ros et al., 2023; Stanley et al., 2016). Human impacted ecosystems such as reservoirs

deserve attention as well given their prevalence in northern boreal areas and are of increasing attention (Bastviken and Johnson, 2025).

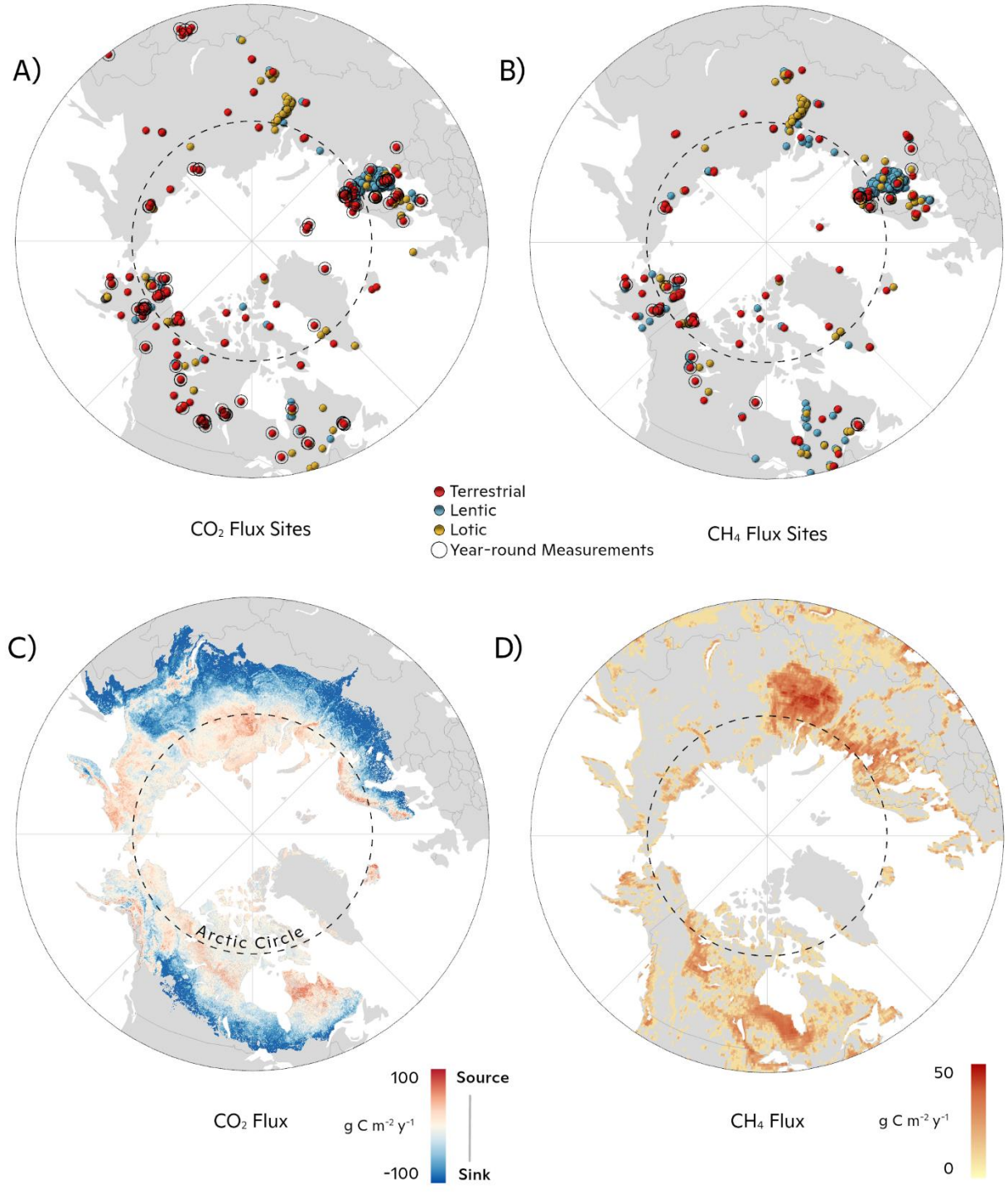

**Figure 2.** The spatial distribution of the Arctic-boreal network of carbon flux observations, based on a recent data synthesis (a & b; Virkkala et al., 2025b), alongside two examples of upscaled Arctic-boreal carbon flux maps. (c) The average terrestrial net ecosystem exchange (NEE) over 2002-2020 from Virkkala et al., (2025a), and (d) wetland methane ($CH_4$) emissions over 2016-2022 based on Ying et al., (2025), mapped across the wetlands north of 45 °N. These upscaled products were developed using random forest models together with gridded meteorological, remote sensing, and soil datasets as predictors.

**Table 1.** Methane ($CH_4$) and carbon dioxide ($CO_2$) budgets for various data-driven upscaling studies targeting various ecosystems and regions. All units are Tg $CH_4$-C $yr^{-1}$ or Tg $CO_2$-C $yr^{-1}$.

| Manuscript | Budget (Min) | Budget (Mean) | Budget (Max) | Target ecosystem(s) | Region |
|---|---|---|---|---|---|
| | | | | **Methane** | |
| Bastviken et al. (2025) | | 0.3 | | Reservoirs | Arctic Boreal Region |
| Bastviken et al. (2025) | | 11.0 | | Lakes | Arctic Boreal Region |
| Ying et al. (2025) | 11.8 | 17.1 | 38.7 | Wetlands | North of 45 Degrees N |
| Jiang et al. (2025) | | 6.9 | | Terrestrial | Arctic Boreal Region |
| Ramage et al. (2024) | 22.0 | | 53.0 | Terrestrial | Arctic Boreal Region |
| Ramage et al. (2024) | 4.5 | 9.4 | 13.1 | Inland Waters | Arctic Boreal Region |
| Song et al. (2024) | 7.6 | 10.7 | 13.9 | Inland Waters | Northern land cryosphere region, incl. Tibetan plateau |
| Song et al. (2024) | 1.7 | 3.5 | 5.3 | Rivers | Northern land cryosphere region, incl. Tibetan plateau |
| Song et al. (2024) | 5.9 | 7.2 | 8.7 | Lakes | Northern land cryosphere region, incl. Tibetan plateau |
| Yuan et al. (2024) | 14.6 | 15.2 | 15.9 | Wetlands | Arctic Boreal Region |
| Chen et al. (2024) | 17.0 | 19.5 | 22.0 | Wetlands | North of 30 Degrees N |
| Rocher-Ros et al. (2023) | | 3.5 | | Rivers | North of 50 Degrees N |
| McNichol et al. (2023) | 8.6 | 12.0 | 15.0 | Wetlands | 60-90 deg. N + West Siberian lowlands & Hudson Bay Lowlands |
| Johnson et al. (2022) | | 7.1 | | Lakes | North of 45 Degrees N |
| Matthews et al. (2020) | 10.4 | 11.8 | 13.3 | Lakes | North of 50 Degrees N |
| Peltola et al. (2019) | 16.1 | | 37.1 | Wetlands | North of 45 Degrees N |
| Treat et al. (2018) | 22.5 | 27.8 | 33.0 | Wetlands | North of 40 Degrees N |
| Holgerson & Raymond (2016) | 6.0 | | 15.0 | Lakes & ponds | Global |
| Wik et al. (2016) | 5.5 | 12.4 | 19.3 | Lakes & ponds | North of 50 Degrees N |
| Tan & Zhuang (2015) | 6.9 | 8.5 | 10.1 | Lakes | North of 60 Degrees N |
| McGuire et al. (2012) | 0.0 | 11.0 | 22.0 | Tundra | Circumpolar |

| | | | | | |
|---|---|---|---|---|---|
| Walter et al. (2007) | 10.3 | 18.2 | 26.0 | Lakes | North of 45 Degrees N |
| Bartlett and Harris (1993) | | 28.5 | | Wetlands & Tundra | North of 45 Degrees N |
| Mathews and Fung (1987) | | 49.1 | | Wetlands | North of 50 Degrees N |
| Mathews and Fung (1987) | | 21.9 | | Wetlands | North of 60 Degrees N |
| Sebacher et al. (1986) | 33.8 | 56.6 | 79.5 | Wetlands | Arctic Boreal Region |
| Ehhalt et al. (1974) | 1.0 | | 9.8 | Tundra | Circumpolar |
| **Manuscript** | **Budget (Min)** | **Budget (Mean)** | **Budget (Max)** | **Target ecosystem(s)** | **Region** |
| | | | | **Carbon Dioxide** | |
| Mu et al. (2025) | 174.0 | 188.0 | 202.0 | Rivers | Arctic Boreal Permafrost Region |
| Virkkala et al. (2025a) | -688.0 | -548.0 | -408.0 | Terrestrial | Arctic Boreal Region |
| Ramage et al. (2024) | -606.0 | | 661.0 | Terrestrial | Permafrost Region |
| Ramage et al. (2024) | 132.4 | 230.6 | 359.8 | Inland Waters | Arctic Boreal Region |
| Song et al. (2024) | 274.0 | 313.4 | 356.6 | Inland Waters | Northern land cryosphere region, incl. Tibetan plateau |
| Song et al. (2024) | 71.2 | 87.5 | 105.5 | Lakes | Northern land cryosphere region, incl. Tibetan plateau |
| Song et al. (2024) | 202.6 | 225.8 | 250.9 | Rivers | Northern land cryosphere region, incl. Tibetan plateau |
| Liu et al. (2022) | | 250.0 | | Rivers | "Arctic" (~boreal-Arctic region) |
| Virkkala et al. (2021) | -449.0 | | -366.0 | Terrestrial | Arctic Boreal Region |
| Holgerson & Raymond (2016) | 439.0 | | 683.0 | Lakes & Ponds | Global |
| Belshe et al. (2013) | 84.0 | 462.0 | 840.0 | Tundra | Circumpolar |
| McGuire et al. (2012) | -297.0 | -103.0 | 89.0 | Tundra | Circumpolar |
| Oechel et al. (1993) | | 190.0 | | Tundra, Lakes, & Rivers | Circumpolar |

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# 3 In-situ Flux and Predictor Data

Observational input data for both target and predictor variables are critical for upscaling, and obtaining spatially and temporally representative data remains a persistent challenge (Munson, 2012; Tweedie et al., 1994). Ideally, observational data are collected and processed using standardized protocols to ensure comparability, reproducibility and to avoid measurement error and bias (Loescher et al., 2022; Pastorello et al., 2020). Upscaling efforts are based on training data that are limited in space and time and in the ecosystem states they represent. A data-driven model must generalize input data patterns to larger areas and to conditions not always represented in the measured data. This is especially challenging in the Arctic-boreal region where carbon flux networks represent less than 40% of the environmental space and are biased towards warmer and undisturbed conditions (Pallandt et al., 2024, 2022; Virkkala et al., 2019). Accordingly, data quantity and quality are factors limiting upscaling efforts in the Arctic-boreal region, particularly during the non-growing season (Arndt et al., 2023), and important factors like extent and severity of disturbances such as wildfires are often unaccounted for (Ramage et al., 2024; Virkkala et al., 2025a).

## 3.1 Carbon Flux Measurements

### 3.1.1 Terrestrial observations

Terrestrial fluxes are primarily collected with the use of eddy covariance (EC) or flux chamber techniques. Other flux methods exist such as snow diffusion fluxes (Mavrovic et al., 2025) but they are less common in upscaling studies and thus are not emphasized in more detail here. EC is a micrometeorological flux measurement technique used to quantify ecosystem-atmosphere energy and trace gas exchange at landscape scales (i.e., 100s of $m^2$ to ~$km^2$ spatial scale), based on the continuous measurement of turbulent atmospheric transport using tower- or tripod-mounted instruments (Aubinet et al., 2012; Baldocchi, 2003). The spatial scale and continuous temporal coverage of EC measurements is convenient when connecting flux observations with geospatial data products as the scale of these observations can be similar (i.e., 250 – 1000 m). Chamber flux measurements (Kwon et al., 2019; Subke et al., 2021) enclose a small portion of the ecosystem (usually <1$m^2$) and derive the surface-atmosphere flux from the gas concentration

change in the headspace over time, with data usually collected manually during episodic campaigns. This allows collection of flux samples from homogeneous sub-units of a mixed landscape, but due to the small footprint the representativeness of individual measurements is challenging to assess.

Arctic-boreal data coverage currently includes around 120 active EC towers (Pallandt et al., 2024), and more than 1,000 flux chamber plots, though less than 30 of those flux chamber sites provide continuous data collected by automated chambers (Vogt et al., 2025). Many previous upscaling studies used just one type of flux data, such as global efforts based on EC fluxes from FLUXNET (Jung et al., 2020; McNicol et al., 2023; Tramontana et al., 2016). Using data from both chambers and EC has the advantage of a more detailed local-scale understanding of flux variability based on their different spatial coverage (Natali & Watts et al., 2019; Virkkala et al., 2021; Watts et al., 2021; Yuan et al., 2024). This also fosters process-understanding given the small-scale heterogeneity of carbon fluxes (Davidson et al., 2016; Juutinen et al., 2022; Virkkala et al., 2024). However, at the same time combining fluxes captured by different techniques adds challenges and uncertainty as these methods may not be directly comparable, although a good match between EC and flux chambers can be achieved (e.g., Parmentier et al., 2011). The user should decide carefully based on the scale of their study and representation of in-situ data in what to include to inform their models.

### 3.1.2 Inland water observations

Water-atmosphere carbon fluxes can be derived using many techniques, such as direct gas flux measurements using chambers (e.g., Rasilo et al., 2015) or bubble traps (e.g., Walter Anthony et al., 2021, 2010), EC towers with footprints covering inland water systems (e.g., Erkkilä et al., 2018; Podgrajsek et al., 2014), or diffusion outgassing estimated based on measured dissolved gas concentrations using Fick's law (Jaynes and Rogowski, 1983) and models for the gas transfer velocity (Hall and Ulseth, 2020; Klaus and Vachon, 2020; Raymond et al., 2012). Current Arctic-boreal data coverage includes 24 EC sites with major footprint fractions placed on open water bodies, while episodic flux chamber data and dissolved gas measurements are available for more than 1300 locations (Vogt et al., 2025). Global and regional data syntheses of carbon fluxes using different techniques have been published for lakes (Golub et al., 2022; Kuhn et al., 2021),

rivers and stream (Liu et al., 2022; Stanley et al., 2023), and inland waters in combination (i.e. lakes, rivers and streams; Song et al., 2024). Furthermore, dissolved gas concentrations were synthesized alongside fluxes (Liu et al., 2022; Stanley et al., 2023).

Similar to studies performing data-driven modelling for terrestrial ecosystems, upscaling studies were performed for inland waters for $CO_2$ (De Eyto et al., 2025; Denfeld et al., 2018; Mu et al., 2025; Ramage et al., 2024; Raymond et al., 2013; Song et al., 2024) and $CH_4$ (Ramage et al., 2024; Rocher-Ros et al., 2023; Song et al., 2024) varying in methodology, spatial extent, type of water body and magnitude of carbon budget (Table 1).

## 3.2 Ancillary in-situ data

The accuracy of flux upscaling models may be improved when *in-situ* environmental and biogeochemical information is available, as extracting from coarser geospatial data may not represent local conditions well. For example, soil moisture models often struggle, especially across the whole Arctic-boreal region (Kemppinen et al., 2023), and are often provided at the 10-50 km scale, which often does not represent fine-scale heterogeneity. While in-situ observations provide the most accurate and spatiotemporally resolved biogeochemical data possible for flux predictions (Knox et al., 2019), leveraging this information requires establishing a link to the gridded predictor dataset that will ultimately be used to scale up fluxes to the larger study domain, and moving between the two may introduce other errors.

For terrestrial systems, the incorporation of in-situ soil and vegetation datasets can improve the predictions of flux upscaling models (Voigt et al., 2023; Watts et al., 2023). Key dynamic variables include air and soil temperature, moisture, thaw-depth, and radiation. Semi-static characteristics are also important to measure, including vegetation community composition, aboveground biomass, canopy height, disturbance history, soil type, and soil carbon density.

For inland water systems, in-situ water quality measurements can be crucial to successfully predicting ebullitive and diffusive fluxes (Sø et al., 2023). In addition, lake freeze status derived from temperature sensors or field cameras at flux measurement sites can improve the modeled relationships to fluxes (Karlsson et al., 2013) while being readily scalable to associated geospatial layers. Conversely, the freeze status of small lakes derived from high resolution

optical imagery can have significant temporal gaps due to limited overpass frequency, cloud coverage and sun-sensor geometry (Giroux-Bougard et al., 2023). Key dynamic variables include water depth, depth-resolved temperature (including sediments), dissolved oxygen, dissolved organic carbon, and variables reflecting biological productivity (Bastviken et al., 2004; Natchimuthu et al., 2016; Rocher-Ros et al., 2023). Key static variables include water body surface area, sediment characteristics, and geologic origin (Wik et al., 2016).

## 3.3 Data Repositories and Carbon Flux Syntheses

Choosing and compiling input data for data-driven upscaling is a key first step towards running any model. There are more than 2,000 sites with carbon flux observations using different systems across the Arctic-boreal region (Vogt et al., 2025), with most flux sites run by independent researchers studying individual scientific questions. Many of these sites are regionally clustered in Alaska and Scandinavia (Metcalfe et al., 2018). While this clustering facilitates a more detailed analysis of small-scale spatio-temporal carbon flux dynamics, these clusters limit the spatial representativeness on broader scales. A considerable fraction of flux datasets have been collected in data repositories that are publicly accessible. EC data repositories are either regional networks or global synthesis initiatives, in both cases providing data that are well-organized and standardized to facilitate integrating measurements from multiple sites (Table 2). Other data sources, like those related to a specific project or publication, also cover observations from chambers or concentration measurements; however, these sources are often less systematic and specialized, therefore making it more difficult to find data, and integrate into larger databases. This highlights the value of synthesis activities such as e.g. ABCFlux or BAWLD-$CH_4$ (Kuhn et al., 2021; Virkkala et al., 2025b, 2022) which standardize and collate data from across various networks and research groups.

**Table 2.** Existing repositories and synthesis data sources for terrestrial and inland water flux data in the Arctic-boreal region.

| **Repository, Flux Network, or Synthesis** | **Measurement method(s)** | **Geographic Coverage** | **Reference or URL** |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Fluxnet | EC | Global | https://fluxnet.org/ |
| Ameriflux | EC | Americas | https://ameriflux.lbl.gov/ |
| NEON | EC & Chamber | United States | https://data.neonscience.org/ |
| ORNL DAAC | EC, Chamber & concentration | Global | https://daac.ornl.gov/ |
| ICOS | EC & Chamber | Europe | https://www.icos-cp.eu/ |
| European Fluxes Database Cluster | EC | Europe | https://www.europe-fluxdata.eu/ |
| AsiaFlux | EC | Asia | https://www.asiaflux.net/ |
| Arctic Data Center | EC, Chamber & concentration | Arctic-boreal zone | https://arcticdata.io/ |
| BAWLD-CH4 | Chamber | Arctic-boreal zone | Kuhn et al., (2021) |
| ABCflux | EC & Chamber | Arctic-boreal zone | Virkkala et al. (2025b, 2022) |
| GRiMe | Chamber and concentration | Global | Stanley et al. (2023) |
| JapanFlux2024 | EC | Asia | Ueyama et al. (2025) |
| SITES | EC, Chamber & concentration | Sweden | https://www.fieldsites.se/ |
| Golub et al. 2023 | EC | Global | Golub et al. (2023) |
| Natali & Watts et al. 2019 | EC & Chamber | Arctic-boreal zone | Natali & Watts et al. (2019) |

| | | | |
|---|---|---|---|
| Treat et al., 2018 | EC & Chamber | Arctic-boreal zone | Treat et al. (2018) |
| Cryosphere Inland Water Greenhouse Gases Database (CIWD-GHG) | Chamber & concentration | Arctic-boreal zone and Tibetan Plateau | https://zenodo.org/records/11054180 |
| Greenland Ecosystem Monitoring | EC & Chamber | Greenland | https://data.g-e-m.dk/ |
| Svalbard Integrated Arctic Earth Observing System (SIOS) | EC, Chamber & concentration | Svalbard | https://www.sios-svalbard.org/ |

# 4 Geospatial environmental data

Effective upscaling of carbon fluxes requires accurate geospatial products representing key predictor variables. These variables should represent the expected processes controlling the target flux and thus may vary depending on the carbon flux and ecosystem considered, although there are some common key predictor variables (e.g., air/soil/water temperature). Categories of environmental correlates used in data-driven upscaling include land cover and waterbody type, vegetation, soil, permafrost, topography, meteorology and climate (see Table 3 for used products).

## 4.1 Current gridded datasets: strengths and limitations

Global optical remote sensing and meteorological datasets have been available for several decades and have formed the foundation for data-driven carbon flux upscaling. Optical remote sensing, providing indices like the normalized difference vegetation index (NDVI; using red and near-infrared spectral bands) from MODIS, have shown strong correlations with carbon fluxes and often explain a significant portion of carbon flux variability (Tramontana et al., 2016; Virkkala et al., 2025a), while gridded meteorological datasets (particularly air temperature, solar

radiation) provided from products such as the ECMWF reanalysis v5 (ERA5-Land Muñoz-Sabater et al., 2021) are primary covariates for temporal dynamics (Feron et al., 2024; Ying et al., 2025). However, while these predictors capture important spatial and temporal dynamics needed for scaling carbon fluxes for many key covariates within the Arctic-boreal region such as surface inundation, soil moisture, soil freeze/thaw status, snow depth, and snow water equivalent, comprehensive datasets with adequate spatial resolution and quality are still lacking. For example, linked to the lack of high-quality subsurface datasets for the high northern latitudes, moisture status covariates have often been underrepresented in carbon flux upscaling studies or, when included, have shown limited importance (Natali & Watts et al., 2019; Virkkala et al., 2025a), despite obvious impacts at the site level. Moreover, optical remote sensing data for the Arctic-boreal domain are often affected by cloud cover, snow, and low sun angles, all of which impact the availability and quality of spaceborne measurements (Duncan et al., 2020).

Beyond dynamic predictors, static geospatial datasets, such as topography, land cover, and soil properties, play a crucial role in carbon flux upscaling. While regional and local datasets of moderate resolution (≤1 km) have been available for years, the scarcity of high-quality geospatial products covering the full Arctic-boreal domain with uniform formatting has limited large-scale carbon flux upscaling efforts. Many global land cover classifications do not include unique characteristics of these regions, including periglacial processes, glacial history, or permafrost characteristics, and misclassify land cover types. For example, the global land cover dataset ESA CCI Landcover underestimates wetland extent (19% accuracy for the entire permafrost region, Palmtag et al., 2022) and misclassifies 60% of Arctic shrub tundra as barren (Bartsch et al., 2024). This misrepresentation is partially attributed to the low spatial and thematic resolution of high-latitude land cover classes in global products and can propagate into carbon flux upscaling, including cases where sources are misrepresented as sinks (Hashemi et al., 2025). Similarly, the SoilGrids 250m dataset, a state-of-the-art high-resolution global product of soil properties based on upscaling observational data with machine learning, is constrained by data sparsity, with the tundra bioclimatic region being represented by only ~800 observations, compared to nearly 50,000 for the temperate broadleaf and mixed forests bioclimatic region, despite being roughly equal in area (Poggio et al., 2021).

Even for the numerous local and regional geospatial datasets that describe the complex and heterogeneous Arctic-boreal environment, the high spatial heterogeneity of these landscapes poses a particular challenge. Case studies capturing such fine-scale variability with high-resolution remote sensing data (<= 30 m, e.g., optical vegetation and thermal indices calculated from Planet, Sentinel and Landsat satellites) are emerging, and demonstrate strong performance when paired with spatial chamber campaigns or EC flux footprint decomposition (Ludwig et al., 2024, 2023; Räsänen et al., 2021). However, substantial work remains to be invested in integrating and extrapolating these high spatial resolution remote sensing data with the high temporal resolution of flux measurements across the entire Arctic-boreal region. Of particular importance for carbon flux upscaling is the high heterogeneity in soil moisture content (Lara et al., 2020). Bartsch et al. (2024) demonstrated in their high-resolution land cover product for the Arctic biome that about 66% of the analyzed landscape was highly heterogeneous with respect to wetness at a 1-km scale. Since wetland type differentiation is still mostly limited to local studies, and ground-truth data are largely lacking in many regions, the ability of data-driven upscaling approaches to accurately represent conditions within larger Arctic-boreal regions remains severely hampered.

For inland water carbon fluxes, scaling is also limited by available geospatial data (Kuhn et al., 2025; Rosentreter et al., 2021; Wik et al., 2016). The scaling efforts to arrive at waterbody carbon budgets often rely on estimates of total waterbody area by regions, sometimes stratified by water body size categories. There are three main challenges to scaling waterbody carbon emissions; first, many of the relevant driver variables are not available as spatial datasets (e.g. water and sediment temperature, dissolved oxygen, dissolved organic carbon concentration and quality, bathymetry, (e.g. water and sediment temperature, dissolved oxygen, dissolved organic carbon concentration and quality, bathymetry, Ludwig et al., 2022). Second, mapping small waterbodies is essential for scaling inland water carbon emissions, particularly in Arctic-boreal regions where small ponds and lakes are abundant and can experience rapid change in area both seasonally and inter-annually (Kyzivat and Smith, 2023; Mullen et al., 2023; Muster et al., 2019). Ponds (<0.01 $km^2$) often have the highest emission rates of $CO_2$ and $CH_4$ (Holgerson and Raymond, 2016), but are not mapped accurately enough by 30-m or coarser imagery to delineate area and separate open surface water from vegetated wetlands and pixel edge effects, leading to double counting (Thornton et al., 2016). Currently, water bodies are mapped at the 10 ha and 1

ha scale (Messager et al., 2016; Wang et al., 2025). Third, temporal components like the ice-covered period are estimated based on remotely sensed data (Zhao et al., 2022); however this technique may miss events based on retrieval times and may miss intermittent ice off periods where emissions occur.

## 4.2 Future upgrades towards Arctic-boreal specific geospatial datasets

Customized geospatial datasets for the Arctic-boreal region have become increasingly available over the past decades. One example is the Boreal Arctic Wetland and Lake Dataset (BAWLD), which provides a novel thematically complex classification of wetland landscapes across the full Arctic-boreal region, and has been used for carbon flux upscaling (Kuhn et al., 2025; Ramage et al., 2024). This data product integrates multiple data sources at broader scales; however, the resulting information is provided at comparably coarse resolution (0.5 degree; Olefeldt et al., 2021), and the thematic classes are designed for $CH_4$ flux upscaling and miss many important classes for $CO_2$ fluxes (e.g., different types of boreal forest or upland tundra vegetation). Spatial and thematic resolution could, however, be improved by fusing available regional products (Briones et al., 2025). Other customized datasets include those describing soil types and carbon stocks as well as active layer thickness and mean annual ground temperatures for the permafrost region (Hugelius et al., 2014; Westermann et al., 2025), though these miss the non-permafrost boreal regions that cover more than 20% of the Arctic-boreal domain.

Microwave satellite observations offer a potential solution to address some of the current gaps in providing proxies for belowground conditions, as they can penetrate clouds and provide critical information on high-latitude processes such as active layer thaw or near surface moisture status (Bartsch et al., 2023). However, the high landscape heterogeneity of Arctic-boreal regions poses significant challenges for retrieving soil moisture information via microwaves, available at spatial resolutions of ~10–25 km (Högström et al., 2018; Högström and Bartsch, 2017; Wrona et al., 2017). Recent studies have demonstrated that microwave derived soil freeze/thaw status could enhance flux estimates and provide deeper insights into seasonal carbon dynamics (Pulliainen et al., 2024; Widhalm et al., 2025). While there are still substantial differences between freeze/thaw products to date, there is the potential for spatial resolution enhancement and improvement through product combination (Bartsch et al., 2025). Further, these more active

remote sensing techniques could aid in data collection over the dark Arctic winters where there is a large paucity of data given the need for solar radiation in passive remote sensing technologies.

Regarding inland water datasets, there are promising avenues that leverage the light absorbed by chlorophyll and chromophoric dissolved organic matter to remotely sense these concentrations in surface waters, which have then been related to $CO_2$ and $CH_4$ in empirical models and used in data-driven models (Griffin et al., 2018; Kutser et al., 2005; Lapierre and Del Giorgio, 2012; Ludwig et al., 2023). Regarding the mapping of small water bodies, there are growing efforts to create very high resolution landcover and inland water maps for the pan-Arctic (Bartsch et al., 2024; Mullen et al., 2023; Wang et al., 2025), which could support high resolution, data-driven scaling of inland water carbon emissions. Both directions hold the potential to boost the quality of upscaled inland water carbon products in future modeling frameworks.

Finally, the geospatial mapping of extent, severity and frequency of occurrence of disturbance features across the Arctic-boreal region poses a special challenge to upscaling efforts. Typical disturbances are wildfires, windthrow, insects, rain-on-snow events and permafrost thaw, including different types of abrupt thaw, lake drainage, ice wedge degradation, and thermokarst (Bhuiyan et al., 2020; Grosse et al., 2011; Schuur and Mack, 2018). Such rapid changes and disturbances greatly impact carbon fluxes, and the ability to monitor and characterize them (Phoenix et al., 2025). Ramage et al (2024) suggest that disturbances, primarily abrupt thaw and fires, pushed the northern permafrost region from a net sink to a source of atmospheric carbon for the period 2000 – 2020, in line with findings from earlier regional studies (e.g., Commane et al., 2017). The rapid landscape changes that occur from these processes cannot be captured by static land cover datasets, instead we require observations from space that are continuous in time and have sufficient spatial resolution. Wildfires are the most documented, including global products such as Copernicus Fire and GFED (Copernicus Atmosphere Monitoring Service, 2022; Van Der Werf et al., 2017); however, these products often disagree, especially in Siberia (Clelland et al., 2024). In addition to fire, some products have been developed specifically for Arctic-boreal disturbance regimes. Some circumpolar datasets map the spatial patterns of disturbances (e.g., Nitze et al., 2025), providing valuable information on regional dynamics in spatial extent and severity. Zhang et al. (2022) used a continuous change detection and classification algorithm to document and classify boreal forest disturbances based on Landsat

satellite imagery, while Runge et al. (2022) reported an 331% increase of areas affected by retrogressive thaw slumps between 2000 and 2019 based on a large-scale, automated detection algorithm using combined Landsat and Sentinel-2 satellite imagery. Available data on ground ice distribution (e.g., O'Neill et al., 2019) could be linked to these studies to project the likelihood of thermokarst disturbances under future climate scenarios. Still, current information on disturbance features is based on only a limited number of observational data years, compared to the typical duration of a disturbance cycle (e.g., Turetsky et al., 2020), and the rate of disturbance formation, recovery and associated fluxes is mostly lacking, all of which are needed to understand the net impact of the disturbances on fluxes. Consequently, such predictors have not yet been utilized adequately in Arctic-boreal carbon flux upscaling.

**Table 3.** Examples of geospatial datasets used as input for Arctic-boreal data-driven upscaling studies. The subclasses describe the specific predictor variables within the broad classes.

| **Broad class** | **Subclass** | **Geospatial dataset** |
|---|---|---|
| Land cover | Land cover: thematic land cover classes and fractional coverages, including wetland and lake extent | Boreal-Arctic Wetland and Lake Dataset (Olefeldt et al., 2021)<br><br>Global Lakes and Wetland Database (Lehner et al., 2025) |
| Vegetation | Vegetation fractional cover: fraction coverage of different types of vegetation (species or generalized classes) | MODIS Continuous Vegetation Fields (DiMiceli et al., 2022) |
| | Vegetation communities: species data, plant community assemblages, plant functional type | Circum-Arctic Vegetation Map (Raynolds et al., 2019) |
| | Productivity/Biomass: Leaf area index, normalized difference vegetation index, enhanced vegetation index, above ground and below ground biomass | MODIS Vegetation Indices (Didan, 2021) |
| Soil properties | Soil texture: Volumetric fraction of sand, silt and clay. | SoilGrids1.0 (Hengl et al., 2017)<br><br>SoilGrids2.0 (Poggio et al., |

| | | |
|---|---|---|
| | | 2021) |
| | Soil carbon: Soil organic carbon (OC) content, calculated from OC and soil bulk density data. | SoilGrids1.0 (Hengl et al., 2017)<br><br>SoilGrids2.0 (Poggio et al., 2021)<br><br>Permafrost Carbon (Hugelius et al., 2014) |
| Permafrost | Extent of permafrost: Probability or aerial coverage. | (Obu et al., 2019; Westermann et al., 2025) |
| | Active layer depth: Depth of active layer at the end of the growing season. Data on seasonal and interannual active layer depth variability | (Westermann et al., 2025) |
| | Permafrost temperature: Degrees, depth of annual zero amplitude | (Obu et al., 2019; Westermann et al., 2025) |
| | Soil freeze/thaw status | (Kim et al., 2017; Luojus et al., 2021) |
| Topography | Elevation and topographic indices such as slope angle, aspect, topographic wetness index and topographic position index | Geomorpho90m (Amatulli et al., 2020) |
| Meteorology | Air, surface and soil temperature | ERA5-Land (Muñoz-Sabater et al., 2021)<br><br>MERRA2 (Global Modeling And Assimilation Office and Pawson, 2015)<br><br>MODIS Land Surface Temperature (Wan et al., 2021)<br><br>TerraClimate (Abatzoglou et al., 2018) |
| | Incoming solar radiation | ERA5-Land (Muñoz-Sabater et al., 2021) |
| | Precipitation, vapor pressure deficit | ERA5-Land (Muñoz-Sabater et al., 2021) |

| | | |
|---|---|---|
| | Soil moisture | ERA5-Land (Muñoz-Sabater et al., 2021)<br><br>SMAP (Lakshmi and Fang, 2023) |
| | Snow cover and depth | ERA5-Land (Muñoz-Sabater et al., 2021)<br><br>MODIS Snow / Ice Global Mapping Product (Hall and Riggs, 2021) |
| Climate | Long-term annual and seasonal averages: mean annual air temperature and precipitation, growing degree days, freezing degree days | WorldclimV2 (Fick and Hijmans, 2017)<br><br>TerraClimate (Abatzoglou et al., 2018) |
| Waterbody types & characteristics | Lake and river types: Thematic lake and river classes and fractional coverages | Boreal-Arctic Wetland and Lake Dataset (Olefeldt et al., 2021) |
| Inland water characteristics | River discharge | (Lin et al., 2019) |
| | Lake, river and catchment shapefiles | HydroLAKES, HydroRIVERS, HydroBASINS (Lehner and Grill, 2013) |
| | Gas transfer velocity | (Liu et al., 2022) |

# 5 Model development for data-driven upscaling

## 5.1 Model selection and set-up

Given the pronounced landscape heterogeneity and resulting data biases described in the previous section, selecting an appropriate model architecture is a critical next step. The characteristics and size of the input dataset drive downstream decisions on which modeling approach and type of machine learning model is appropriate and feasible (see the flowchart in

460 figure 3 as one possible approach to decide on a strategy). Complex nonlinear methods such as
461 neural networks (Hochreiter and Schmidhuber, 1997; Jain and Chandrasekaran, 1982; Lipton et
462 al., 2015; Van Der Ploeg et al., 2014) are difficult to construct and computationally intensive,
463 especially when employed with spatial or temporal context, but they excel at handling complex
464 data and have greater ability to extrapolate beyond the normal range of input data. Decision tree-
465 based models (Breiman, 2001; Chen and Guestrin, 2016) offer robustness and scalability, but
466 struggle with extrapolation and tend to produce estimates closer to the mean of training data.
467 However, decision tree models often behave more robustly than neural networks when presented
468 with limited training data (Jiang et al., 2020), which is important in the Arctic-boreal context
469 where training data are sparse. Consequently, the majority of recent upscaling studies exploring
470 carbon budgets at high northern latitudes focused on random forest approaches (Peltola et al.,
471 2019; Ramage et al., 2024; Virkkala et al., 2025a; Yuan et al., 2022). Smaller datasets would
472 preferably be analyzed with simple linear or non-linear regression approaches (e.g. linear mixed-
473 effects models), while simple regional averaging is also a commonly used method.

## 474 5.2 Data pre-processing

475 Careful pre-processing is critical to ensure that only high-quality data are used in upscaling
476 models. For example, data may need to be standardized or normalized, outliers removed, missing
477 values imputed (i.e., gap-filled), and/or collinearity addressed (see also figure 3). It is critical to
478 consider detailed method procedures, local conditions, and mechanistic understanding behind the
479 flux dynamics when evaluating data quality. Some large fluxes can be event-driven, making
480 “outlier” flux values real and important to keep (e.g. ebullition events), while other outliers can
481 be artifacts. Measurement artifacts (e.g. low turbulence conditions in EC data, low sun angles in
482 remote sensing data, the presence of snow in remote sensing indices) risk propagation to
483 upscaled fluxes if not corrected in quality checks. For missing data, careful imputation may be
484 necessary from a technical standpoint, as some machine learning methods cannot handle data
485 gaps. Even if the chosen upscaling approach can handle gaps, gap-filling may be advisable to
486 ensure the dataset is representative; however, data imputation also holds the potential to
487 introduce new artifacts in the input data or circularity in the modelling approach by common
488 predictor variables in the imputation and model training steps. Therefore, careful consideration

should be given to whether/how to impute the data, which method to use, and imputed data should be carefully checked.

Scale mismatches between in-situ and associated coarser geospatial data sets may potentially result in dissimilar behavior of the data across scales, and hence between the training and the inference step. This is another potential source of inaccuracies in upscaling studies, and different approaches exist for addressing them. For instance, the global FLUXCOM-X-BASE dataset (Nelson & Walther et al., 2024) uses in-situ meteorological and land cover data, and MODIS remote sensing data for training, which are then upscaled across the globe using corresponding gridded data at a coarser spatial resolution. While this minimizes scale mismatches among predictors and the target variable in training, the distribution in the training data may be different for the same variable in the predictor data and therefore lead to higher uncertainties in the upscaled products. In contrast, other recent efforts have relied solely on gridded data for model training (e.g., Natali & Watts et al., 2019; Rocher-Ros et al., 2023; Virkkala et al., 2025a), thus avoiding the distribution shift at the cost of potentially reduced accuracy of training data at the site level.

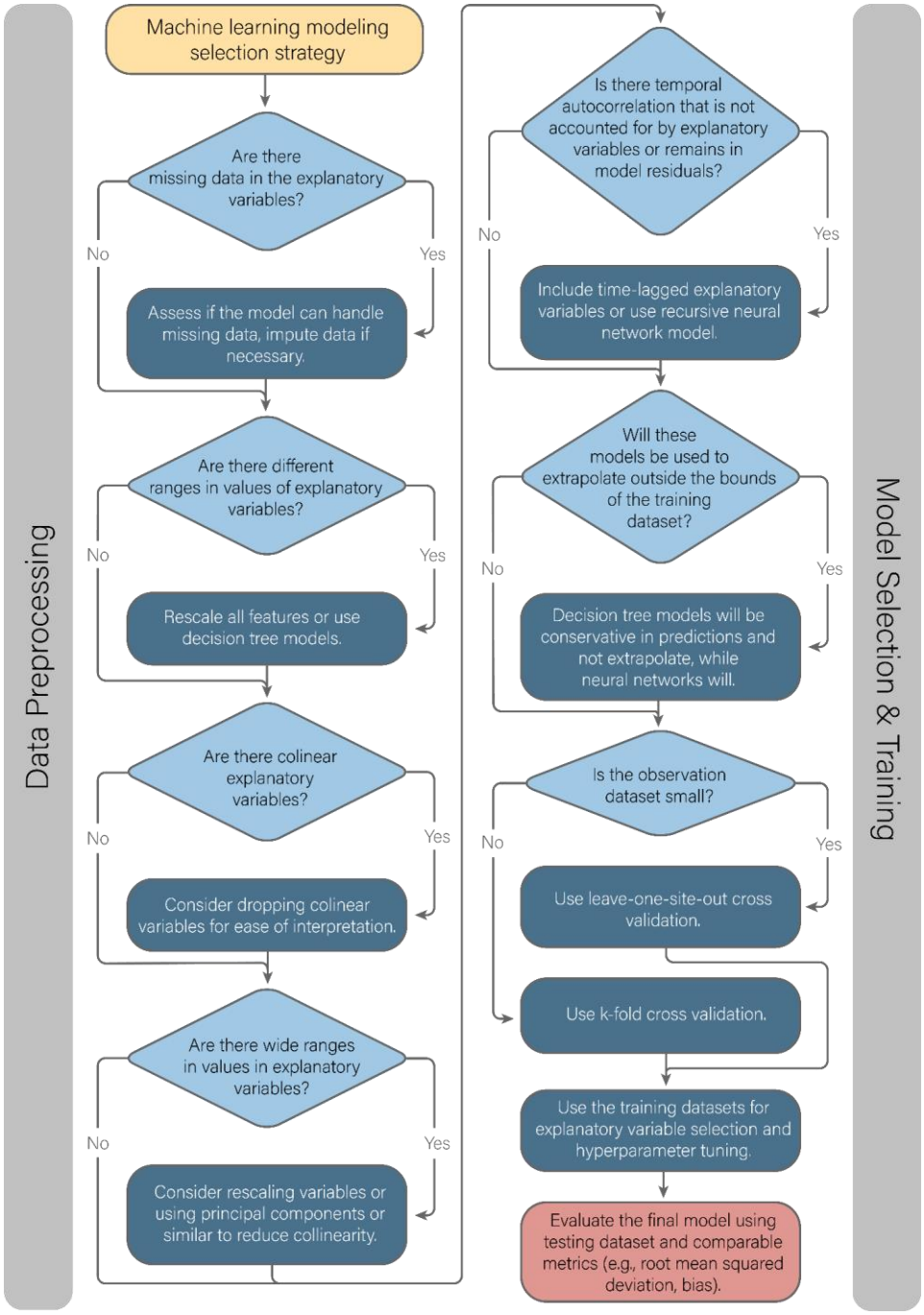


**Figure 3.** Decision flowchart for a potential way forward for selecting an appropriate strategy for a carbon flux machine learning model. Please note that the outlined selection process focuses on some core aspects discussed within this overview text and does not aim at being comprehensive. Accordingly, there are methods that may not be represented here.

## 5.3 Model testing and evaluation: strategies and metrics

For the comparatively small datasets that are commonly available for carbon flux upscaling studies, cross validation methods are recommended for this purpose, which involve resampling and sample splitting to use different portions of the available data to validate and train a model. For example, in the global FLUXCOM framework cross validation is done using a 'X-fold leave-site-out' strategy (Nelson & Walther et al., 2024). This splits the available data into a number (X) of folds, or groups of sites, iteratively leaves a fold out of model training, and tests model performance at the sites in the fold that has been left out. It is therefore a good measure to test the model's ability to extrapolate beyond training conditions (Ploton et al., 2020); however, while X-fold leave-site-out would be a gold standard for cross validation, it might not be feasible if categorical predictors (e.g. land cover) include some classes that have very little data, because this can lead to a situation where the training and/or test sets completely lack data from some of the classes (Meyer and Pebesma, 2022).

When data are limited, cross-validation approaches based on leaving a smaller part than a fold of the full dataset out for validation have been used, with leave-one-site-out being the most frequent (Virkkala et al., 2021). Other strategies, including leave-X-fold (Natali & Watts et al., 2019), leave-one-observation/row-out, and random k-fold cross validation, may provide overly optimistic model performance estimates (Roberts et al., 2017), not explicitly testing the model's ability to extrapolate since data from the same site could be included both in the training and validation data. Although the leave-one-site-out approach solves this issue, nearby sites with similar flux dynamics might still be included in training and validation datasets, similarly biasing the performance metrics. To remedy this issue, a spatially blocked cross validation can be used. Instead of relying on site identification as the grouping, this type of validation will block out spatial areas to ensure nearby sites are similarly included in the same groupings (Orndahl et al., 2025; Peltola et al., 2019; Roberts et al., 2017).

Acceptable accuracy is identified by good performance in complementary metrics (e.g. bias, RMSE, Nash-Sutcliffe- efficiency, correlation, etc.; Kvalseth, 1985; Nash and Sutcliffe, 1970). These metrics quantify the relationship between the in-situ carbon flux observations and predictions for both the training data *and* the test data which has not been used in training. A

model is overfit if model performance is high on the training data but low on the test data. Insufficient performance on both the training and test data indicates an underfit model. Both underfit and overfit models will not be able to extrapolate reliably.

In addition, model accuracy may change when analyzed at different levels of temporal aggregation, e.g. using daily, monthly, or intra-annual timesteps (Nelson & Walther et al., 2024; Virkkala et al., 2025a; Ying et al., 2025). For example, assessments consistently show that while dominant intraannual flux patterns can be predicted relatively well, data-driven upscaling often struggles to accurately capture long-term trends and interannual variability. This is mostly linked to the short data time series available, especially for $CH_4$ and inland water fluxes compared to $CO_2$ and terrestrial fluxes, respectively. This should be a growing research field as in-situ datasets grow in length and long-term trends can better be addressed with real validation data.

Extrapolation into regions that are different from those represented by available data can result in higher model uncertainty and systematic errors. This underscores the importance of a representative distribution of training data – both spatially, temporally, and statistically – for effective upscaling as well as of a thorough quantification of the model representativeness and uncertainty. Transitioning from site level to upscaled flux estimates covering large spatial scales requires researchers to assess the generalizability of the trained model in situations with limited data coverage. Comparison of the range of conditions included in training data with those spanned by the data used in upscaling indicates potential extrapolation areas (Elith et al., 2010; Jung et al., 2020; Meyer and Pebesma, 2021; Pallandt et al., 2024). In the data-poor Arctic-boreal region, extrapolation areas are often extensive (Pallandt et al., 2022), requiring data-driven models to operate well beyond observed environmental conditions. To deal with these errors, researchers may consider carefully utilizing other in-situ datasets for validation (e.g., chambers over relatively homogenous areas when only EC was used in training data) or comparing results to other modeled products to test agreement. Of course, other modeled products may have their own errors and comparisons should be made here.

Finally, cross-comparisons and benchmarking of flux estimates between scaling approaches, including data-driven upscaling, process-based upscaling and atmospheric inversions, are a standard practice; however, drawing conclusions from such is challenging given strong

differences in model set-up, training data, and uncertainty estimates (e.g., Bruhwiler et al., 2021; Peltola et al., 2019; Treat et al., 2024; Virkkala et al., 2025a). Further tests for evaluating model fitness include e.g. testing for particularly influential sites or predictors. For instance, earlier upscaling studies have shown that Arctic-boreal $CO_2$ flux budgets can vary by as much as ±150 Tg C $yr^{-1}$ (approximately ±30% of the total budget) due to relatively minor changes in flux site distribution introduced through bootstrapping (Virkkala et al., 2025a, 2021), or repeated model runs while leaving out some, often random, portion of the data. Regarding predictors, the option to weigh certain observations more than others (e.g., Jung et al., 2020; Pallandt et al., 2024), for example to better capture patterns for a particular carbon species, reproduce extreme events or deal with disproportionate data coverage, should be further explored.

# 6 New insights and future needs

## 6.1 Improvements in data provision

The ongoing expansion of in situ flux sites continues to improve spatio-temporal data coverage and has promise to reduce uncertainty (Pallandt et al., 2024, 2022). Still, important gaps in Arctic-boreal data coverage persist, calling for coordination within the research and funding community to upgrade observational capacities (Table 4). Temporal gaps in winter data coverage call for expansion of year-round monitoring sites, which is limited due to the harsh climate in the Arctic-boreal region. Regular maintenance and continuous power pose an enormous challenge outside the growing season, particularly for remote sites. Consequently, the winter observational network lagging behind growing season and the winter network is currently the size the growing season network was 15 years ago (Pallandt et al., 2022); though winters are changing rapidly and are critical for annual carbon budgets (Falvo et al., 2025; Natali & Watts et al., 2019; See et al., 2024). Considerable network gaps exist in Siberia, and the high-Arctic and specific representativeness analysis should be followed if designing a wider flux site network (Pallandt et al., 2022; Schuur et al., 2024).

Moreover, current observation sites often are situated in ecosystems with expected high fluxes, such as wetlands for $CH_4$. Consequently, low-flux ecosystems such as high-Arctic polar deserts and high-altitude alpine ecosystems are under sampled. Even though such ‘cold spots’ likely do

not substantially contribute to regional carbon budgets, constraining their carbon fluxes with representative observation sites should reduce uncertainties in upscaling efforts and provide insight into the dynamics of these systems. Finally, limited information is provided on managed ecosystems such as drained peatlands, forests harvested for lumber, and reservoirs which should also be a priority as these are intricately linked parts of the landscape and have direct management implications (e.g., Kim et al., 2016; Korkiakoski et al., 2023; Tikkasalo et al., 2025).

To improve the representation of disturbances in models, more advanced geospatial products should be used in models supported by complementary in situ data. Current data-driven models have shown wildfires may have some response to vegetation indices in models given the ties to biomass and greenness (Virkkala et al., 2025a), but more work is needed to properly represent recovery processes common in regrowth following fire. In situ data exists on forest recovery sites, often in a chrono-sequence of time since fire which could be used to inform how models should respond, although these data are sparse (Goulden et al., 2011; Oliveira et al., 2021; Schulze et al., 2025; Ueyama et al., 2019). Permafrost thaw, especially abrupt thaw resulting in active layer detachments and drastic landscape changes, are increasing over the landscape and understanding how they impact fluxes will be crucial with 20% of the permafrost region vulnerable to these types of thaw (Turetsky et al., 2020). Missing predictor datasets from remote sensing for thaw are nearing development at circumpolar scales thanks largely to high-resolution satellite imagery (Nitze et al., 2025) and could be used for a post-hoc estimate of the changing carbon balance due to these features as many are sub-grid cell size (<1 km).

Geospatial information on sub-surface parameters including soil properties, moisture levels, and carbon content lack representation in global datasets and thus often result in inaccuracies in the high latitudes. This could be improved with more representative data across the region but also specialized high latitude products could aid in more accurate products as they would be informed by data only from similar ecosystems. Also, a clear definition of uniform formatting rules, including the development of a standardized approach to better harmonize data, could advance the quality of data-driven upscaling products by making products easier to merge and cross compare.

New geospatial products require both appropriate thematic resolution (i.e. differentiating between land-covers which have distinct carbon flux magnitudes) and appropriate spatial resolution to avoid issues of mosaic averaging (Hashemi et al., 2025). Robust high-resolution mapping and data would allow better understanding of drivers of carbon fluxes in resultant products, especially for inland water ecosystems where ecosystems can have large impacts on the carbon balance despite or because of their small size (Holgerson and Raymond, 2016). However, thought should be given to what is reasonable given the scale of input data, for example, upscaling carbon fluxes at a one-meter scale using only flux tower data may not be advisable. However, more value could be pulled from flux tower observations by partitioning EC data into flux fingerprints for different land cover types in the footprint (Ludwig et al., 2024; Pirk et al., 2024), in addition to chamber flux observations that cover smaller areas. Moreover, a sufficient number of spatially dispersed and georeferenced in situ measurements should be made around a measurement site's central location (e.g., Siewert, 2018) to appropriately match the chosen grid of the geospatial dataset. These data should be ideally collected according to a standardized protocol and in a manner such that they can be harmonized with the land cover classification scheme used during flux upscaling (Raynolds et al., 2019). To keep heterogeneity of ecosystems and use a coarser scale, more products like BAWLDs approach could be created which have percent landcover breakdowns within coarser 0.25-degree grid cells.

## 6.2 Improvements in data-driven modeling frameworks

New statistical data-driven modeling approaches beyond the commonly used random forest models should be tested. Deep learning tools hold the potential to assist in developing fast and efficient models, identifying the best tradeoff between effort and complexity of data-driven modeling frameworks, and accuracy and understandability of novel model output. There are indications that deep learning can partly compensate for missing pieces of information (Kraft et al., 2025). Identifying the most powerful machine learning applications, and customizing and upgrading them to support frameworks for upscaling of carbon fluxes, should therefore be a primary priority for this research community (Lucarini et al., 2024).

One major priority is the development of combined machine learning-based estimates for both terrestrial and inland water $CO_2$ and $CH_4$ fluxes together, using similar modeling frameworks

wherever possible. This would allow for seamless integration across ecosystems, facilitate direct comparisons, and provide a clearer understanding of how different landscapes contribute to the net carbon balance. At the same time, potential biases like the above-mentioned double counting, or pixel edge effects, could be avoided. Spatio-temporally explicit upscaling of lake and river $CO_2$ fluxes needs special attention, as such data-driven modeling efforts remain rare, and estimates have substantial variability and uncertainties.

## 6.3 Strengthening links between data-driven carbon flux models and other scaling approaches

The combined use of data-driven upscaling frameworks with other modeling concepts will advance insights into feedbacks between the carbon cycle and climate change within the Arctic-boreal region. For example, data-driven upscaling outputs can be integrated to model evaluation platforms such as International Land Model Benchmarking (ILAMB) that include statistical analyses and figures designed to provide insights into the strengths and weaknesses of multiple models or model versions (Braghiere et al., 2023; Collier et al., 2018). In addition, data-driven upscaling frameworks hold a strong potential for deriving links between carbon flux processes and control factors that may deviate from functional relationships commonly implemented in process models. Comparing gridded output fluxes between model types (e.g., process-based and data-driven model derived) can reveal such differences, and insights from resulting patterns should be used to upgrade process-based models to subsequently extrapolate such relationships into future climate scenarios.

Moreover, spatio-temporally continuous, data-driven estimates of carbon fluxes are highly suitable to serve as priors in atmospheric inverse modeling frameworks. As opposed to coarse-resolution flux grids provided by process-based models, using high-resolution grids from data-driven approaches can help reconcile top-down and bottom-up approaches by reducing biases and improving model convergence. Comparisons between data-driven upscaling and geostatistical inverse modeling (Michalak et al., 2004) offers another promising pathway to reconcile scaling approaches. Geostatistical inversions do not use prior flux fields, but instead they generate these prior patterns from a superposition of geospatial data layers, so-called auxiliary variables. Comparing the choice and weighing of environmental relationships selected

to reproduce different carbon observations from very different sources (data-driven upscaling: surface fluxes; atmospheric inversion: atmospheric mixing ratios) offers opportunities to better understand differences in modeling approaches, and the role of environmental predictors in this context. Since inland water carbon flux upscaling outputs may not be spatio-temporally continuous, their usefulness as prior inputs in atmospheric inversions are still limited. As a potential solution, terrestrial and inland water flux fields could be combined into a merged prior flux field for inversions. As a result, comparisons with inversion outputs have largely focused on terrestrial flux estimates, leaving a significant gap in our understanding of the full-system differences across approaches (Bruhwiler et al., 2021; Treat et al., 2024).

Fusing data-driven approaches with process modeling or inverse modeling frameworks holds the potential of maximizing the information gain from diverse databases and thus minimizing output uncertainties. Adding key ecosystem processes from process-based models as additional constraints into machine learning approaches offers a great opportunity to develop hybrid models that can better capture current and future ecosystem dynamics. The combination of the high predictive power of machine learning tools with the mechanistic structure of process-based models can lead to robust estimates of carbon cycle processes across spatial and temporal dimensions (Liu et al., 2024).

## 6.4 Advancing near real-time data integration and upscaling, and fostering collaboration between scientists and modeling approaches

The required upgrades in modeling tools and in particular the extension of observational capacities constitute enormous challenges and thus can only be approached in a collaborative manner. To achieve this goal, a continuous exchange of information between the modelling community, field scientists collecting in-situ measurements, and remote sensing specialists developing geospatial data products will be essential. Effective collaboration could help overcome a lack of observational data by allowing the scientific community to maximize currently available information and jointly work on a targeted improvement of the future observational coverage. This includes offering incentives to share new observational datasets in a timely manner to facilitate near real-time data integration products (Falvo et al., 2025), and include efforts by larger networks like the integrated carbon observing system (ICOS) or the

National Ecological Observing Network (NEON) which offer near-real time data from many of their observing sites.

Enhanced collaboration should include shared field work and field visits between researchers across disciplines to develop an understanding of critical processes and the challenges, benefits, and limitations of field measurements and/or models. Furthermore, there are opportunities to better include and engage local stake- and rights-holders in the design and implementation of observational networks. Discussions on how best to design and manage observational networks should be guided by standardized concepts for environmental monitoring and data processing (e.g., Boike et al., 2022) across scientific and Arctic-boreal communities. There is a need for observational platforms as well as modeling frameworks that could quantify uncertainties in data and model performance and output, and rank sources of uncertainties by their relevance. Information on the impact of missing parameters, uncertainties in provided observational products, and spatial and/or temporal gaps in observational coverage on model performance, could help the observational community upgrade monitoring networks and remote sensing products towards gaining a substantial improvement of upscaling approaches.

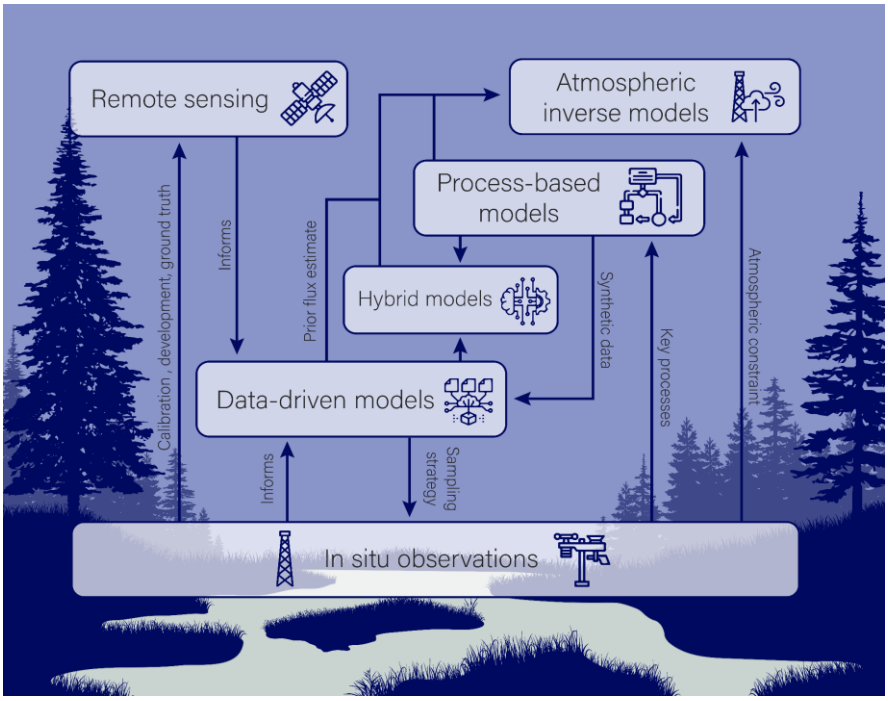

**Figure 4**. The role of data-driven models in understanding Arctic-boreal carbon cycle dynamics. These models can be used to inform other types of models such as process-based models and atmospheric inversions, can inform future in situ sampling strategies.

A collaborative data assimilation scheme will leverage a tailored computing infrastructure that facilitates data input across the Arctic-boreal domain in near-real-time. It would also allow researchers to communicate insights such as the impact of an anomalously wet or hot and dry year to policymakers and the public. Such infrastructure would have important societal and climate policy benefits, and could help raise awareness for Arctic climate change, ideally before the worst consequences of climate change are realized. Moreover, these modeling tools would facilitate more accurate reporting of carbon emissions, and help in assessing the impact of potential interventions of climate mitigation (Hugelius et al., 2024). Finally, this infrastructure could be leveraged by researchers to accelerate process-level understanding across multiple disciplines, which in turn can inform process-model development and improvements (Figure 4).

There are multiple pathways through which the continued improvement of data-driven upscaling methods contributes to high-latitude carbon cycle science. Given the importance of the Arctic-boreal region in the global carbon budget, and especially how sensitively it will react to climate change in the coming decades, an integration of data-driven methods with other modeling platforms will maximize the use of existing information and reduce associated uncertainties. Furthermore, these integrated methods can provide enhanced and closer to real-time estimates of carbon emissions from the Arctic-boreal region and highlight their relevance to the global climate system to stakeholders. This is foundational to establishing proper baselines with which to develop and demonstrate the efficacy of emission reduction goals.

749 **Table 4.** A summary of key gaps contributing to uncertainties in data-driven carbon flux models and potential solutions.

| **Theme** | **Topic** | **Current status** | **Potential solutions** | **Importance (1=highest, 3=lowest)** |
|---|---|---|---|---|
| Carbon Flux | General gaps in $CO_2$ and $CH_4$ flux data | -Data gaps during the non-growing season and in certain regions (Siberia, Canada, high-Arctic and alpine regions) and ecosystems (larch forests, sparsely/barren vegetated ecosystems), and primarily in undisturbed ecosystems<br><br>-Many chamber datasets are sporadic and limited to daytime measurements | -Establish year-round monitoring sites in these ecosystems and regions<br><br>-Foster data collection in disturbed ecosystems<br><br>-Carefully assess the uncertainties related to utilizing different flux measurement techniques in upscaling | 1 |
| | Gaps in terrestrial $CO_2$ and $CH_4$ flux data | -The distribution of year-round long-term $CO_2$ and $CH_4$ flux sites is limited<br><br>-Most $CH_4$ flux sites are in wetland ecosystems | -Maintain existing flux sites<br><br>- Coordinate the flux network to target underrepresented regions<br><br>-Establish $CH_4$ flux sites in upland ecosystems to avoid observation bias towards high-emitting sites<br><br>- Sustained and frequent synthesis updates to ensure data are available and public | 2 |
| | Gaps in inland water $CO_2$ and $CH_4$ flux data | - Few long-term observation sites | - Develop new long-term monitoring sites<br><br>- Collect data during ice-on/ice-off periods | 1 |

| | | | | |
|---|---|---|---|---|
| | | -High variability within and across river networks and individual lakes that is not fully understood<br><br>-Few measurements from spring ice-break up | - Improve spatial representativeness of sampling within waterbodies<br><br>- Integrate flux measurements across techniques and emission pathways (e.g., EC vs. other methods, including ebullition) | |
| Predictor variables | Uncertain or missing gridded terrestrial predictors | - GPP is generally well predicted due to the availability of climate and vegetation-related predictor data<br><br>- Key predictors for other fluxes (e.g., soil moisture, disturbance, soil carbon, nutrients, ice content, temperature) are often only available at regional scales or coarse spatial resolutions | - Develop remote sensing-based soil datasets with lower uncertainties and improve below ground parameter estimates (e.g., soil properties, moisture, etc.)<br><br>- Create ongoing disturbance datasets of fires, thaw slumps, insect outbreaks etc. | 2 |
| | Uncertain or missing gridded inland water predictors | - Lack of inland water depth and water quality and sediment characteristics<br><br>- Poor representation of circumpolar seasonal changes in water extent and productivity | -Develop missing predictor datasets<br><br>-Integrate indices from optical remote sensing to data-driven models | 1 |
| | Land–waterbody type separation | - Coarse-resolution wetland and lake classifications across the domain<br><br>- Lack of high-resolution, intra-annual lake extent datasets | -Use high-resolution satellite data to track dynamic small and seasonal waterbodies<br><br>- Prefer continuous predictors over categorical<br><br>- Merge existing higher-resolution regional datasets to harmonize land cover products | 2 |

| | | | | |
|---|---|---|---|---|
| | Eddy covariance flux footprint-informed predictor data extraction | - Gridded predictors are often extracted from the single pixel containing the flux tower<br><br>- No accounting for actual flux footprint | - Use site-specific flux footprints to better represent predictor variables where large heterogeneity exists | 3 |
| Modeling resolution | Spatial resolution | - Terrestrial $CO_2$ upscaled at ~1 km<br><br>- Wetland, lake, and river $CH_4$ fluxes and river $CO_2$ fluxes often modeled at 10–50 km<br><br>- No spatially explicit lake $CO_2$ flux upscaled outputs | - Improve upscaling to 0.5–1 km resolution across ecosystems<br><br>- Aim for meter-scale resolution using Landsat, Sentinel, PlanetScope, etc., utilizing chamber data and plot-level data from eddy covariance footprint decomposition | 2 |
| | Temporal resolution | Fluxes are often modeled at monthly or seasonal scales, though some daily outputs are available | - Move toward daily resolution to better capture short-term and extreme events | 2 |
| Modeling approaches and performance | Limited diversity in modeling approaches | - Most studies rely on random forest models | -Test several types of neural networks (e.g., convolution neural network) and deep learning (e.g. U-net) | 2 |
| | Poor performance for temporal trends | -Models perform worse for long-term trends than for mean annual fluxes | - Use time-lagged predictors<br><br>- Apply recursive neural networks to capture temporal and spatial variability (requires sufficient long-term data) | 1 |
| Model evaluation strategies | Factorial model experiments | - Rarely applied in Arctic–boreal context (except for some chamber vs. tower comparisons, e.g., FLUXCOM) | - Apply factorial modeling experiments to systematically test drivers and configurations | 2 |
| | Extrapolation | -Area of extrapolation only rarely thoroughly reported and discussed although approaches for such assessment exist | - Adopt standard reporting frameworks, including documentation of extrapolated areas | 1 |

| | | | | |
|---|---|---|---|---|
| | Uncertainty evaluation framework | - Basic approaches (e.g., bootstrapping) assess sensitivity to site distribution and model structure | - Develop more comprehensive frameworks incorporating site distribution, model structure variability, residuals, and measurement uncertainties for robust and comparable model evaluations | 2 |

# 7 Conclusion

Data-driven upscaling has grown significantly over the past few decades as new technologies, in-situ data collecting techniques and machine learning models have been developed. There is still much to be done to continue to improve modeling techniques and workflows, especially around data collection of both in-situ flux data and gridded products to use for predicting and extrapolating carbon flux estimates. These models are not only useful estimating carbon budgets but can also be useful tools in other modeling types such as informing top-down and process-based bottom-up models and should be integrated into other modeling structures. There is vast potential to significantly improve estimations of carbon fluxes from the Arctic-boreal region at a time when these estimates are crucial to our global climate agreements and continuing to refine our upscaling techniques is a vital tool to meeting climate goals.

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# 773 Data Availability Statement

774 All data used in this paper are open and free to use. Data created for Figure 1 can be found in the Supplementary Information (SI) in
775 SI Table 1. Data for sites in Figure 2 can be found in Virkkala et al., (2025b); https://doi.org/10.3334/ORNLDAAC/2448. Carbon
776 dioxide upscaled data are from Virkkala et al., (2025a); https://doi.org/10.3334/ORNLDAAC/2377, and methane upscaled data are
777 from Ying et al., (2025); https://doi.org/10.5281/zenodo.10802153.

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# Supplementary Information for "Data-driven modeling of carbon dioxide and methane fluxes across the Arctic-boreal region: recent achievements and future opportunities"

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***Table S1:*** *Upscaling Methods and Input data from previous upscaling studies which include or are within the Arctic-boreal region.*

| Year | Bin | Manuscript | Upscaling Method | Input Data | GHG | Target ecosystem(s) | Region |
|---|---|---|---|---|---|---|---|
| 1974 | 1971-1975 | Ehhalt et al. (1974) | Area times flux rate | Chambers | CH4 | Tundra | Circumpolar |
| 1986 | 1986-1990 | Sebacher et al. (1986) | Area times flux rate | Chambers | CH4 | Wetlands | Arctic Boreal Region |
| 1987 | 1986-1990 | Matthews and Fung (1987) | Area times flux rate | Chambers | CH4 | Wetlands | North of 60 Degrees N |
| 1992 | 1991-1995 | Kling et al. (1992) | Area times flux rate | Diffusion | CO2, CH4 | Lakes & Rivers | North Slope of Alaska |
| 1993 | 1991-1995 | Oechel et al. (1993) | Area times flux rate | Chambers | CO2 | Tundra | Circumpolar |
| 1993 | 1991-1995 | Bartlett and Harris (1993) | Area times flux rate | Chambers, Bubble Traps | CH4 | Wetlands & Tundra | North of 45 Degrees N |
| 1997 | 1996-2000 | Zimov et al. (1997) | Area times flux rate | Chambers, Diffusion | CH4 | Lakes | North Siberia |
| 2006 | 2006-2010 | Walter et al. (2006) | Mass balance stoichiometry | Bubble Traps | CH4 | Lakes | North Siberia |
| 2007 | 2006-2010 | Walter et al. (2007) | Mass balance stoichiometry | Bubble Traps | CH4 | Lakes | Circumpolar |
| 2008 | 2006-2010 | Bartsch et al. (2008) | Area times flux rate | Chambers | CH4 | Lakes | Taymyr peninsula |
| 2009 | 2006-2010 | Schneider et al. (2009) | Area times flux rate | Chambers | CH4 | Terrestrial & Inland Water | Lena River Delta |
| 2012 | 2011-2015 | McGuire et al. (2012) | Area times flux rate | EC, Chambers, Diffusion, Models | CO2, CH4 | Tundra | Circumpolar |
| 2013 | 2011-2015 | Ueyama et al. (2013) | Machine learning | EC | CO2 | Terrestrial | Alaska |
| 2013 | 2011-2015 | Marushchak et al. (2013) | Area times flux rate | EC, Chambers, Diffusion | CO2 | Terrestrial & Lakes | Northeast European Russian Tundra |
| 2013 | 2011-2015 | Belshe et al. (2013) | Linear regression | EC, Chambers, Diffusion, Models | CO2 | Tundra | Circumpolar |
| 2016 | 2016-2020 | Holgerson & Raymond (2016) | Area times flux rate | Diffusion | CO2, CH4 | Lakes & ponds | Global |
| 2016 | 2016-2020 | Wik et al. (2016) | Area times flux rate | EC, Diffusion, Bubble Traps | CH4 | Lakes & ponds | North of 50 Degrees N |
| 2018 | 2016-2020 | Treat et al. (2018) | Linear mixed-effect modeling | EC, Chambers, Diffusion | CH4 | Wetlands | North of 40 Degrees N |
| 2019 | 2016-2020 | Peltola et al. (2019) | Machine learning | EC | CH4 | Wetlands | North of 45 Degrees N |
| 2019 | 2016-2020 | Natali & Watts et al. (2019) | Machine learning | EC, Chambers, Diffusion | CO2 | Terrestrial | Permafrost Region |
| 2020 | 2016-2020 | Matthews et al. (2020) | Area times flux rate | Chambers, Diffusion | CH4 | Lakes | North of 50 Degrees N |

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| 2021 | 2021-2025 | Watts et al. (2021) | Machine learning | EC, Chambers | CO2 | Terrestrial | Permafrost Affected Alaska and Western Canada |
| 2021 | 2021-2025 | Virkkala et al. (2021) | Machine learning | EC, Chambers, Diffusion, Models | CO2 | Terrestrial | Arctic Boreal Region |
| 2022 | 2021-2025 | Johnson et al. (2022) | Area times flux rate | Chambers, Diffusion | CH4 | Lakes | North of 45 Degrees N |
| 2022 | 2021-2025 | Liu et al. (2022) | Machine learning | Diffusion | CO2 | Rivers | Arctic Boreal Region |
| 2023 | 2021-2025 | Rocher-Ros et al. (2023) | Machine learning | Chambers, Diffusion | CH4 | Rivers | Global |
| 2023 | 2021-2025 | McNichol et al. (2023) | Machine learning | EC | CH4 | Wetlands | Global |
| 2024 | 2021-2025 | Song et al., (2024) | Area times flux rate | Chambers, Diffusion, Bubble Traps | CO2, CH4 | Inland Water | Permafrost Region |
| 2024 | 2021-2025 | Yuan et al. (2024) | Machine learning | EC, Chambers | CH4 | Wetlands | Arctic Boreal Region |
| 2024 | 2021-2025 | Chen et al. (2024) | Machine learning | EC, Chambers | CH4 | Wetlands | North of 30 Degrees N |
| 2024 | 2021-2025 | Ramage et al. (2024) | Area times flux rate | EC, Chambers, Diffusion, Models | CO2, CH4, N2O | Terrestrial & Inland Water | Permafrost Region |
| 2025 | 2021-2025 | Virkkala et al. (2025) | Machine learning | EC, Chambers | CO2 | Terrestrial | Arctic Boreal Region |
| 2025 | 2021-2025 | Bastviken & Johnson (2025) | Area times flux rate | Chambers, Diffusion | CH4 | Lakes & Reservoirs | Arctic Boreal Region |
| 2025 | 2021-2025 | Ying et al. (2025) | Machine learning | EC | CH4 | Wetlands | North of 45 Degrees N |

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