

Integrating Characteristic Arctic Vegetation in a Land Surface Model Improves Representation of Carbon Dynamics Across a Tundra Landscape

Bailey A. Murphy¹, Benjamin N. Sulman¹, Fengming Yuan¹, Verity G. Salmon¹, Daryl Yang¹, Jitendra Kumar¹, Sigrid Dengel², Elizabeth Herndon¹, Sean Fettrow¹, Colette Brown³, Margaret S. Torn², Oriana E. Chafe², Elaine F. Pegoraro², Colleen M. Iversen¹

¹Environmental Sciences Division, Oak Ridge National Laboratory, Oak Ridge, TN, USA

²Climate and Ecosystem Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, CA, USA

³University of California Berkeley, Berkeley, CA, USA

Corresponding author: Bailey A. Murphy (murphyba@ornl.gov)

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Key Points

- Refined Arctic plant functional types in simulations improved landscape-level fluxes, but carbon allocation parameters need further review.
- Incorporating representative tundra vegetation increased spatial variability in biomass and productivity, better aligning with observations.
- Representing vegetation heterogeneity boosted predictive understanding of carbon dynamics, facilitating model and remote-sensing scaling.

Abstract

Arctic warming is altering vegetation and carbon dynamics with global implications, yet Earth System Model (ESM) predictions in the Arctic remain highly uncertain, in part due to historically limited data for model parameterization and validation. As such, ESMs typically

represent Arctic ecosystems in an oversimplified manner. Recently, nine plant functional types (PFTs) designed to realistically represent tundra vegetation were integrated into the Energy Exascale Earth System Model (E3SM) Land Model (ELM) and parameterized using plot-scale observations from a single site. Additional evaluation was needed to determine their transferability across the Arctic. Here, we evaluated whether refined representation of tundra vegetation improved model accuracy by conducting spatially explicit 100×100 m resolution ELM simulations on Alaska's Seward Peninsula. Simulations with the default two-PFT configuration and with the nine Arctic-specific PFTs were benchmarked against observations of net ecosystem exchange, gross primary production, and aboveground biomass from multiple data streams including an eddy covariance flux tower, flux chambers, and aircraft and unoccupied aerial system hyperspectral remote sensing. Evaluation revealed that Arctic-specific PFT simulations produced more realistic landscape-level carbon exchanges, and better captured observed heterogeneity in biomass and productivity, explaining 60–70% of spatial variance ($R^2 = 0.6$ – 0.7) compared to just 12–18% ($R^2 = 0.12$ – 0.18) with the default configuration. However, the refined model failed to reproduce observed aboveground biomass for highly productive alder-willow communities, requiring further evaluation of carbon allocation parameterizations for tall shrubs that are increasingly expanding across tundra landscapes. Our results demonstrate that enhanced representation of vegetation heterogeneity boosts predictive understanding of tundra carbon dynamics, facilitating regional to pan-Arctic model and remote-sensing scaling.

Plain Language Summary

Arctic warming is changing vegetation and carbon dynamics, potentially affecting the Earth system. Predicting the impact of warming is difficult because models tend to over-simplify Arctic environments due to a lack of observational data. Recent model improvements have added more detailed categories of tundra plants, using new data from a project called the 'Next Generation Ecosystem Experiments in the Arctic (NGEE Arctic)'. Our study used these improvements to simulate Arctic carbon cycles on Alaska's Seward Peninsula at a spatial resolution approximately 1,000 times greater than the resolution typically used for global model simulations. We compared these new simulations with observations from various sources, including ground-based sensors, drones, and aircraft. The version of the model with more detailed and representative plant categories provided more accurate predictions of carbon

exchanges, but overestimated the amount of carbon stored as aboveground biomass for highly productive vegetation types. The new model also showed greater spatial variation in carbon dynamics across the tundra, better reflecting real-world conditions. Overall, our findings show that including a greater variety of tundra plants in models leads to more accurate predictions of carbon dynamics, which is crucial for understanding how the Arctic interacts with the Earth system.

Keywords: Arctic tundra vegetation, land surface modeling, model evaluation, Arctic carbon dynamics, vegetation heterogeneity

1. Introduction

The Arctic is warming at a rate two to four times faster than the global average (IPCC, 2013; AMAP, 2021; Rantanen et al., 2022; Ballinger et al., 2023), a concept referred to as Arctic amplification (Serreze et al., 2009; Overland et al., 2013). Arctic warming has strong implications for the Earth system, in part because of the large amount of carbon stored in permafrost soils (Schuur et al., 2022; Mack et al., 2004; Schuur et al., 2008) that is vulnerable to release as permafrost thaws in response to warming (Romanovsky et al., 2016; Smith et al., 2010; Liljedahl et al., 2016; Koven et al., 2015; Schuur et al., 2022; Schuur et al., 2008, Koven et al., 2011). Arctic warming is also driving widespread changes in vegetation; many studies have found evidence of increased plant productivity and altered community composition (Walker et al., 2006; Frost & Epstein, 2014; Myers-Smith et al., 2015; Salmon et al., 2016), particularly increased shrub dominance (Myers-Smith et al., 2011; Mekonnen et al., 2021; Frost and Epstein, 2014), in response to elevated temperatures and CO₂ concentrations, increased nutrient availability, and longer growing seasons. These observed shifts in vegetation could enhance sequestration of atmospheric carbon and offset some of the release of permafrost soil carbon (Chapin et al., 1995; Schuur et al., 2008; McGuire et al., 2018; Shaver et al., 2000; Walker et al., 2006; Koven et al., 2011; Sitch et al., 2007; Salmon et al., 2016; Rogers et al., 2017; Mekonnen et al., 2021). However, assessments of vegetation responses to warming exhibit a wide range of variability (Walker et al., 2006; Myers-Smith et al., 2020; Frost et al., 2023), as evidenced for example by the substantial spatial variation in greening versus browning trends observed by remote sensing of normalized difference vegetation index (NDVI) in the Arctic (Walker et al.,

2006; Frost and Epstein 2014; Ju and Masek 2016; Sitch et al., 2007; Beck and Goetz 2011). This variability constitutes a high degree of uncertainty in the net response of Arctic ecosystems to environmental change (Schuur et al., 2018; Sitch et al., 2007; Fisher et al., 2014a; McGuire et al., 2012), emphasizing the limitations of extrapolating site-level or satellite-based observations across the region to estimate future trends. Process-based Earth System Models (ESMs), specifically their terrestrial components known as terrestrial biosphere models (TBMs), are a critical tool for integrating diverse data sources and projecting ecosystem responses under future environmental conditions. This underscores the need for high-resolution model simulations that are capable of representing the true heterogeneity of Arctic landscapes.

However, model intercomparison efforts have highlighted disagreements in predictions of Arctic vegetation responses amongst models as well as compared to observations (McGuire et al., 2016; Fisher et al., 2014a; Fisher et al., 2018; McGuire et al., 2012; Commane et al., 2017). One factor contributing to this disagreement could be tied to how Arctic vegetation is represented in TBMs. Owing in part to the historically limited availability of observational data in Arctic regions for model parameterization and validation (Fisher et al., 2018; McGuire et al., 2012; Schuur et al., 2022; Berner et al., 2024), the representation of Arctic vegetation in global-scale models has traditionally been highly simplistic. Although the need for Arctic-specific ecophysiological parameterizations was recognized as early as the mid-1990s, leading to the development of Arctic-focused vegetation models (Epstein et al., 2000; Kaplan et al., 2003), these advances were largely not incorporated into ESMs. For example, the default configuration of ELM (Yang et al., 2019), the land model component of the Department of Energy's Energy Exascale Earth System Model (E3SM; Golaz et al., 2019), divides Arctic vegetation into only two plant functional types (PFTs): a broadleaf deciduous boreal shrub and a C3 grass (Walker et al., 2006). Furthermore, Arctic PFTs often rely on parameterizations derived from temperate species (Rogers et al., 2017), despite Arctic plants frequently having disparate traits compared to their temperate or tropical counterparts (Rogers et al., 2017; Iversen et al., 2015; Hobbie, 1992; Wang et al., 2016). For example, in the Arctic tundra, 62-90% of plant biomass is belowground (Saugier et al., 2001; Iversen et al., 2015; Jackson et al., 1996; Wang et al., 2016), compared to 15-23% in temperate forests (Saugier et al., 2001; Jackson et al., 1996). Variability in plant functional traits has demonstrated effects on global carbon cycling (Verheijen

et al., 2015), and functional diversity is increasingly recognized as an important determinant of how biomes respond to climate change (Fisher et al., 2014b; Callaghan et al., 2004). In the Arctic specifically, high intraspecific trait variability has been identified as a key factor supporting the functional resilience of vegetation in the face of climate warming (Jónsdóttir et al., 2022). Therefore, representing the unique traits of Arctic vegetation and their variation across PFTs is a priority for reducing model predictive uncertainty (Sulman et al., 2021a; Rogers et al., 2017; Mevenkamp et al., 2023).

A representative range of functional types of vegetation found in the Arctic was recently integrated into ELM (Sulman et al., 2021a) using extensive observational data from ‘Next Generation Ecosystem Experiments in the Arctic’ (NGEE Arctic), a project funded by the U.S. Department of Energy to improve understanding and model projections of Arctic ecosystems. Sulman et al. (2021a) parameterized nine new Arctic-specific PFTs in ELM based on detailed plot-level (1 – 5 m) observations from the NGEE Arctic Kougark Hillslope intensive field site on Alaska's Seward Peninsula. The new PFTs included nonvascular mosses and lichens, graminoids, forbs, evergreen dwarf shrubs, three height classes of deciduous shrubs (dwarf, low, and low to tall), and a separate class for deciduous alder shrubs due to their ability to host nitrogen-fixing actinomycetes, which significantly alters tissue chemistry relative to other low to tall shrubs (Sulman et al., 2021a; Salmon et al., 2019). The new PFTs were parameterized to reflect properties specific to Arctic tundra vegetation, such as enhanced belowground biomass allocation and seasonally persistent fine roots. Key parameters that were adjusted include the ratio of root to leaf as well as stem to leaf carbon allocation, the ratio of coarse roots to stems, leaf and fine root carbon to nitrogen ratios, the fraction of leaf nitrogen in Rubisco, specific leaf area, and the maximum rooting depth (Sulman et al., 2021a). In the current model, mosses and lichens are treated as small plants with adjusted photosynthetic parameters and minimal belowground biomass allocation, and the model does not yet include changes to water transport and other physiological processes unique to non-vascular plant species.

This new formulation of ELM has been tested at the plot scale where the parameterizations were defined (Sulman et al., 2021a), with results indicating improved representation of variability in biomass, particularly for alder shrublands, and enhanced

belowground biomass allocation. However, evaluation at broader spatial scales is required to determine whether the incorporation of diverse Arctic-specific PFTs can improve simulations of vegetation and carbon dynamics across the Arctic. Before extending these simulations to the pan-Arctic, the transferability of the refined model across heterogeneous Arctic landscapes needed to be evaluated at an intermediate scale. Permafrost processes and annual freeze-thaw cycles significantly alter tundra microtopography and localized hydrological regimes, which exert strong controls over vegetation distributions and soil biogeochemistry, resulting in a high degree of heterogeneity over relatively small spatial scales ($<0.1 - 10$ m) (Jonasson et al., 2001; Lara et al., 2020; Shaver & Jonasson, 2001; Nelson et al., 2022). Consequently, the magnitude of localized variability in Arctic ecosystems can be significantly greater than the magnitude of differences observed across the Arctic's latitudinal range (Shaver & Jonasson, 2001). For example, organic matter content and primary production can vary by a factor of 1,000 between Arctic vegetation communities (e.g. tall shrub or wet sedge, with the former being the more productive of the two) within one region, while the magnitude of variation within the same vegetation community located across different regions might be closer to a factor of 10 (Shaver & Jonasson, 2001). This spatial heterogeneity in topography, hydrology, vegetation, and microclimate leads to significant spatiotemporal variability in carbon storage and fluxes. When aggregated to the landscape scale and beyond, these variations can collectively influence the carbon cycle in meaningful ways, yet they remain difficult to capture with existing ESMs.

Here, we conducted spatially explicit, high-resolution simulations with the default (2-PFT) and refined Arctic-specific vegetation (9-PFT) formulations of ELM. This allowed us to capture the impact of land surface heterogeneity on tundra carbon stocks and fluxes including net ecosystem exchange (NEE), gross primary production (GPP), and aboveground biomass (AGB). Simulations were conducted at the Council intensive field site on Alaska's Seward Peninsula, a site at the interface of the boreal-tundra biomes. Model evaluation was conducted using multiple streams of observational data to overcome the biases and limitations associated with using any single observational benchmark, while also supporting a more comprehensive process-based understanding. Observational data platforms used for model evaluation included an eddy covariance (EC) flux tower, distributed ground-based flux chambers, and airborne hyperspectral- and unoccupied aerial system (UAS)-based remote sensing. To evaluate the ability of the

tundra-vegetation-informed model formulation to produce realistic spatial patterns and landscape budgets of carbon stocks and fluxes, observationally-derived NEE, GPP, and AGB data were scaled to a common grid size for comparison against simulations. Model performance was evaluated by comparing simulations with the default and Arctic-specific PFT parameterizations to field measurements and assessing the degree of bias in predictions, the ability of the two model formulations to reproduce spatial patterns, and how closely the simulated landscape-level budgets aligned with observations. Specifically, we sought to address the following research questions: *1) Does the formulation of ELM with improved representation of Arctic vegetation, parameterized at the plot scale, better capture the spatial variability in carbon stocks and fluxes at a novel location, and 2) does representation of landscape heterogeneity result in more realistic averages of AGB, GPP, and NEE at the landscape-scale?*

2. Methods

2.1 Site Description

This study focused on a 6.4 km $\times$ 3.3 km landscape at the NGEE Arctic Council intensive field site, a large watershed situated at the tundra-forest ecotone underlain with discontinuous permafrost. The Council site is located on the Seward Peninsula of Alaska, USA near mile marker 71 on the Council Road ~120 km northeast of Nome, Alaska (Figure 1).

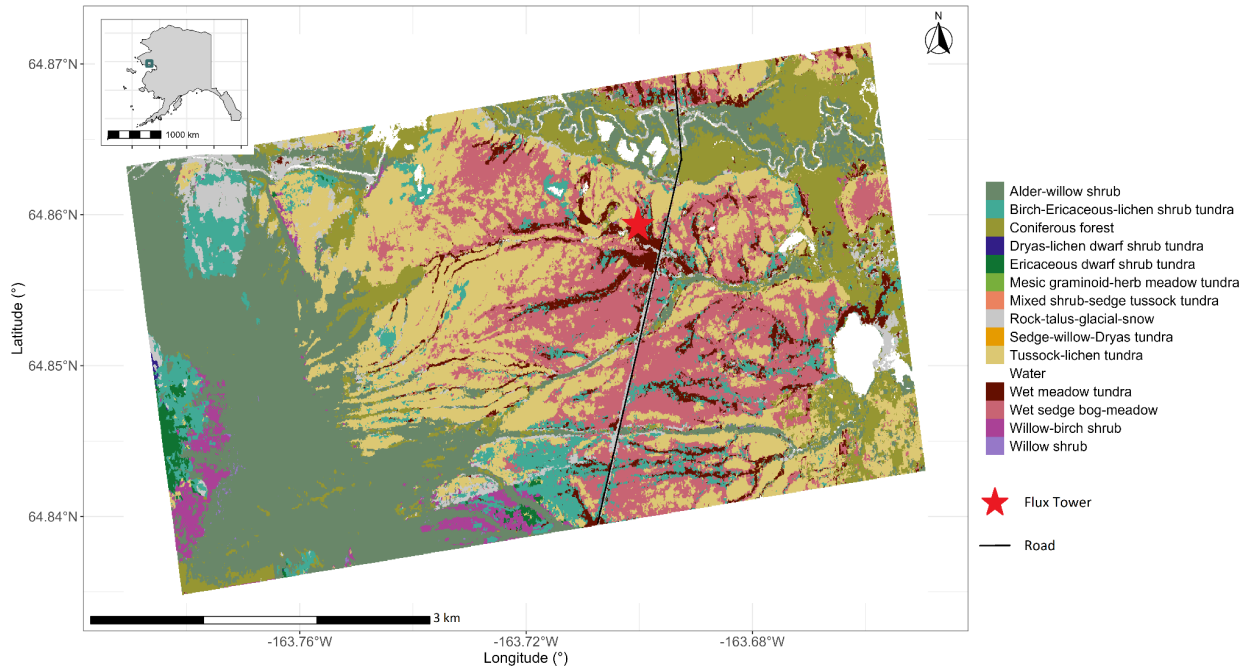


Figure 1. Vegetation community distribution (5-m resolution) within the Council model domain. The red star indicates the location of the US-NGC EC flux tower. The inset map of Alaska (upper left) shows the location of the Council intensive field site (blue box) on Alaska's Seward Peninsula, near the historic Council Village.

The mean growing season (June – August) air temperature at Council is $11.23 \pm 0.24^{\circ}\text{C}$ and growing season precipitation is 182.51 ± 15.06 mm (1999–2021 climatology, note that precipitation data was only available for 2001–2004, 2012–2017, and 2019–2021). The Council field site is located on land stewarded by the Council Native Corporation, a federally recognized governing body for the community of Council, Alaska. In recent decades, this site has experienced drainage of permafrost lakes as well as thermokarst formation (Yoshikawa & Hinzman, 2003), increasing the already high degree of spatial heterogeneity in vegetation, micro-topography, and soil moisture regimes (Lloyd et al., 2003).

Vegetation in the Council modeling domain (from 64.83°N to 64.87°N latitude and from 163.79°W to 163.65°W longitude) is primarily alder-willow shrub (27.86% coverage) and tussock-lichen tundra (24.21%), based on 5-m resolution plant community maps (Figure 1, Konduri et al., 2022). Approximately 93% of the domain is vegetated, and comprises 13 vegetation communities, including mixed-shrub tussock tundra, wet sedge bog-meadow, and coniferous forest (Figure 1). The spatial distribution of vegetation at Council is governed by

topographic and hydrological variation (Lloyd et al., 2003). Well-drained upland areas are primarily tussock-lichen tundra, while large alder and alder-willow deciduous shrub communities dominate the upper shoulder and backslope. Tall willow shrubs populate streams and drainages (Yang et al., 2023), and saturated thermokarst areas are a mix of sedge-dominated bog meadow and wet meadow tundra. Large patches of white spruce forests are established on flat toe slopes around legacy thermokarsts and along the Niukluk River.

2.2 Observational Datasets

2.2.1 Vegetation Community Data

A high-resolution (5-m) map of vegetation community distributions on Alaska's Seward Peninsula from Konduri et al. (2022) was subset to the Council model domain. The vegetation map was generated using hyperspectral remote sensing data from NASA Arctic Boreal Vulnerability Experiment (ABoVE)'s Airborne Visible / Infrared Imaging Spectrometer - Next Generation (AVIRIS-NG) over the 2017–2019 period and field vegetation surveys (Breen et al., 2020) conducted through the NGEE Arctic project. A deep neural network was trained on the AVIRIS-NG hyperspectral imagery and vegetation survey data to classify vegetation community types, with a classification accuracy exceeding 93% (Konduri et al., 2022). The level two classification map was used here, which characterizes the land surface into 14 vegetation communities, open water, or rock/snow. Each vegetation community comprises multiple ELM PFTs in different relative cover fractions. For example, tussock-lichen tundra communities are dominated by graminoid and lichen PFTs, dryas-lichen dwarf shrub communities are dominated by evergreen dwarf shrub and lichen PFTs, and wet sedge bog-meadow communities contain a mix of graminoid, bryophyte, and forb PFTs. Our evaluation focused on vegetation communities rather than individual PFTs (the definitions of which can also vary by model) because communities represent real-world, spatially coherent units that can be reliably mapped (e.g., the Circumpolar Arctic Vegetation Map (CAVM), Raynolds et al., 2019) at high resolutions using remote sensing and field observations. Evaluating at the PFT level across the entire domain was not feasible here due to observational limitations. However, recently developed high-resolution PFT fractional cover maps (e.g., Steckler et al., 2025) will enable such analyses in future studies.

2.2.2 Eddy Covariance Flux Tower Data

Tower-based CO₂ fluxes were measured by a 3.96 m tower (AmeriFlux site US-NGC; Torn & Dengel, 2020) instrumented with an IRGASON Integrated CO₂ and H₂O Open-Path Gas Analyzer and 3-D Sonic Anemometer (Campbell Scientific, Logan, UT USA). IRGASON data were collected at a frequency of 10 Hz and recorded to a CR6 Campbell Scientific datalogger. Data were processed using LI-COR's EddyPro (version 6.2.1) software (<https://www.licor.com/env/products/eddy-covariance/software.html>), and both gas flux and meteorological data were output as 30-minute averages for the duration of the measurement period, which spanned from July 2017 through August 2023. Instrument calibration and quality analysis and control procedures adhered to AmeriFlux BASE data product standards (Chu et al., 2023), and standard flux corrections including the Massman (2000) frequency correction and the Webb-Pearman-Leuning density fluctuation correction (Webb et al., 1980) were applied. Additional information on flux tower instrumentation, data processing, and meteorological measurements is provided in Torn & Dengel (2020). EC flux data (Torn & Dengel, 2021) gap filled following AmeriFlux ONEFlux protocols (Pastorello et al., 2020) were used for comparison against upscaled chamber fluxes. The location of the flux tower within the study domain and approximate footprint extent are shown in Figure S1.

2.2.3 Chamber Flux Data

Closed-loop chambers (25-cm diameter, 12 – 20 cm height) were used to periodically measure summer CO₂ and CH₄ fluxes at 35 locations at the Council site from August 2016 through June 2019 and at eight locations in early September 2023 as part of the NGEE Arctic research effort (Chafe et al., 2023). Chamber flux measurements were primarily made using a Los Gatos Research, Inc. Ultraportable Greenhouse Gas Analyzer, with some measurements in 2018 and 2019 made using a Picarro G4301 Mobile Gas Concentration Analyzer and measurements made in 2023 using a Gasmeter DX4040. Additional information on sampling protocols and instrument details is provided in Chafe et al. (2023). For this study, only measurements from transparent chambers within the 70% tower footprints with coinciding available EC tower data were used (n = 58). This included 19 measurement locations, with data available for July 2017, June 2018, June 2019, and September 2023. The September chamber data was collected on September 1, and therefore it was included in analysis despite being

outside the June-August analysis period. Only transparent chambers were used to estimate NEE because opaque chambers block incoming photosynthetically active radiation (PAR). Chamber flux measurements within the footprint were located in tussock-lichen tundra ($n = 13$), wet sedge bog-meadow ($n = 4$), and wet meadow tundra vegetation communities ($n = 2$), according to the Konduri et al. (2022) classification. The locations of the flux chambers within the study domain are shown in Figure S2.

2.2.4 Remote Sensing Data

Remote sensing data used in this study include reflectance measurements from the AVIRIS-NG hyperspectral instrument, NDVI generated with multispectral data collected with a UAS, and AGB data derived from airborne Light Detection and Ranging (LiDAR). AVIRIS-NG reflectance data (Green et al., 2023) were collected at the Council intensive field site as part of the NASA ABoVE project (Kasischke et al., 2010). We used data from three AVIRIS-NG flights that took place on July 13, 2017 (flight ang20170713t015932), August 14, 2018 (flight ang20180814t191455), and July 7, 2019 (flight ang20190707t201743). The approximate spatial coverage of the three UAS flights is shown in Figures S1 and S2. The flights were conducted between 10:30 and 14:30 Alaska Standard Time at an average flight altitude of ~ 5.4 km above ground level. AVIRIS-NG measures reflected radiance at 5 nm intervals in the visible to shortwave infrared spectral range (380 – 2500 nm). Measurements are radiometrically and geometrically calibrated and provided at approximately 5.2-m spatial resolution (version 1.2; Miller et al., 2019). Additional post-processing of data involved topographic and Bidirectional Reflectance Distribution Function (BRDF) correction. The BRDF correction was applied using the Ross-Thin BRDF model from the HyTools Python library (version 1.3.0; Chlus et al., 2022) and topographic correction was done using the sun-canopy-sensor topographic correction (CSC + C; Soenen et al., 2005). Level 2 surface reflectance data from each flight line was extracted for the Council model domain, and red and near-infrared bands were used to calculate NDVI as shown in equation (1), where ρ_{NIR} indicates reflectance in the near-infrared band (900 nm) and ρ_{Red} is the reflectance in the visible red band (685 nm). NDVI is a spectral index used to quantify canopy greenness and has demonstrated sensitivity to variations in aboveground biomass in Arctic tundra ecosystems (Boelman et al., 2011; Berner et al., 2018).

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad (1)$$

UAS-based remote sensing data was collected with a Parrot Sequoia+ 4-band sensor and RGB camera mounted on a 3DR SOLO UAS (Yang & Serbin, 2023). Three flights were conducted at the Council intensive field site on August 21, 2021, around midday as part of the NGEE Arctic project, at a flight height of 80 m. Data were georeferenced by the data producer and processed to generate a set of data products, including 0.05-m resolution NDVI maps. We applied an NDVI threshold of 0.3 to filter non-vegetated areas.

Plant AGB across the model domain was mapped at 30-m resolution from high-resolution LiDAR data using a machine learning-based AGB model (Yang et al., 2025). The model was trained on >450 ground AGB plot surveys and >150 high-resolution UAS or airborne flights collected across the Arctic, including Alaska, Canada, Europe, and Russia. Five canopy metrics were calculated for each AGB plot as predictors in the machine-learning model: minimum, maximum, mean, median, and 90% of canopy height. The model had a R^2 of 0.79 and RMSE of 0.336 kg m² when validated against reserved validation points (Yang et al., 2025). In this study, we applied the model to a high-resolution airborne LiDAR dataset at the Council intensive field site collected in 2021 by the National Center for Airborne Laser Mapping (NCALM; Singhania et al., 2023). Conifer-dominated areas were removed, as the AGB model construction emphasized tundra vegetation and did not include tree species.

2.3 Determination of Carbon Cycle Variables and Upscaling Approach

Vegetation community-specific daytime NEE (referred to hereafter as NEE_{day}) was determined using two approaches because several key vegetation types present within the Council model domain were not captured by the flux tower footprint (Figure S1). The footprint captured four tundra vegetation communities including birch-ericaceous-lichen shrub tundra, tussock-lichen tundra, wet meadow tundra, and wet sedge bog-meadow. The size and spatial extent of EC tower footprints are dynamic in time due to shifting wind conditions, but the total footprint area was on average 8.68% birch-ericaceous-lichen shrub tundra, 62.87% tussock-lichen tundra, 6.34% wet meadow tundra, and 24.06% wet sedge bog-meadow. Six vegetation communities observed within the local watershed, including alder-willow shrub, dryas-lichen dwarf shrub tundra, ericaceous dwarf shrub tundra, willow shrub, coniferous forest,

and willow-birch shrub were not captured by the tower footprint. For communities within the footprint, NEE_{day} was determined from EC measurements of CO_2 flux (NEE_{Tower}), and spatially distributed chamber-based flux measurements were used to validate tower estimates of CO_2 flux within the flux footprint (Figure 2). For communities outside the footprint, NEE_{day} was calculated from AVIRIS-NG hyperspectral data and UAS-derived NDVI using PLIRTLE ($NEE_{PLIRTLE}$; Shaver et al., 2007; Shaver et al., 2013), a simple empirical model linking NDVI and environmental conditions to primary productivity. PLIRTLE was developed specifically for Arctic vegetation and has been used extensively to estimate carbon flux in Arctic landscapes (Loranty et al., 2011; Prager et al., 2017; Shaver et al., 2013; Rastetter et al., 2010; Stoy et al., 2009). Remotely-sensed NDVI was also used to calculate growing season (JJA) community average GPP following the PLIRTLE approach, and the LiDAR biomass product was used to estimate community average AGB (Figure 2). Additional details on the spatiotemporal coverage and use-case of observational datasets are provided in table S1.

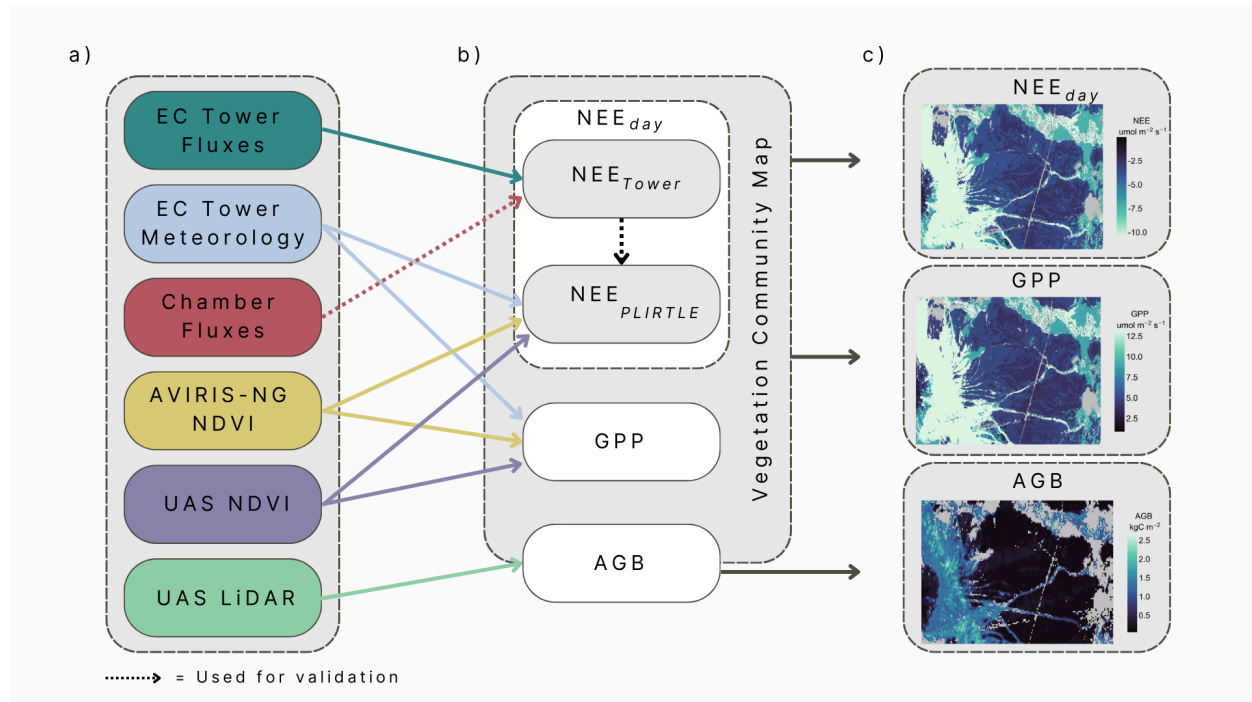


Figure 2. Illustration of observational data (a) used to calculate vegetation community averages for carbon cycle variables (b), including daytime net ecosystem exchange (NEE_{day}), gross primary production (GPP), and aboveground biomass (AGB). For vegetation communities within the flux tower footprint, NEE_{day} is represented by NEE_{Tower} , and for communities outside the tower footprint NEE_{day} is represented by $NEE_{PLIRTLE}$. Average values were upscaled to generate spatially explicit maps of carbon cycle variables (c). Grey areas in panel (c) show

regions classified as non-vegetated, as well as masked coniferous forest areas in the case of AGB. Solid arrows indicate the carbon cycle variables calculated with each dataset, and dashed arrows convey that a dataset was used for validation purposes.

The vegetation community map (Figure 1; Konduri et al., 2022) was used to determine community-specific average seasonal NEEday, GPP, and AGB. Of the 13 vegetation communities in the study domain (Figure 1), three (mesic graminoid-herb meadow tundra, mixed shrub-sedge tussock tundra, and sedge-willow-dryas tundra) were omitted from the analysis due to an insufficient number of pixels to calculate reliable community averages. These three communities collectively made up less than 0.05% of the landscape, so the impact of their omission is minimal. Conifers were masked in the LiDAR-derived AGB map; therefore, they were also excluded from AGB analysis. A single representative AGB value per vegetation community was calculated by aggregating the 5-m vegetation map to 30-m resolution to match the resolution of the LiDAR AGB estimates, overlaying the two maps, and averaging by community. To facilitate model-data comparison, community average NEEday and GPP were scaled to the 100-m resolution of ELM output using the percent coverage of each vegetation class within each $100\text{ m} \times 100\text{ m}$ model gridcell. Because spatially explicit AGB was already available for the Council intensive field site at 30-m resolution (Yang et al., 2025), data were simply averaged to the ELM resolution for comparison.

2.3.1 Determination of Gross Primary Production

Spatially explicit AVIRIS-NG (July, August) and UAS (August, averaged to 5-m resolution) NDVI from individual flights were overlaid on the vegetation map to calculate the average monthly NDVI values associated with each vegetation community, which were then combined to generate a representative map of average community-specific growing season NDVI. Because high-resolution data was not available in June, August NDVI values were used as a proxy. This decision was informed by analysis of MODIS seasonal NDVI trends across multiple years, which showed that June and August NDVI values were often comparable in this environment. This approach allowed us to estimate average landscape-scale productivity during the growing season, rather than capture dynamic or year-specific NDVI patterns. Community specific leaf area index (LAI), a vegetation density metric that is positively correlated with NDVI, was estimated from NDVI using the transfer function developed by Street et al. (2007)

for Arctic vegetation and generalized by Shaver et al. (2007), as shown in equation (2), and GPP was calculated following the PLIRTLE approach, as shown in equation (3).

$$LAI = 0.0026 \times e^{(8.0783 \times NDVI)} \quad (2)$$

$$GPP = \frac{P_{MaxL}}{k} \times \ln \frac{P_{MaxL} + E_0 \times I}{P_{MaxL} + E_0 \times I \times e^{(-k \times LAI)}} \quad (3)$$

Here, P_{MaxL} is the light-saturated photosynthetic rate (14.747 $\mu\text{mol m}^{-2} \text{ leaf s}^{-1}$), k is a Beer's law extinction coefficient (fixed at 0.5 $\text{m}^2 \text{ ground m}^{-2} \text{ leaf}$), and E_0 is the quantum yield at low light (0.041 $\mu\text{mol CO}_2 \text{ fixed } \mu\text{mol}^{-1} \text{ photons absorbed}$). Photosynthetically active radiation (PAR) from the EC tower was used for I , the top of the canopy photon flux density (PPFD; $\mu\text{mol photons m}^{-2} \text{ s}^{-1}$). Growing season PAR data from years with overlapping NDVI data availability were used to maintain consistency. P_{MaxL} and E_0 are PLIRTLE estimated parameters (Table 2, Shaver et al., 2013), low-Arctic values were used as the Seward Peninsula of Alaska is classified as part of the low-Arctic region.

2.3.2 Determination of Daytime Net Ecosystem Exchange

Footprint-weighted flux maps produced using the Kormann and Meixner (2001) analytical flux footprint model were used to determine the flux contributions of vegetation communities within the tower footprint (NEETower), following the approach outlined by Rey-Sanchez et al. (2022). Footprint-weighted flux maps are produced by combining EC flux data with footprint modeling and landcover information to map the contributions of each patch of ground surrounding the tower to the overall flux measured by the tower, repeated over many measurement periods (Rey-Sanchez et al., 2022). In doing this, they provide information on the spatial heterogeneity of fluxes within the tower footprint, and when combined with high resolution vegetation maps they can be used to determine community-level fluxes of measured scalars (e.g. CO_2 , CH_4 , H_2O , or sensible heat flux). Analysis was restricted to the active growing season (JJA) over the available measurement period (2017–2023).

The footprint model was run at half-hourly resolution on a $800\text{ m} \times 800\text{ m}$ grid surrounding the tower at 8-m resolution to produce a footprint for each measurement period, where the total footprint is a product of the cross-integrated footprint function (a function of flux length scale, wind velocity, and eddy diffusivity) and a cross wind dispersion function. The weight of each footprint is distributed across the cells in the grid, and once the gridded footprint weights are created, the footprint contours are delineated. Following this approach, a footprint function and a flux are determined for each cell within each tower footprint. By evaluating multiple footprints over time (e.g. monthly footprint climatologies, as was done here), a footprint-weighted flux can be calculated for each cell based on the measured EC flux and footprint function associated with that cell, and a footprint-weighted flux map is produced that conveys the average contribution to the measured flux when the footprint intersects a given grid cell (see Rey-Sanchez et al., 2022 for the full suite of equations).

Weighted flux maps were produced using daytime CO_2 fluxes only (NEE_{day}) due to underdeveloped turbulence during stable nighttime conditions (Finn et al., 1996; Burba & Anderson 2013), and to minimize temporal variability in fluxes introduced by diurnal temperature variations, both of which increase the error associated with flux maps (Rey-Sanchez et al., 2022). Restricting analysis to within the 80% footprint contour is typically recommended (Chu et al., 2021) because flux contributions beyond this contour often have a low signal to noise ratio due to the difficulties of accurately measuring source contributions from long footprints during neutral and stable conditions. In this study, flux maps were restricted to the 70% contour due to a change in elevation between the 70 and 80% contour in the northernmost portion of the footprint (i.e., as the watershed approached the toeslope of a hillslope dominated by alder-willow shrubs). To calculate community-specific $\text{NEE}_{\text{Tower}}$, the vegetation community map was upscaled from 5- to 8-m resolution using the nearest neighbor resampling method to align with the flux map resolution. The interpolated vegetation map was then overlaid on the monthly weighted flux maps and trimmed to the 70% footprint contours, so that each grid cell within a flux footprint was defined by a weighted flux value and an associated vegetation class that the flux could be attributed to. Spatially resolved fluxes were grouped by vegetation type and averaged over the area of each footprint to calculate the seasonal $\text{NEE}_{\text{Tower}}$ associated with each vegetation community.

Chamber measurements were upscaled to the EC tower level to validate tower fluxes and vegetation community specific footprint weighted flux estimates. The chamber measurements represent spatially distributed intermittent fluxes and were collected during the day, whereas EC tower-based fluxes were collected continuously and are representative of a broader spatial area. Consequently, comparing chamber and tower-based fluxes without temporal correction and spatial upscaling can lead to inaccurate results (Morin et al., 2017; Forbrich et al., 2011; Desai et al., 2015). Temporal correction involved multiplying the chamber flux by the ratio of CO₂ EC tower flux during the two-hour window surrounding the chamber measurement and the daytime EC tower flux average on the day that the chamber measurement was taken (Morin et al., 2017). To spatially upscale the chamber measurements, the temporally adjusted flux for each vegetation type was multiplied by the fractional coverage of that vegetation type within the EC tower footprint during the period that the chamber measurements were taken.

PLIRTLE empirical relationships were used to calculate the average NEE_{day} associated with vegetation communities not represented in the footprint (NEE_{PLIRTLE}), as shown by equation (4) and equation (5), with GPP calculated following equation (3).

$$NEE_{PLIRTLE} = R_E - GPP \quad (4)$$

$$R_E = (R_0 \times e^{\beta T} \times LAI) + R_x \quad (5)$$

Here, R_E is ecosystem respiration, R_0 is the basal respiration rate (1.177 $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ leaf s}^{-1}$), β is an empirically fit parameter (0.046 per $^{\circ}\text{C}$), T is air temperature ($^{\circ}\text{C}$), and R_x (0.803 $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ ground s}^{-1}$) is a secondary source of CO₂ (independent of LAI and T) corresponding to respiration from deeper soil horizons that prevents R_E from going to zero when LAI is zero. R_0 , β , and R_x are low-Arctic PLIRTLE estimated parameters (Shaver et al., 2013). EC tower PAR and air temperature were subset to daytime measurements using a PAR threshold

of $100 \mu\text{mol m}^{-2} \text{s}^{-1}$ (Voigt et al., 2023) to maintain consistency with $\text{NEE}_{\text{Tower}}$. The PLIRTLE approach was validated by calculating $\text{NEE}_{\text{PLIRTLE}}$ for vegetation communities within the tower footprint and comparing $\text{NEE}_{\text{PLIRTLE}}$ estimates to $\text{NEE}_{\text{Tower}}$ values for those same vegetation communities (see supplement text S1 and Table S2).

2.3 Model Simulations

Simulations of terrestrial biogeochemical cycles were performed with the E3SM (Golaz et al., 2019) Land Model, ELM (Ricciuto et al., 2018; Yang et al., 2019), and predicted NEE, GPP, and AGB were compared to observationally-derived values. Features of ELM that made it an optimal choice for this study include the representation of landscape heterogeneity through a hierarchical subgrid structure, vertically resolved soil processes, inclusion of coupled carbon-nitrogen-phosphorus dynamics, and representation of permafrost extent and dynamics. Additional detail on the representation of permafrost in ELM is included in the Supplement (text S2). Simulations were conducted with two configurations of vegetation in ELM; one with the two default ELM Arctic PFTs and one with a set of nine Arctic-specific PFTs (Sulman et al., 2021a). Parameter names and major parameter changes in the Arctic-specific PFT configuration are described in the introduction and archived in Sulman et al. (2021b). ELM represents vegetation as multiple patches of individual PFTs sharing a soil column within a grid cell, and the relative area of each PFT within a grid cell is prescribed. Uptake of water and nutrients from the soil is partitioned among PFT fractions based on the relative demand for each resource, scaled by depth using PFT-specific rooting depth distributions as well as limited by depth to impermeable permafrost or bedrock.

Spatially explicit 100-m resolution ELM simulations were conducted across an approximately $6.4 \text{ km} \times 3.3 \text{ km}$ domain at the Council intensive field site for a total of 2,112 simulated grid cells under each ELM vegetation configuration. Simulations were spun up with 200 years of accelerated decomposition (Thornton & Rosenbloom, 2005), followed by 600 years of regular spinup (Koven et al., 2013), repeatedly cycling a fixed climatology to remove the influence of long-term climate trends. Transient simulations were performed from 1850 until 2014, using $1 \text{ km} \times 1 \text{ km}$ gridded sub-daily meteorological data from Daymet-adjusted Global Soil Wetness Project Phase 3 (Daymet-GSWP3; Kao et al., 2024) forcing and rising atmospheric CO_2 annually from 278 ppm in 1765 to 385 ppm in 2007 and afterward

(https://web.lcrc.anl.gov/public/e3sm/inputdata/atm/dtm7/CO2/fco2_datm_1765-2007_c100614.nc). The 1 km forcing was applied uniformly to all nested 100 m $\times$ 100 m grid cells within each 1 km cell, ensuring consistency between scales while maintaining the intended resolution of vegetation and soil heterogeneity.

Land surface data used to initialize ELM includes land cover characterization (vegetated fraction, slope, elevation, maximum fractional saturated area) and soil and vegetation properties (Oleson et al., 2013). Soil properties including vertically resolved soil texture and organic matter content at 250 m $\times$ 250 m were obtained from SoilGrids (<https://files.isric.org/soilgrids/latest/data/>) and linearly interpolated to 100 m $\times$ 100 m resolution to match the resolution of the PFT maps. Spline smoothing was applied to the vertical layers of SoilGrid soils to align with ELM soil layer intervals. The fractional coverage of the Arctic-specific ELM PFTs within vegetation communities (Table S3), classified and quantified as shown in Figure 4(c) in Sulman et al. (2021a), were derived from the Konduri et al. (2022) vegetation maps. We aggregated the Konduri et al. (2022) 5 m resolution vegetation community maps to 100 m resolution and quantified the fractional coverage of each community type within the coarser grid cells. Plot-level data from three NGEE Arctic intensive field sites on the Seward Peninsula (Council, Teller, and Kougarak) provided estimates of PFT composition within each community, from which we calculated mean fractional PFTs by community type. Finally, these mean community-level PFT fractions were combined with the fractional community coverage at each grid cell to estimate PFT fractions at 100 m resolution, which were then used to generate model surface datasets. To create surface files for simulations using the default PFT set, we reclassified these Arctic-specific PFTs into the two Arctic-relevant default model PFTs: (1) all shrub PFTs were grouped into the default “broadleaf deciduous boreal shrub” PFT, and (2) all graminoids, forbs, bryophytes, and lichens were grouped into the default “C3 arctic grass” PFT. For additional details on the composition and relative abundance of PFTs within each vegetation community, please refer to Sulman et al. (2021a). Additional details about model processes and components relevant to this study are provided in Table S4, and additional figures of model inputs are provided in Figures S3 – S5.

2.4 Model Evaluation

Spatially-explicit ELM outputs from June, July, and August were averaged over the final five years of simulations (2010 – 2014) and compared against gridded, upscaled observationally-derived NEE_{day} , GPP, and AGB. Due to limited temporal coverage of the available observational data for model evaluation, this study focuses on the spatial patterns and average growing season productivity and carbon uptake rather than interannual variability or temporal trends. Model simulations extended only through 2014 due to the temporal limit of the available Daymet-GSWP3 meteorological forcing. Therefore, comparisons were made between pooled observational data and the mean of the final five years of model output. Climate conditions during these two periods are comparable; over the 2010-2014 period average growing season temperature and precipitation were 11.18°C (SD=0.51) and 199.33 mm (SD=37.43), and over the 2017-2021 period average growing season temperature and precipitation were 11.21°C (SD=1.04) and 200.50 mm (SD=58.80). We recognize that combining observations collected over different time periods may introduce uncertainty, as temporal variability is not fully captured in the pooled dataset. To evaluate ELM configured with two different representations of Arctic vegetation, simulations were compared against observations with a set of summary statistics as well as a set of detailed model performance metrics. For the purposes of this section, x represents the spatial dimension of the carbon cycle variable being evaluated (NEE_{day} , GPP, or AGB), the subscript *mod* reflects that a variable is from a model simulation data set, and the subscript *obs* indicates the variable is from an observationally-derived data set. $\underline{V}_{mod}(x)$ and $\underline{V}_{obs}(x)$ are the temporally averaged grid-level (spatial variables, denoted by the presence of (x)) model output and observed values (respectively), and $\underline{V}_{mod}$ and $\underline{V}_{obs}$ are the spatially averaged landscape-level model output and observed values (respectively). First, $\underline{V}_{mod}$ and $\underline{V}_{obs}$ and their standard deviations (SD; representing spatial variability) were assessed. Landscape-level totals and totals disaggregated by vegetation type were calculated to analyze vegetation community-specific contributions to landscape-level budgets. Model simulations were also evaluated by comparing $\underline{V}_{mod}(x)$ and $\underline{V}_{obs}(x)$ using the coefficient of determination (R^2) to determine how well the models explained the observed variance. The magnitude of bias between simulations and observations was measured to identify systematic errors, where bias was

calculated for each grid cell as the difference in the mean model value and the mean observed value over the period of reference (equation (6)).

$$bias(x) = \underline{V}_{mod}(x) - \underline{V}_{obs}(x) \quad (6)$$

Additionally, the spatial Pearson correlation (R) of $\underline{V}_{mod}(x)$ and $\underline{V}_{obs}(x)$ was calculated to determine if the model accurately represented spatial patterns in carbon stocks and fluxes. Finally, $RMSE$ across the model domain was calculated to quantify the average magnitude of error in model predictions (equation (7)).

$$RMSE = \sqrt{\frac{\sum(\underline{V}_{mod}(x) - \underline{V}_{obs}(x))^2}{n}} \quad (7)$$

Model bias, spatial correlation of values, and $RMSE$ were calculated and assigned scores adapted from evaluation protocols outlined in Collier et al. (2018) for use in the International Land Model Benchmarking (ILAMB) project. To synthesize model performance across datasets with varying units and magnitudes, scores were normalized to a [0,1] interval based on relative error (Collier et al., 2018), where a score closer to one indicates less error, or better model-data agreement. The relative error in bias ($\epsilon_{bias}(x)$) was calculated as shown in equation (8), the bias score for each grid cell ($S_{bias}(x)$) was calculated as shown in equation (9), and the scalar bias score for the overall model domain (S_{bias}) was calculated as the mean of grid cell level bias scores.

$$\epsilon_{bias}(x) = \frac{|bias(x)|}{|\underline{V}_{obs}(x)|} \quad (8)$$

$$S_{bias}(x) = e^{-\epsilon_{bias}(x)} \quad (9)$$

The normalized SD (σ) was computed (equation (10)) and used along with the spatial Pearson correlation (R) to calculate the spatial distribution score (S_{dist}) for the overall model domain (equation (11)).

$$\sigma = \frac{SD(V_{mod}(x))}{SD(V_{obs}(x))} \quad (10)$$

$$S_{dist} = \frac{2(1+R)}{(\sigma + \frac{1}{\sigma})^2} \quad (11)$$

The relative error of $RMSE$ was calculated (equation (12)) and used to calculate the $RMSE$ score (S_{RMSE}) for the overall model domain (equation (13)).

$$\epsilon_{RMSE} = \frac{RMSE}{V_{obs}} \quad (12)$$

$$S_{RMSE} = e^{-\epsilon_{RMSE}} \quad (13)$$

Bias, spatial distribution, and RMSE scores were aggregated to obtain a single scalar score for model performance (equation (14)). In accordance with Collier et al. (2018), the $RMSE$ score carried twice the weight of the other scores to emphasize its importance in determining overall model performance.

$$S_{overall} = \frac{S_{bias} + S_{dist} + 2S_{RMSE}}{1 + 1 + 2} \quad (14)$$

3. Results

3.1 EC Footprint Validation

When scaled to the tower footprint, chamber-based NEE ($-1.29 \pm 0.35 \mu\text{mol m}^{-2} \text{s}^{-1}$) was calculated to be approximately half of EC tower-based NEE ($-2.77 \pm 0.16 \mu\text{mol m}^{-2} \text{s}^{-1}$), where

negative values indicate carbon uptake by vegetation. Temporally corrected chamber-based CO₂ fluxes ($\pm$ standard error) averaged -1.63 ± 0.26 , -0.32 ± 0.21 , and $-2.90 \pm 0.06 \mu\text{mol m}^{-2} \text{s}^{-1}$ for tussock-lichen tundra, wet sedge bog-meadow, and wet meadow tundra, respectively. In comparison, EC tower-based fluxes were -2.27 ± 0.02 , -2.30 ± 0.02 , and $-2.15 \pm 0.03 \mu\text{mol m}^{-2} \text{s}^{-1}$ for the same communities (Table 1). Chamber flux measurements were only available for three vegetation communities within the EC flux tower footprint, so footprint-level estimates based on their weighted average (using fractional coverage) are likely slightly underestimated. However, since these communities comprise 92.72% of the footprint area on average, the impact of this limitation is likely minimal.

3.2 Community-level Carbon Dynamics

Remote-sensing-based AGB for each community ranged from 0.18 to 1.25 kg C m⁻², with the highest average AGB reported for the alder-willow shrub and willow shrub vegetation communities (Table 1) with tall, woody shrub PFTs. Tussock-lichen tundra, wet meadow tundra, wet sedge bog-meadow, dryas-lichen dwarf shrub tundra, and ericaceous dwarf shrub tundra communities with lower-statured PFTs had similar average AGB, ranging from 0.18 to 0.26 kg C m⁻². Observationally-derived NEE_{day} ranged from -0.04 to -10.44 $\mu\text{mol m}^{-2} \text{s}^{-1}$, and GPP ranged from 0.91 to 13.15 $\mu\text{mol m}^{-2} \text{s}^{-1}$. Both fluxes were the highest and most variable for the alder-willow shrub and willow shrub communities and the lowest for the dryas-lichen dwarf shrub tundra and ericaceous dwarf shrub tundra communities (Table 1). To validate community average NEE_{day} determined using the PLIRTLE approach (NEE_{PLIRTLE}), fluxes were compared against NEE_{Tower} for the four vegetation communities represented within the EC tower footprint. NEE_{PLIRTLE} values were 1.52 times higher on average than NEE_{Tower} estimates, but NEE_{Tower} values were within one standard deviation of NEE_{PLIRTLE} averages (see supplement Text S1 and Table S2 for additional details).

Table 1. Vegetation community fractional coverage across the Council intensive field site model domain and observationally-derived average ($\pm$ standard error) growing season aboveground biomass (AGB), gross primary production (GPP), and daytime net ecosystem exchange (NEE_{day}). Vegetation communities within the EC tower footprint with NEE_{day} derived from flux footprint mapping (NEE_{Tower}) are denoted with an asterisk. Vegetation community average NEE_{day} values without an asterisk were derived using the PLIRTLE approach (NEE_{PLIRTLE}), as those communities did not exist within the EC tower footprint.

Vegetation Community	Domain Fractional Coverage	AGB (kg C m^{-2})	GPP ($\mu\text{mol m}^{-2} \text{s}^{-1}$)	NEE_{day} ($\mu\text{mol m}^{-2} \text{s}^{-1}$)
Alder-willow shrub	27.86%	1.25 ± 0.00	13.15 ± 0.17	-10.44 ± 0.16
Birch-Ericaceous-lichen shrub tundra	7.06%	0.45 ± 0.01	4.64 ± 0.05	$-2.15 \pm 0.02^*$
Coniferous forest	11.74%	NA	9.08 ± 0.11	-7.34 ± 0.10
Dryas-lichen dwarf shrub tundra	0.03%	0.24 ± 0.03	0.91 ± 0.01	-0.04 ± 0.01
Ericaceous dwarf shrub tundra	0.75%	0.18 ± 0.01	2.46 ± 0.03	-1.47 ± 0.02
Tussock-lichen tundra	24.21%	0.26 ± 0.00	5.07 ± 0.06	$-2.27 \pm 0.02^*$
Wet meadow tundra	4.12%	0.24 ± 0.01	4.74 ± 0.05	$-2.15 \pm 0.03^*$
Wet sedge bog-meadow	15.88%	0.18 ± 0.00	3.73 ± 0.04	$-2.30 \pm 0.02^*$
Willow-birch shrub	1.82%	0.40 ± 0.01	8.30 ± 0.10	-6.68 ± 0.09
Willow shrub	0.07%	0.69 ± 0.20	12.56 ± 0.16	-10.04 ± 0.15
Unvegetated	6.46%	NA	NA	NA

3.3 Landscape-level Carbon Dynamics

3.3.1 Evaluation of Model Performance

Comparison of standardized model performance scores showed that the Arctic-specific PFT ELM formulation outperformed the default PFT formulation for GPP and NEE_{day} across all three individual metric scores as well as for the overall composite scores (Figure 3). However, the default PFT ELM formulation outperformed the Arctic-specific PFT model formulation for representation of AGB with respect to the bias, RMSE, and overall scores. The superior performance of the default PFT model with regards to representation of AGB was primarily a consequence of the Arctic-specific PFT formulation of ELM exhibiting a strong positive bias in AGB estimates for highly productive alder-willow shrub communities. Despite this, both model formulations performed similarly across other AGB evaluation metrics (Figure 3). Our analysis

showed that the Arctic-specific PFT model formulation excelled in capturing observed spatial patterns and variability of carbon fluxes. Spatial distribution scores for all three carbon cycle variables evaluated were 0.12 to 0.29 points higher on the standardized 0 to 1 scoring interval for the Arctic-specific PFT simulations, with the greatest improvement observed for the representation of GPP.

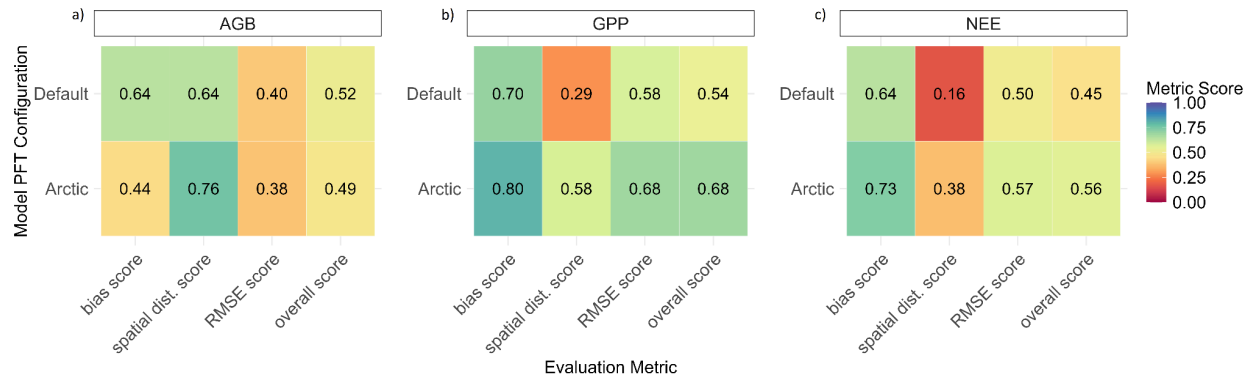


Figure 3. Standardized model evaluation metrics and overall model performance scores for (a) AGB, (b) GPP, and (c) NEE_{day} from the default and refined Arctic-specific PFT ELM simulations. Performance metrics are scored on a 0 to 1 interval, where a score closer to 1 indicates superior model-data agreement.

Averaged across the landscape, observationally-derived AGB ($0.62 \pm 0.01 \text{ kg C m}^{-2}$) was greater than the output of the default ELM simulations ($0.40 \pm 0.01 \text{ kg C m}^{-2}$) but lower than the output from the Arctic-specific ELM simulations ($0.99 \pm 0.02 \text{ kg C m}^{-2}$) (Figure 4). Despite this discrepancy, the Arctic-specific PFT formulation of ELM explained 60% of the spatial variation in the observationally-derived AGB dataset (RMSE = 0.61 kg C m^{-2}), whereas the default PFT formulation of ELM only explained 12% of the spatial variation (RMSE = 0.57 kg C m^{-2}). The distribution of AGB values from simulations with the Arctic-specific PFTs more closely aligned with the bimodal distribution of observationally-derived AGB (Figure 4), although simulations with the Arctic-specific PFT representation overestimated AGB compared to observations, particularly for high biomass communities.

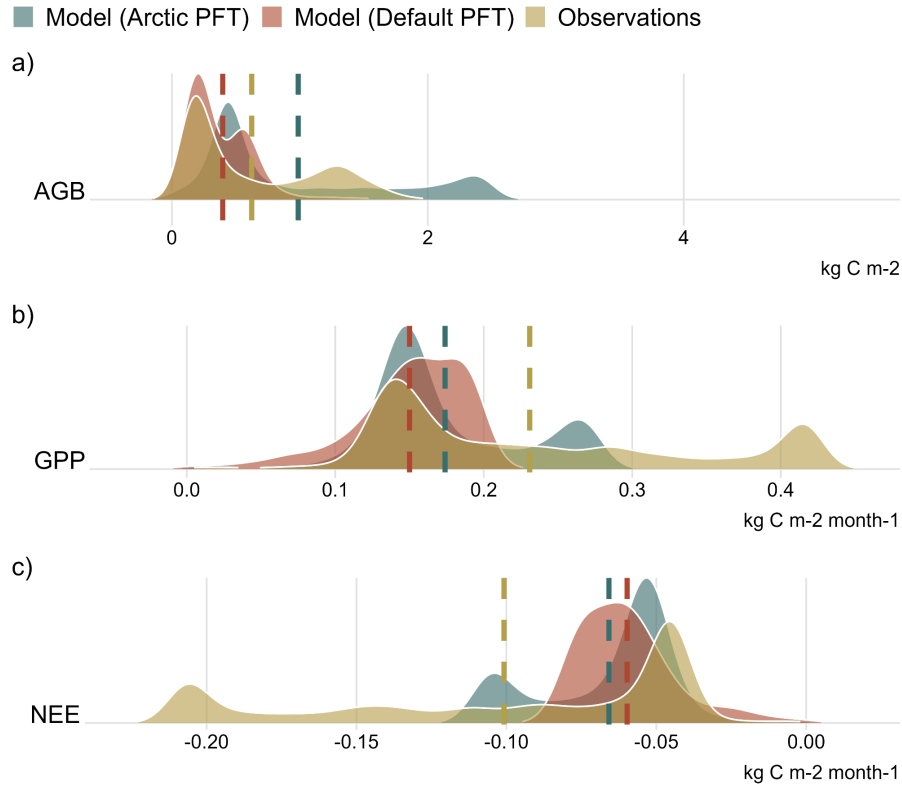


Figure 4. Smoothed histograms of seasonally averaged spatially gridded (a) aboveground biomass (AGB), (b) gross primary production (GPP), and (c) daytime net ecosystem exchange (NEE_{day}) distributions, color coded by data source. Dashed lines indicate distribution means.

Both model formulations underestimated GPP and NEE_{day} (Figure 4). Observationally-derived average GPP was $0.23 \pm 0.00 \text{ kg C m}^{-2} \text{ month}^{-1}$, compared to 0.17 and $0.15 \text{ kg C m}^{-2} \text{ month}^{-1}$ predicted by the Arctic-specific and default PFT ELM formulations, respectively. Observationally-derived average NEE_{day} was $-0.10 \pm 0.00 \text{ kg C m}^{-2} \text{ month}^{-1}$, versus -0.07 and $-0.06 \text{ kg C m}^{-2} \text{ month}^{-1}$ predicted by the Arctic-specific and default PFT ELM formulations, respectively. However, the Arctic-specific PFT formulation explained more of the variance in observationally-derived GPP and NEE_{day} , capturing 70% of the variability in GPP and 69% of the variability in NEE_{day} , compared to only 17% and 18% of the variance in GPP and NEE_{day} explained by the default PFT model formulation. The improved performance of the Arctic-specific PFT model formulation is likely due to its ability to capture highly productive areas across the landscape and represent a more realistic gradient in productivity, as shown in Figure 5. Although the Arctic-specific PFT model formulation underestimates the highly

productive tails of the GPP and NEE_{day} distributions, its bimodal distribution more closely aligns with the observationally-derived GPP and NEE_{day} distributions (Figure 4).

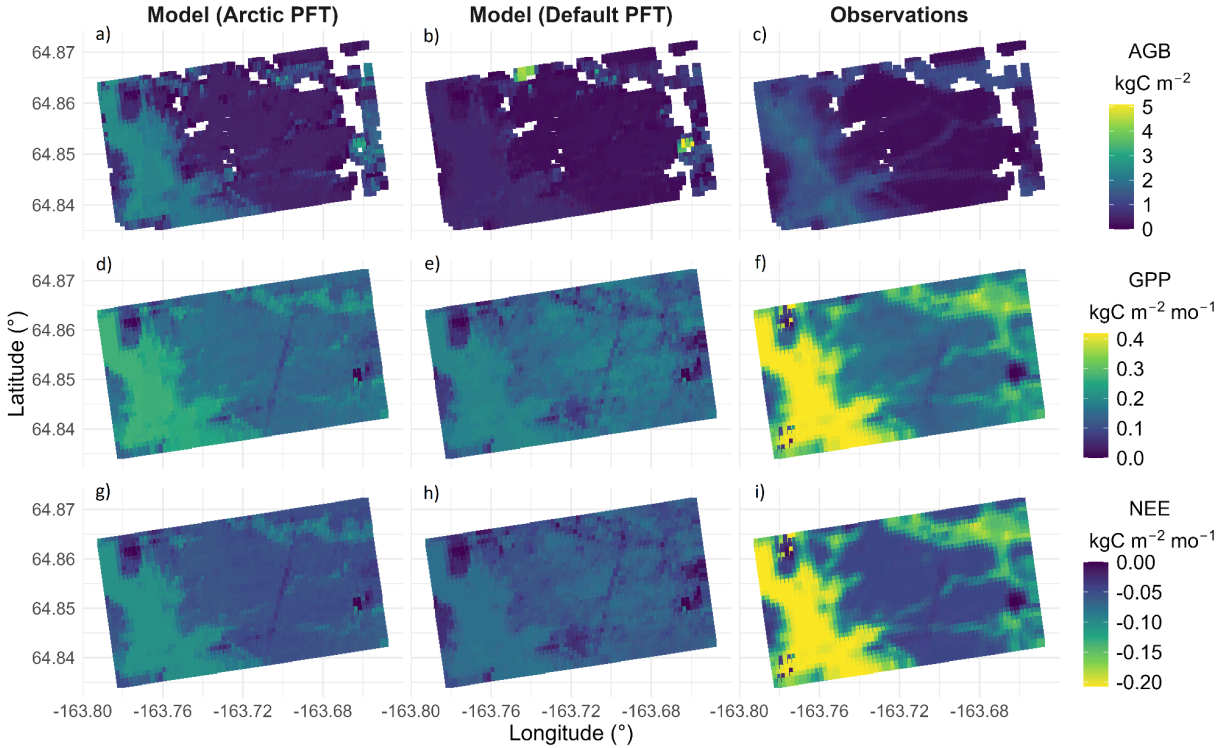


Figure 5. Seasonally averaged aboveground biomass (AGB), daytime net ecosystem exchange (NEE_{day}), and gross primary production (GPP) from ELM simulations with the Arctic-specific PFT representation (a, d, g), the default PFT representation (b, e, h), and from observations scaled to ELM 100 m resolution (c, f, i). Blank spaces in AGB subplots correspond to locations dominated by conifers, which were not included in the analysis.

3.3.2 Carbon Budgets

Scaled to the landscape level, observationally-derived AGB totaled $1,088.30 \pm 0.51$ kg C across the full 21 km² model domain (for summed values ‘ $\pm$ ’ denotes standard deviation). Simulations using the default PFTs underestimated total AGB by 36.33% (with a total biomass of 692.91 ± 0.40 kg C), whereas simulations with Arctic-specific PFTs overestimated AGB by 58.25%, estimating total AGB at $1,722.20 \pm 0.76$ kg C. The default PFT formulation of ELM underestimated AGB from essentially all vegetation communities, while the Arctic-specific model formulation overestimated AGB contributions, and was particularly biased for the alder-willow shrub community. Given the significant alder-willow shrub coverage at Council,

this resulted in a dramatic overestimation of total AGB. It should be noted that the landscape level totals presented here represent an underestimate due to the omission of conifer-dominated areas, which accounted for approximately 12% of the landscape. The inability of both model formulations to capture fluxes from highly productive communities (Figure 5) resulted in an underestimation of mean GPP and NEE_{day} at the landscape level. Both model formulations reasonably captured contributions from less productive communities such as wet sedge bog-meadow, wet meadow tundra, and birch-ericaceous-lichen shrub tundra to landscape-level GPP, but underestimated contributions from alder-willow shrub and coniferous forest communities, resulting in a domain total GPP of $349.08 \pm 0.05 \text{ kg C mo}^{-1}$ for the Arctic-specific PFT model configuration and $302.44 \pm 0.04 \text{ kg C mo}^{-1}$ for the default PFT configuration, compared to the observationally-derived estimate of $487.79 \pm 0.10 \text{ kg C mo}^{-1}$. With respect to NEE_{day} , both model formulations slightly overestimated the net uptake from tussock-lichen tundra, and again underestimated carbon sequestration by the alder-willow shrub. Observationally-derived landscape-level NEE_{day} was $-212.88 \pm 0.06 \text{ kg C mo}^{-1}$, compared to -132.09 ± 0.02 and $-120.48 \pm 0.02 \text{ kg C mo}^{-1}$ estimated by the Arctic-specific PFT and default PFT formulations of ELM, respectively.

4. Discussion

In this study, we used high-resolution, spatially explicit simulations to evaluate how incorporating refined Arctic-specific PFTs influenced model predictions of landscape-scale tundra carbon stocks and fluxes. By comparing simulations using default and Arctic-specific ELM configurations against diverse observational data streams, we assessed model performance in capturing spatial variability and landscape-level budgets of NEE, GPP, and AGB at a novel testing location.

4.1 EC Footprint Validation

Chamber-based estimates of NEE were similar to tower-based estimates at the community scale, but upscaled chamber observations ultimately characterized the area as less of a net carbon sink than was estimated by the EC tower. Some disagreement between the two methods was expected, as numerous studies have shown that upscaled chamber estimates and EC flux estimates tend to deviate (Forbrich et al., 2011; Desai et al., 2015), even when accounting

for the fractional cover of different land cover or vegetation groups (Boonman et al., 2024; Morin et al., 2017). For instance, closed chambers have been shown to overestimate soil CO₂ efflux particularly under conditions of low atmospheric turbulence (Brændholt et al., 2017), and pulses of gas caused by surface disturbance near the soil collars during measurements cannot be completely ruled out. Conversely, EC towers have been shown to systematically underestimate the influence of soil respiration on net CO₂ fluxes (Phillips et al., 2017), due in part to assumptions inherent to the EC approach, such as negligible horizontal mean advection. While both methods are subject to unique limitations and biases (Barba et al., 2018), the similarity in scaled flux magnitudes between the approaches suggests that the tower footprint weighted flux estimates derived here are reliable, and the chamber estimates remain useful for validating tower-based fluxes.

4.2 Community-level Carbon Dynamics

Vegetation at the Council intensive field site is characterized by a mix of low-statured nonvascular bryophytes and lichens, graminoid-dominated tussocks, and shrub-dominated communities (Figure 1). The distribution of vegetation types across the landscape is likely heavily influenced by subsurface conditions (Figures S6 and S7), with topographic gradients in moisture availability (i.e. upland versus lowland) exerting strong controls over plant community composition and productivity, as documented in studies across multiple Arctic sites (Campbell et al., 2021; Chapin et al., 1988). All vegetation communities were net sinks of carbon during the growing season, but productivity varied substantially across the different vegetation types (Table 1). Of the vegetation communities that exist at Council, the alder-willow shrub community was the most productive, exhibiting the highest average observationally-derived AGB, GPP, and NEE_{day}, while dwarf shrub communities, particularly the dryas-lichen dwarf shrub tundra and ericaceous dwarf shrub tundra communities, exhibited the lowest average carbon uptake and storage, consistent with other studies (Jonasson et al., 2001; Phillips & Wurzbarger, 2019; Berner et al., 2018; Berner et al., 2024; Street et al., 2018; Chapin et al., 1980). Lowland wet meadow vegetation types exhibited slightly higher GPP and NEE_{day} than the dwarf shrub tundra communities yet had comparable average AGB. The slightly higher productivity observed in wet tundra communities could be linked to increased water availability (Chapin et al., 1988) and species-specific adaptations that allow access to nutrients from deeper soil layers that may be out

of reach for the shallower root systems of dwarf shrubs. However, it should be noted that estimates of AGB derived from LiDAR can be biased by vegetation height (Yang et al., 2022), often underestimating biomass for low-stature vegetation (Poley & McDermid, 2020).

Our findings are consistent with other assessments of community-specific productivity in Arctic vegetation; evergreen dwarf shrubs tend to be slow growing, whereas tall deciduous shrubs tend to have the highest biomass and productivity rates (Jonasson et al., 2001; Phillips & Wurzburger, 2019; Berner et al., 2018; Berner et al., 2024; Street et al., 2018; Chapin et al., 1980), although the community-specific AGB estimates presented here are slightly higher than comparable estimates for low-Arctic vegetation types (Berner et al., 2024; Street et al., 2018). Tall shrubs such as alder and willow often exist in areas with surface or subsurface flowing water, so favorable hydrological conditions at Council could compound competitive advantages due to the lifeform properties of deciduous shrub species (growth patterns, leaf structure, rooting depth, influence on soil dynamics, etc.) to maintain high levels of productivity (Jonasson et al., 2001; Shaver & Jonasson, 2001). Alder shrubs in particular have a competitive advantage due to their ability to symbiotically fix atmospheric nitrogen, which is key in Arctic ecosystems where plant growth is frequently limited by nitrogen availability (Salmon et al., 2016; Iversen et al., 2015; Phillips & Wurzburger, 2019; Shaver et al., 1992). The high degree of spatial variability observed in willow and alder-willow shrub carbon dynamics at Council likely reflects the impact of this tight coupling between subsurface conditions and aboveground productivity, highlighting how advantages related to nutrient access and water availability enable shrubs to thrive in Arctic ecosystems.

Validation of the PLIRTLE approach showed that community $NEE_{PLIRTLE}$ values were 1.52 times higher on average than NEE_{Tower} estimates, but NEE_{Tower} community fluxes were within one standard deviation of the $NEE_{PLIRTLE}$ averages, indicating that the values obtained through both methods are representative. However, we were unable to directly validate $NEE_{PLIRTLE}$ estimates for some of the most productive vegetation communities such as alder-willow shrub, as they did not exist within the 70% tower footprint. Other studies comparing measured and PLIRTLE-determined CO_2 fluxes in Arctic ecosystems (Prager et al., 2017; Loranty et al., 2011) similarly show close agreement between the two approaches. A

nutrient enrichment study by Prager et al. (2017) found that differences in NEE, GPP, and ecosystem respiration between the two methods were only significant under treatments with the highest level of nutrient addition. The slightly higher $NEE_{PLIRTLE}$ values can likely be attributed to the PLIRTLE approach only directly constraining vegetation productivity with temperature, light availability, and leaf area, while other constraints on photosynthesis such as nutrient limitation or water stress are not accounted for, which could be particularly important in chronically nutrient limited Arctic ecosystems (Prager et al., 2017; Shaver et al., 1992; Hobbie, 1992).

4.3 Performance of a Model Parameterized for Arctic Vegetation: Landscape-level Carbon Dynamics

By employing the upscaling approach presented here, we were able to move beyond individual vegetation community carbon stocks and fluxes and estimate landscape-level carbon budgets. While our upscaling approach does not resolve fine-scale differences in productivity within a vegetation type driven by microclimatic variation, the community averages were derived from observations across the study domain, which likely capture much of the broader variability relevant for landscape-scale comparisons. Landscape-scale evaluation of model performance showed that the Arctic-specific PFT ELM formulation outperformed the default PFT formulation for GPP and NEE_{day} , but had lower overall performance scores for AGB (Figure 3). This demonstrates that the majority of the Arctic-specific PFT parameterizations developed at the Kougarkok site using a limited selection of representative communities (Sulman et al., 2021a) remain applicable and improve model representation of carbon fluxes when tested at broader spatial scales at an independent Arctic site. However, the diminished ability of ELM to simulate AGB—particularly in highly productive alder-willow shrublands—indicates a mismatch in the representation of stored carbon. This suggests that carbon allocation and storage parameters derived from a single site may not capture the full range of structural and functional variation present in communities across the Arctic. Additional work is needed to evaluate and refine these parameters to better represent spatial variability in biomass allocation and carbon storage. Additionally, while the Arctic-specific PFT formulation of ELM predicted higher landscape-mean GPP and NEE_{day} , and was able to reproduce observed bimodal distributions (Figure 4), both model formulations struggled to accurately capture fluxes from highly productive communities (e.g., alder-willow shrub), leading to an underestimation of total GPP

and NEE_{day} at the landscape scale. In particular, our analysis showcased the superior performance of the Arctic-specific PFT ELM formulation in capturing the observed spatial representation and variability in carbon fluxes (Figure 3, Figure 5), and the subsequent improvement in landscape scale carbon budgets. This finding is consistent with other studies that have evaluated the effect of incorporating local-scale tundra heterogeneity on broader scale simulations of carbon dynamics. For example, Lara et al. (2020) showed that categorizing polygonal tundra landscapes into wet and dry landforms reduced predictive uncertainty in regional-scale simulations of soil carbon dynamics, highlighting the critical role of hydrology in tundra carbon cycling. Our study builds on this by showing that incorporating finer-scale variations in plant structure and functional traits through more detailed classification of Arctic-specific PFTs on the more diverse hillslopes of the Low Arctic further enhances model representation and leads to more realistic predictions of tundra land-atmosphere exchange and productivity.

Modeled AGB from Arctic-specific PFT simulations overestimated biomass from all vegetation communities, particularly for alder-willow shrub and tussock-lichen tundra communities, which resulted in an overestimation of landscape-level means. Considering the overestimation of AGB in the context of underestimated GPP and NEE_{day} suggests that the model is likely overestimating carbon allocation to aboveground biomass and underestimating allocation to belowground biomass, a known bias in the model. This mismatch is also reflected in simulated LAI (Figure S8), which is higher than is typically observed for tundra vegetation. The Arctic-specific PFT simulations produce LAI values ranging from 3 to 10 across the landscape, whereas field observations are typically below 4 (Spadavecchia et al., 2008; Chang et al., 2022). Because ELM calculates LAI from leaf biomass using a prescribed specific leaf area (SLA), this overestimation likely arises from excessive allocation of assimilated carbon to foliage rather than to belowground pools. As a result, the model can produce unrealistically high AGB and LAI while still underestimating GPP and NEE. In addition, the bryophyte PFT is assigned a very high SLA compared to vascular plants. While high bryophyte LAI is consistent with previous observations (Niinemets and Tobias, 2019), it is not easily comparable to vascular plant LAI due to structural differences between bryophytes and vascular plants, and therefore the presence of bryophytes in simulated tundra plant communities could bias LAI relative to observations. Both SLA and the ratio of carbon allocation to roots versus leaves are flexible

PFT-specific parameters in ELM. While we lack landscape-level observations of belowground biomass to verify this hypothesis, it is consistent with Sulman et al. (2021a), which found that the Arctic-specific PFT formulation of ELM improved estimates of total biomass relative to the default PFT formulation at the plot level, but when segregated into above- and belowground contributions, tended to overestimate aboveground biomass and underestimate belowground biomass. One possible explanation could be related to the parameterization of the Arctic-specific PFTs and how they interact with the environment, while another possible explanation could be tied to the representation of hydrology and its relationship to carbon dynamics in ELM. The current model parameterization underestimates belowground productivity especially for alder shrub communities (Sulman et al., 2021a), which allocate a higher proportion of their biomass belowground compared to graminoid or ericaceous plants (Phillips & Wurzbarger, 2019; Chapin et al., 1980). Alder shrubs also have high rates of inputs of labile litter to the soil, which decomposes quickly and enhances the availability of soil nutrients (Hobbie, 1992), creating a positive feedback loop supporting their own growth (Phillips & Wurzbarger, 2019; Hobbie, 1992). Some studies have even suggested that the enriched soil N from alder's association with symbiotic nitrogen-fixing bacteria suppresses decomposition in shrub-conditioned tundra soils, resulting in lower heterotrophic respiration rates compared to other shrub species such as birch and willow (Phillips & Wurzbarger, 2019; Frey et al., 2014; van Diepen et al., 2017), and therefore higher NEE. Since belowground productivity plays a crucial role in driving net carbon exchange at the landscape level, this could contribute to the underestimation of NEE_{day} in simulations. The discrepancy in AGB at the landscape level could suggest that Arctic vegetation prioritizes root growth to enhance resource acquisition or storage more than previously accounted for. This is supported by recent evidence suggesting that roots extend growth later into the fall than aboveground tissues (Gallois et al., 2025), a process that isn't currently represented in the model but that could affect the balance of above-and-belowground carbon dynamics in subsequent growing seasons.

From a hydrological perspective, tundra systems with discontinuous permafrost exhibit dynamic hydrology due to ongoing freeze-thaw cycles (Schuur et al., 2022; Liljedahl et al., 2016; Lara et al., 2020), which create heterogeneous soil and vegetation patterns that impact land-atmosphere exchange (Campbell et al., 2020; Olivas et al., 2010). ELM does include

spatially explicit initialization of organic matter content and soil texture, and it dynamically simulates changes in soil moisture and active layer thickness (Figures S3–S7). While we were able to capture the resulting patterns in vegetation distribution using observationally-derived plant community maps, some of the heterogeneous hydrology and subsurface conditions driving that distribution are not represented in the current model. In particular, ELM does not include lateral water flow across grid cells, and as a result it fails to represent accumulation of water and higher water tables in low-lying parts of the landscape. For instance, the model fails to represent seasonal inundation of low-lying areas, which inhibits ecosystem respiration by reducing oxygen availability in saturated soils (Oechel et al., 1998). This likely contributes to the model's underestimation of NEE; hydrological manipulation studies have shown that decreased water table depth negatively affects NEE, shifting tundra ecosystems from a net sink to a net source of CO₂ (Olivas et al., 2010; Oechel et al., 1998). Some studies such as Jonasson et al. (2001) posit that hydrological conditions are the primary factor shaping Arctic ecosystems, citing the influence of hydrology on turnover rates, rooting depth, decomposition of litter inputs, and the ratio of soil organic matter to net primary production. Microcosm experiments using tundra soils have similarly shown that hydrological conditions (rather than temperature) exert the main control on carbon exchange, primarily affecting respiration, although both photosynthesis and respiration are affected (Johnson et al., 1996; Berns-Herrboldt et al., 2025). While not evaluated here, hydrology is also the primary control on tundra methane fluxes, which are an important component of greenhouse gas exchange in Arctic ecosystems. Beyond hydrological controls on NEE via respiration, many studies have demonstrated strong links between topographically driven hydrology and tundra plant productivity (Myers-Smith et al., 2015; Chapin et al., 1988; Campbell et al., 2021), with enhanced nutrient cycling and productivity observed in areas with subsurface water drainage compared to adjacent non-water track areas (Chapin et al., 1988). Finally, although our analysis focuses on the growing season, legacy effects of winter processes also influence growing season carbon dynamics. Specifically, snow entrainment by tall shrubs can influence soil thermal and moisture regimes (Shirley et al. 2025; Lathrop et al. 2024), and the timing of snowmelt has demonstrated linkages to the temporal patterns of growing season CO₂ sequestration and productivity (Zona et al., 2022).

4.4 Implications for model projections and evaluation in Arctic ecosystems

Our results suggest that variation in plant communities, especially high-productivity shrub-dominated communities, are a key factor controlling landscape-level carbon cycling in tundra ecosystems. Shrub expansion has been identified as an important driver of ecosystem change in warming tundra ecosystems (Myers-Smith et al., 2011; Mekonnen et al., 2021; Myers-Smith et al., 2015), and while our results show that improving Arctic shrub parameterization can increase land surface model accuracy, these results also suggest that representation of shrub expansion over time via dynamic vegetation modeling is critical for projecting changes in tundra carbon cycling. Specifically, these findings highlight the need to incorporate community-level variation and trait diversity into model structures, as this variability strongly influences GPP and NEE dynamics. Models that assume uniform vegetation characteristics at coarse scales risk misrepresenting future feedbacks under shrub expansion scenarios.

An important end goal of land surface model improvements is to improve the accuracy of Earth system scale projections of carbon cycle feedbacks to climatic warming. Our results suggest that simulations of Arctic terrestrial carbon cycling would benefit from more detailed representation of tundra plant communities, vegetation traits, and spatial changes over time. Incorporating these factors into model simulations at the pan-Arctic scale will require large-scale spatial mapping of plant communities (e.g., CAVM, Reynolds et al., 2019) with representation of Arctic plant structure and physiology in the configuration of global-scale models. However, the current model formulation's overestimation of AGB and slight underestimation of GPP and NEE_{day} for tundra landscapes suggest a carbon allocation bias for highly productive vegetation types, with excess carbon directed aboveground and insufficient allocation belowground. The lack of consistent belowground biomass observations constrains our ability to directly parameterize PFT-specific belowground carbon allocation for tundra vegetation. As new trait-based and belowground datasets become available at additional sites across the Arctic (e.g., Iversen et al., 2017; Bjorkman et al., 2018; Berner et al., 2024), incorporating these data could help refine carbon allocation parameterizations, enhancing confidence in regional to pan-Arctic projections of tundra carbon dynamics. While a detailed sensitivity analysis and re-calibration of allometric parameters using data from a range of Arctic sites is beyond the scope of this study,

we recognize that such an analysis represents an important area for future research. Encouragingly, recent work by Yazbeck et al. (2025) explored the effects of calibrating the fraction of leaf nitrogen in the Rubisco enzyme in the Arctic-specific PFT model by adjusting the (FLNR) parameter which impacts photosynthetic activity in the model, and found that calibration improved agreement between simulated and observed carbon fluxes at a third site in the Canadian Arctic.

Our approach demonstrates the high value of multifactor model evaluation and the value of combining multiple observational techniques across scales. Our study included a broad range of measurement scales, from chambers (~ 1 m) to flux towers (~ 100 m) to drones (~ 1 km) to airborne remote sensing platforms (~ 10 km). By combining measurements across these scales, we were able to simultaneously characterize the fine-scale variability of fluxes across plant communities and the larger-scale variation in biomass and fluxes across the broader landscape. This study plays an important role in bridging the fine scale at which tundra observations are made and model parameterizations are typically developed and the intermediate scales required for robust validation before applying these relationships to regional or global domains. Many studies apply vegetation structure–function parameterizations that were derived at the plot scale directly to the regional or global level without testing how those parameterizations hold as spatial heterogeneity increases. Our results provide a critical intermediate-scale assessment, helping ensure that parameterizations are transferable and accurate at scales relevant for Earth system modeling. This step is essential for improving the fidelity of pan-Arctic projections of tundra carbon cycling under future climate change. While further research is required to better represent the links between vegetation and belowground properties in land surface models like ELM and understand the scale at which these connections occur and their impacts on larger-scale carbon dynamics, the effort described here and its consequences for facilitating model scaling represent an important step in this direction.

5. Conclusions

The goal of this study was to assess whether refined representation of Arctic vegetation in the E3SM land model (ELM) could improve landscape-level model simulations of tundra carbon dynamics. Specifically, we evaluated whether ELM formulated with Arctic-specific PFTs

parameterized at the plot scale using limited representative communities was 1) able to capture the spatial variability in carbon stocks and fluxes at a novel testing location, and 2) whether representation of that variability resulted in more realistic landscape-level mean aboveground biomass, ecosystem productivity, and net land-atmosphere carbon exchanges. By conducting high-resolution spatially explicit simulations using the default and Arctic-specific vegetation formulations of ELM, and evaluating model performance against a suite of upscaled observational data streams, we were able to show that the model formulation with refined representation of Arctic vegetation produced more realistic spatial patterns and landscape mean tundra carbon fluxes, but was not able to reproduce observed carbon stocks, particularly for highly productive tall shrub communities, suggesting further evaluation of carbon allocation parameterizations is required. This study addresses persistent uncertainties in predicting the response of Arctic ecosystems to changing environmental conditions, which arise in part due to simplistic representation of Arctic vegetation in existing models. Given the heterogeneous nature of Arctic ecosystems, evaluating these model improvements at intermediate spatial scales is essential before expanding to larger, pan-Arctic assessments of carbon dynamics under a changing climate. Furthermore, this study presents a comprehensive approach for model evaluation that integrates multiscale observational data including eddy covariance and chamber-based carbon fluxes, and airborne hyperspectral and UAS-based remote sensing.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

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Open Research

E3SM model code is accessible as a GitHub repository (E3SM Project, 2024) under a BSD open-source license. The ELM configuration with refined representation of Arctic-specific PFTs is archived in the NGEE Arctic Data Collection (Sulman et al., 2021b). North American Daymet–GSWP3 gridded meteorological forcing data (Kao et al., 2024) is archived in the Constellation data repository. Site-specific meteorological forcing, model inputs (surface, domain, and parameter files), and model output files are archived in the NGEE Arctic Data Collection (Murphy et al., 2025b). The 5 m resolution maps of vegetation community average growing season NEE and GPP are also archived in the NGEE Arctic Data Collection (Murphy et al., 2025a). Eddy covariance flux data used in this study (AmeriFlux site US-NGC) are available in the NGEE Arctic Data Collection (Torn & Dengel, 2020), and gap filled flux data are available through AmeriFlux (Torn & Dengel, 2021). Code to generate footprint weighted flux maps is archived on Zenodo (Rey-Sanchez, 2022). Chamber-based flux data are available through the NGEE Arctic Data Collection (Chafe et al., 2023). UAS-based remote sensing data are available in the NGEE Arctic Data Collection (Yang & Serbin, 2023). AVIRIS–NG reflectance data (Green et al., 2023) are available through the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL-DAAC), the specific flight lines used are listed in section 2.2.4. The aboveground biomass estimation algorithm code and data used for model training and validation are archived on Zenodo (Yang, 2025).

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