



Evaluation of terrestrial pan-Arctic carbon cycling using a data-assimilation system

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15 **Abstract.** There is a significant knowledge gap in the current state of the terrestrial carbon (C) budget. The Arctic accounts for approximately 50% of the global soil organic C stock, emphasizing the important role of Arctic regions in the global C cycle. Recent studies have pointed to the poor understanding of C pools turnover, although remain unclear as to whether productivity or biomass dominate the biases. Here, we use an improved version of the CARDAMOM data-assimilation system, to produce pan-Arctic terrestrial C-related variables without using traditional plant functional type or steady-state assumptions.

20 Our approach integrates a range of data (soil organic C, leaf area index, biomass, and climate) to determine the most likely state of the high latitude C cycle at a $1^\circ \times 1^\circ$ resolution for the first 15 years of the 21st century, but also to provide general guidance about the controlling biases in the turnover dynamics. As average, CARDAMOM estimates 513 (456, 579), 245 (208, 290) and 204 (109, 427) $\text{g C m}^{-2} \text{yr}^{-1}$ (90% confidence interval) from photosynthesis, autotrophic and heterotrophic respiration respectively, suggesting that the pan-Arctic region acted as a likely sink -55 ($-152, 157$) $\text{g C m}^{-2} \text{yr}^{-1}$, weaker in

25 tundra and stronger in taiga, but our confidence intervals remain large (and so the region could be a source of C). In general, we find a good agreement between CARDAMOM and different sources of assimilated and independent data at both pan-Arctic and local scale. Using CARDAMOM as a benchmarking tool for global vegetation models (GVM), we also conclude that turnover time of vegetation C is weakly simulated in vegetation models and is a major component of error in their forecasts. Our findings highlight that GVM modellers need to focus on the vegetation C stocks dynamics, but also their respiratory losses,

30 to improve our process-based understanding of internal C cycle dynamics in the Arctic.



1 Introduction

Arctic ecosystems play a significant role in the global carbon (C) cycle (Hobbie et al., 2000; McGuire et al., 2009; McGuire et al., 2012; van der Molen et al., 2007). Slow organic matter decomposition rates due to cold and poorly drained soils in combination with cryogenic soil processes have led to an accumulation of large stocks of C stored in the soils, much 35 of which is currently held in permafrost (Tarnocai et al., 2009). The permafrost region soil organic C (SOC) stock is more than twice the size of the atmospheric C stock; and accounts for approximately half of the global soil organic C stock (Hugelius et al., 2014; Jackson et al., 2017). High latitude ecosystems are experiencing a warming increase that is nearly twice the global average (AMAP, 2017). SOC mineralisation may increase rapidly in response to warming, which may lead to an increase in release of carbon dioxide (CO₂) through heterotrophic respiration (Schuur et al., 2015) and thus increased emissions of CO₂ 40 through ecosystem respiration (R_{eco}). However, temperature-induced vegetation changes (Lucht et al., 2002; Zhou et al., 2001) may mitigate those effects by photosynthetic enhancement (Abbott et al., 2016; Myers-Smith et al., 2015; Myneni et al., 1997). Consequently, phenology shifts may feedback on climate with unclear magnitude and sign (Anav et al., 2013; Murray-Tortarolo et al., 2013; Peñuelas et al., 2009). As a result of the significant changes that are already affecting the structure and 45 function of Arctic ecosystems, it is critical to understand and quantify the C dynamics of the terrestrial tundra and taiga and their responses to climate change (McGuire et al., 2012).

Despite the importance of Arctic tundra and taiga biomes in the global C cycle, our understanding of controls interacting between C storage and turnover is deficient (Hobbie et al., 2000). There are large gaps of knowledge in the current state of the pan-arctic terrestrial C budget that is mainly due to the vast uncertainties in C allocation, C stocks and transit times at global scales (Bloom et al., 2016; Carvalhais et al., 2014; Friend et al., 2014). At local scale, the net ecosystem exchange 50 (NEE) of CO₂ between the land surface and the atmosphere is usually measured using eddy covariance EC techniques (Balocchi, 2003). International efforts have led to the creation of global networks such as FLUXNET (<http://fluxnet.fluxdata.org/>) and ICOS (<https://www.icos-ri.eu/>), to harmonise data and support the reduction of uncertainties around the C cycle and its driving mechanisms. However, upscaling field observations to estimate regional to global C budget presents important challenges due to insufficient spatial coverage of measurements and heterogeneous landscape mosaics 55 (McGuire et al., 2012). Furthermore, harsh environmental conditions in high latitude ecosystems and their remoteness complicates the collection of high quality data (Grøndahl et al., 2008; Lafleur et al., 2012). Given the lack of continuous, spatially distributed ground-based scale observations of NEE in the Arctic, it remains a challenging task to calculate with certainty whether or not the Arctic is a net C sink or a net C source, and how the net C balance will evolve in the future (Fisher et al., 2014).

60 Beyond direct ground observations, C cycle modelling in process-based global vegetation models (GVMs) typically relies on pre-arranged parameters retrieved from literature, prescribed plant-functional-type (PFT) or spin-up processes until the C stocks (biomass and SOC) reach their steady state (Clark et al., 2011; Friend and White, 2000; Ito and Inatomi, 2012; Pavlick et al., 2013; Sitch et al., 2003; Smith et al., 2001; Woodward et al., 1995). Further, inherent differences of model structure contribute more significantly to GVM uncertainties (Exbrayat et al., 2018; Nishina et al., 2014), than from differences 65 in climate projections (Ahlström et al., 2012). Although the land surface is estimated to offset 30% of anthropogenic emissions of CO₂ (Canadell et al., 2007; Le Quéré et al., 2018), the terrestrial C cycle is currently the least constrained component of the global C budget (Bloom et al., 2016). Many model intercomparison projects have demonstrated a lack of coherence in future projections of terrestrial C cycling (Ahlström et al., 2012; Friedlingstein et al., 2014). Recently, many studies have used simulations from the first phase of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) (Warszawski et al., 70 2014) to evaluate the importance of key elements regulating vegetation C dynamics, but also the estimated magnitude of their associated uncertainties (Exbrayat et al., 2018; Friend et al., 2014; Nishina et al., 2014; Nishina et al., 2015; Thurner et al., 2017). For example, the interactions between the land C cycling and climate is primarily determined by C turnover and productivity (Carvalhais et al., 2014). However, the spatial variability with climate has been more studied for NPP than for C



turnover processes (Thurner et al., 2017). Global scale vegetation model development has intensely concentrated on ecosystem
75 productivity whereas the dynamics of C turnover, here addressed as transit time (Ceballos-Núñez et al., 2017; Sierra et al.,
2017), has been less studied (Friend et al., 2014). Friend et al., 2014 detailed that transit time dominates uncertainty in terrestrial
vegetation responses to future climate and atmospheric CO₂. They found a 30% larger variation in modelled vegetation C
change than response of NPP. Nishina et al. (2015) also suggested that long term C dynamics within ecosystems (vegetation
turnover and soil decomposition) are more critical factors than photosynthetic processes (i.e. GPP or NPP). The respective
80 contribution of bias from biomass and NPP to biases in transit times remain unquantified. Without an appropriate
understanding of current state of basic components of the C cycle, the understanding of C cycle feedbacks to climate change
remains highly uncertain (Hobbie et al., 2000; Koven et al., 2015a).

Over the past decade, an increasing number of datasets has improved our understanding of the terrestrial C dynamics,
including global scale vegetation dynamics. These range from machine-learning based upscaling of FLUXNET data, remotely-
85 sensed biomass products or the creation of a harmonized soil databases. Despite the increasing volume of C-cycling related
products, they do not provide estimates of the internal dynamics which regulate the C cycle and its response to changes. An
approach to circumvent these issues is to integrate models and data to estimate these dynamics in agreement with observations.
Here, we use the CARbon DAta MOdel framework (CARDAMOM) (Bloom et al., 2016; Smallman et al., 2017) to retrieve
the pan-Arctic terrestrial carbon cycle for the 2000-2015 period in agreement with gridded observations of LAI, biomass and
90 SOC stocks.

In this paper, we compare analyses of C dynamics of Arctic tundra and taiga for the period 2000-2015 for (a) global
products of GPP (Jung et al., 2017; Tramontana et al., 2017) and heterotrophic respiration (R_h) (Hashimoto et al., 2015); (b)
NEE, GPP and R_{eco} field observations from 8 sub- and high- Arctic sites included in the FLUXNET2015 dataset (Belelli
Marchesini et al., 2007; Bond-Lamberty et al., 2004; Goulden et al., 1996; Ikawa et al., 2015; Kutzbach et al., 2007; López-
95 Blanco et al., 2017; Lund et al., 2012; Sari et al., 2017), and (c) 6 GVM (HYBRID, JeDi, JULES, LPJmL, SDGVM and VISIT)
from the ISI-MIP comparison project (Warszawski et al., 2014). Our objectives are (1) to present and evaluate the retrievals
and uncertainties of the current state of the pan-Arctic terrestrial C cycling using a model-data fusion system, (2) to quantify
the degree of agreement between our better constrained product with several sources of data available, from local to global
scale, and (3) to use CARDAMOM as a benchmarking tool for the ISIMIP models to provide general guidance towards GVM
100 improvements. Finally, we suggest future work to be done in the context of pan-Arctic C cycling modelling at the global scale.

2 Data and methods

2.1 Pan-Arctic region

The spatial domain we considered in this study (Figure S1) corresponds to the extent of the Northern Circumpolar
Soil Carbon Database version 2 (NCSCDv2) dataset (Hugelius et al., 2013a; Hugelius et al., 2013b), bounded by latitudes
105 44°N - 80°N and longitudes 180°W - 180°E, and at a spatial resolution of 1° x 1°. This area of study totals 18.7 million km² of
land area. We used the GlobCover vegetation map product developed by the European Space Agency (Bontemps et al., 2011)
to separate regions dominated by non-forested and forested land cover types (hereafter referred as tundra and taiga,
respectively) (Figure S1). The differentiation between tundra and taiga grid cells is in agreement with the tree line delimited
by Brown et al. (1997) together with the tundra domain defined from the Regional Carbon Cycle Assessment and Processes
110 (RECCAP) Activity reported by McGuire et al. (2012). However, the tundra region extends into taiga regions without presence
of trees in some areas such as the extensive grasslands in South Russia and Mongolia (Figure S1). This classification of tundra
and taiga totals 9.0 and 9.7 million km² of land area, respectively.



2.2 The CARbon DATA MOdel framework

Here we use the CARbon DATA MOdel framework (CARDAMOM; Bloom et al., 2016) to retrieve terrestrial C cycle dynamics, including explicit confidence intervals, in the pan-Arctic region. CARDAMOM is centred around the Data Assimilation Linked Ecosystem Carbon version 2 (DALEC2), to simulate land-atmosphere C fluxes and the evolution of six C stocks (foliage, labile, wood, roots, soil organic matter (SOM) and surface litter) and corresponding fluxes (Bloom and Williams, 2015; Williams et al., 2005). DALEC2 includes 17 parameters controlling the processes of plant phenology, photosynthesis, allocation of primary production to respiration and vegetation carbon stocks, plant and organic matter turnover rates, all established within specific prior ranges based on ecologically viable limits (Table S1). DALEC2 simulates GPP and its allocation to the four plant stocks and autotrophic respiration (R_a) as time-invariant fraction. Plant C decays into litter and soil stocks where microbial decomposition generates heterotrophic respiration (R_h). In each plant, litter and soil stock turnover is simulated using temperature dependent first-order kinetics. The Net Ecosystem Exchange (NEE) is calculated as the difference between GPP and the sum of the respiration fluxes ($R_{eco} = R_a + R_h$), while Net Primary Productivity (NPP) is the difference between GPP and R_a .

CARDAMOM is driven by climate data from the European Centre for Medium-Range Weather Forecast (ECMWF) Reanalysis interim (ERA-interim) dataset (Dee et al., 2011) for the 2000-2015 period. A Bayesian Metropolis-Hastings Markov chain Monte Carlo (MHMCMC) algorithm is used to retrieve the posterior distribution of 17 process parameters according to observational constraints and Ecological and Dynamic constraints (EDCs; Bloom and Williams, 2015). EDCs ensure that DALEC2 simulates the terrestrial carbon cycle in agreement with ecological theory. Observational constraints include monthly time series of Leaf Area Index (LAI) from the MOD15A2 product (Myneni et al., 2002), estimates of vegetation biomass and soil organic carbon content. In this paper, there are two main differences with the global approach described in Bloom et al. (2016). First, the biomass constraints used by Bloom et al. (2016) only cover tropical regions. Instead, here we use global biomass estimates from Carvalhais et al. (2014) which are based on remotely-sensed forest biomass (Thurner et al., 2014) and upscaled GPP based on data driven estimates (Jung et al., 2011) covering the pan-Arctic domain. Second, we constrained the storage of soil organic carbon (SOC) in the 0-1 m topsoil from the Circum-Arctic permafrost region (Brown et al., 1997) using the NCSCD spatial explicit product (Hugelius et al., 2013a; Hugelius et al., 2013b) instead of the Harmonized World Soil Database (HWSD) (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012). While we report results using this configuration, we provide estimates of the sensitivity of retrievals to the choice of SOC database and the inclusion or omission of C_{veg} prior (global biomass product) in the Supplement.

We apply the setup described above to 3433 $1^\circ \times 1^\circ$ pixels (1815 in tundra; 1618 in taiga) using a monthly time step. Each pixel is treated independently without assuming a prior land cover type. Prior values for two parameters (fraction of GPP respired and canopy efficiency) are set according to Bloom et al. (2016). The MHMCMC is performed three times until convergence and a total of 1500 parameter sets is sampled from the posterior distribution of parameter sets which allow producing corresponding density function of all C fluxes and stocks. In the following we report highest confidence results (median; P50) and the uncertainty represented by the 90% confidence interval (5^{th} percentile to 95^{th} percentile, (P_{05}^{95})). We aggregated the different C stocks into photosynthetic (C_{photo}), vegetation (C_{veg}) and soil (C_{dom}) C stocks. In this study, we addressed C turnover rates and decomposition processes as their inverse rates, this is the C transit time (TT_{photo} , TT_{veg} and TT_{dom}), represented as the ratio between each C stock and NPP. Transit time is an important diagnostic metric that is independent of model internal structure, and good candidate to compare among models.



2.3 Model evaluation at local and pan-Arctic scales

At the pan-Arctic scale, we compared our CARDAMOM GPP with FLUXCOM data from Jung et al. (2017).
155 FLUXCOM is based on a machine-learning approach to upscale local GPP data from eddy-covariance towers and provide gridded estimates of monthly fluxes at $0.5^\circ \times 0.5^\circ$ resolution. FLUXCOM has been used in previous studies as a benchmark for simulated GPP (Exbrayat et al., 2018; Slevin et al., 2017). At a local scales, we compare CARDAMOM NEE and its partitioned components GPP and R_{eco} estimates against monthly aggregated values from the FLUXNET2015 dataset. We selected 8 sites located across sub- and high-Arctic latitudes, covering locations with different climatic conditions and 160 dominating ecotypes (Table S2). For this evaluation, we compared the same years for both observations and CARDAMOM, and we selected data using daytime method (Lasslop et al., 2010) due to the absence of true nighttime period during Arctic summers in some locations. Additionally, we selected variable u^* threshold to identify insufficient turbulence wind conditions from year to year similar to López-Blanco et al. (2017). For readability purposes, in this data-model comparison we included the median (P_{50}) \pm the 50% confidence interval (percentile 25th to 75th; (P_{25}^{75})) including both random and u^* filtering 165 uncertainty following the method described in Papale et al. (2006). Some of the sites lack wintertime measurements and we filter out data for months with less than 10 % observations. Only NEE follows the standard micrometeorological sign convection presenting the uptake of C as negative (sink), and the release of C as positive (source); both GPP and R_{eco} are reported as positive fluxes.

2.4 Benchmark of Global Vegetation Models

170 We examined the pan-Arctic annual changes in net primary production (NPP), vegetation biomass carbon stocks (C_{veg}) and vegetation transit times (TT_{veg} ; $TT_{\text{veg}} = C_{\text{veg}}/NPP$) using CARDAMOM as benchmark tool for six participating GVMs in the ISI-MIP comparison project (Warszawski et al., 2014). In this study we have considered HYBRID4 (Friend and White, 2000), JeDi (Pavlick et al., 2013), JULES (Clark et al., 2011), LPJml (Sitch et al., 2003), SDGVM (Woodward et al., 1995), and VISIT (Ito and Inatomi, 2012). The specific properties and degree of complexity of each ISI-MIP model are 175 summarized in Table S3, and more detailed information can be found in Friend et al. (2014) and Thurner et al. (2017).

In this study, each model simulation has been conducted under multiple General Circulation Models (GCM). Here we included HadGEM2-ES (Collins et al., 2011), IPSLCM5A-LR (Dufresne et al., 2013), MIROC-ESM-CHEM (Watanabe et al., 2011), GFDL-ESM2M (Dunne et al., 2012), and NorESM1-M (Bentsen et al., 2013) GCMs from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) experiment (Arora et al., 2013; Taylor et al., 2012), which is temperature 180 and precipitation bias corrected following (Hempel et al., 2013). The comparisons with CARDAMOM for each GVM included the mean ensemble of all GCM forcings. The comparisons have been performed under the same spatial resolution as the CARDAMOM spatial resolution for the 2000-2004 period ($1^\circ \times 1^\circ$ resolution).

3 Results

185 The CARDAMOM framework quantified C fluxes, C stocks and transit times in plant, litter and soil carbon stocks over the pan-Arctic land region (including the tundra and taiga partitioning) for the period 2000-2015 (Table 1). The system is likely a small C sink, although the 90% confidence intervals remain large (and so the region could be a source of C) (Table 1). Our analysis indicates that SOC is successfully assimilated (1:1 agreement), biomass stocks are 28% lower than earth observation mapping (Figure 1), and that GPP is 50% lower than FLUXCOM (Figure 2). We also suggest that R_h is lower in the tundra and higher in the taiga than upscaled estimates (Figure 2). We note that independent tests at EC locations suggests 190 that CARDAMOM's GPP is 30% biased high (Figure 3). This mismatch is important in the context of FLUXCOM, as noted (Figure 2). We benchmarked six GVMs to compare to not only their spatial variability across the pan-Arctic, tundra and taiga region (Figure 4), but also the degree of agreement between their mean model (6 GVMs – 5 GCMs) ensemble within the 90%



confidence interval of our framework (Figure 5, Table 3). We finally found that turnover time of vegetation C is weakly simulated in GVMs and is a major component of error in their forecasts (Figure 6).

195 3.1 Pan-Arctic retrievals of C cycle

Overall, we found that the pan-Arctic region (Table 1) acted as a consistent sink of C (area-weighted P50) over the 2000-2015 period with an average of $-55.8 \left(\begin{smallmatrix} 1158.1 \\ -260.5 \end{smallmatrix} \right) \text{ g C m}^{-2} \text{ yr}^{-1}$, P50 ($\begin{smallmatrix} P95 \\ P05 \end{smallmatrix}$). However, tundra regions presented a weaker sink compared to taiga regions, this is $-13.0 \left(\begin{smallmatrix} 1107.7 \\ -158.5 \end{smallmatrix} \right) \text{ g C m}^{-2} \text{ yr}^{-1}$ and $-104.1 \left(\begin{smallmatrix} 1215.0 \\ -375.4 \end{smallmatrix} \right) \text{ g C m}^{-2} \text{ yr}^{-1}$ respectively, but also lower uncertainties with nearly $1265.5 \text{ g C m}^{-2} \text{ yr}^{-1}$ between P05 and P95 in tundra. In general, the photosynthetic inputs exceeded the respiratory outputs ($\text{GPP} > \text{R}_{\text{eco}}$; Table 1), although the much larger uncertainties stemming from R_{eco} , and more specifically from R_{h} , compared with GPP complicate the net C sink/source estimate beyond the median's average ensembles. In the pan-Arctic region approximately half of GPP is autotrophically respiration resulting in an NPP of $263.3 \left(\begin{smallmatrix} 376.6 \\ 177.4 \end{smallmatrix} \right) \text{ g C m}^{-2} \text{ yr}^{-1}$. Carbon use efficiency (NPP/GPP) averages $0.51 \left(\begin{smallmatrix} 0.55 \\ 0.46 \end{smallmatrix} \right)$, and marginally varied across tundra $0.50 \left(\begin{smallmatrix} 0.54 \\ 0.46 \end{smallmatrix} \right)$ and taiga $0.52 \left(\begin{smallmatrix} 0.56 \\ 0.46 \end{smallmatrix} \right)$. Despite these apparent small variations, tundra photosynthesized and respiration (respectively $315.0 \left(\begin{smallmatrix} 450.1 \\ 226.9 \end{smallmatrix} \right) \text{ g C m}^{-2} \text{ yr}^{-1}$ and $300.0 \left(\begin{smallmatrix} 1515.0 \\ 119.3 \end{smallmatrix} \right) \text{ g C m}^{-2} \text{ yr}^{-1}$) 205 approximately half as much as the Taiga region ($736.5 \left(\begin{smallmatrix} 940.9 \\ 564.9 \end{smallmatrix} \right) \text{ g C m}^{-2} \text{ yr}^{-1}$ and $618.98 \left(\begin{smallmatrix} 2106.3 \\ 276.6 \end{smallmatrix} \right) \text{ g C m}^{-2} \text{ yr}^{-1}$).

The total size of the pan-Arctic vegetation C stock (C_{veg}) averaged $1.4 \left(\begin{smallmatrix} 6.0 \\ 0.5 \end{smallmatrix} \right) \text{ kg C m}^{-2}$, an estimate 94% smaller than the soil C stock (C_{dom}), $24.4 \left(\begin{smallmatrix} 47.6 \\ 10.3 \end{smallmatrix} \right) \text{ kg C m}^{-2}$. The soil C stock (fresh litter and soil organic matter, SOM) is clearly dominated by C_{som} , accounting for the 98.8%, which also dominates the terrestrial C stock in the pan-Arctic. Among the living C stocks, 91% of the C is allocated to the structural stocks (wood and roots; $1.3 \left(\begin{smallmatrix} 5.8 \\ 0.4 \end{smallmatrix} \right) \text{ kg C m}^{-2}$) compared to 9% to the photosynthetic stock (leaves and labile; $0.1 \left(\begin{smallmatrix} 0.1 \\ 0.1 \end{smallmatrix} \right) \text{ kg C m}^{-2}$). On average, the total ecosystem carbon density in the pan-Arctic region is 210 $26.2 \left(\begin{smallmatrix} 51.1 \\ 11.7 \end{smallmatrix} \right) \text{ kg C m}^{-2}$, with slightly lower stocks in tundra ($24.6 \left(\begin{smallmatrix} 50.7 \\ 10.8 \end{smallmatrix} \right) \text{ kg C m}^{-2}$) than taiga ($28.0 \left(\begin{smallmatrix} 52.0 \\ 12.8 \end{smallmatrix} \right) \text{ kg C m}^{-2}$). In general, the taiga region accumulated on average ~44 %, ~55 % and ~10 % more C than tundra region in photosynthetic, structural and soil C stocks, respectively. In other words, taiga accumulates ~12 % more total C than tundra. Uncertainties in estimates of 215 soil C stock are notably higher than for living C stocks, highlighting the lack of observational and mechanistic constraint on heterotrophic respiration.

The global mean C transit time is $1.4 \left(\begin{smallmatrix} 2.2 \\ 0.9 \end{smallmatrix} \right)$ years in leaves and labile plant tissue (TT_{photo}), $4.3 \left(\begin{smallmatrix} 15.3 \\ 1.6 \end{smallmatrix} \right)$ years in stems and roots (TT_{veg}), and $129.3 \left(\begin{smallmatrix} 981.1 \\ 10.9 \end{smallmatrix} \right)$ years in litter and SOM (TT_{dom}). The total C transit time (TT_{tot}) ($142.5 \left(\begin{smallmatrix} 1089.4 \\ 11.9 \end{smallmatrix} \right)$ years) is clearly dominated by the soil C stock, highlighting the very long periods of times that C particles can persist in Arctic soils. Interestingly, CARDAMOM estimates longer TT_{veg} in Taiga compared to tundra with $5.9 \left(\begin{smallmatrix} 8.6 \\ 3.2 \end{smallmatrix} \right)$ years vs $3.5 \left(\begin{smallmatrix} 13.0 \\ 1.4 \end{smallmatrix} \right)$ years (for 220 tundra), but also shorter transit times in TT_{photo} and TT_{dom} with $1.6 \left(\begin{smallmatrix} 2.0 \\ 1.3 \end{smallmatrix} \right)$ and $157.3 \left(\begin{smallmatrix} 329.9 \\ 63.1 \end{smallmatrix} \right)$ years respectively compared to $1.1 \left(\begin{smallmatrix} 1.6 \\ 0.7 \end{smallmatrix} \right)$ years and $97.9 \left(\begin{smallmatrix} 660.2 \\ 8.9 \end{smallmatrix} \right)$ years in tundra. The turnover rates estimated by CARDAMOM in tundra regions suggest a tendency towards longer transit times in the photosynthetic and soil C stocks, likely affected at some degree by low temperatures, wet soils, and thus slower decomposition processes.

Additionally, we performed a sensitivity analysis using four different experiments to assess the impact of using 225 different soil C datasets (NCSCD and HWSD) and with-without biomass constraints (Table S4). These results show that the differences introduced by biomass constraints were significantly larger compared to the differences introduced by different soil C databases. Also, the difference between soil C databases resulted in shifts of 22% up to 20% in the total mean carbon stock (C_{tot}) and transit time (TT_{tot}). Our results showed significant ($p < 0.01$) differences whether biomass constraint was used in the framework or not. In simulations with biomass constraints, C_{photo} , C_{veg} , and C_{dom} stocks decreased the C stored ~ 78%, 230 62% and 10% respectively. Moreover, introducing biomass shortens retrievals the TT_{photo} and TT_{veg} by 87% and 60%, but also



their uncertainties (97.3% and 66% respectively). While using biomass constraints only has a negligible effect on productivity, increased respiration fluxes induce weaker C sink strengths.

3.2 Data assimilation and evaluation: from global to local scale

CARDAMOM retrieved the terrestrial C cycle in good agreement with priors of SOC and biomass. The agreement 235 for SOC is a 1:1 relationship ($R^2 = 1.0$; RMSE = 0.97 kg C m⁻²) while for biomass is close to 1:1 ($R^2 = 0.97$; RMSE = 0.46 kg C m⁻²) (Figure 1). Using Carvalhais et al. (2014)'s biomass product led to a tendency towards larger accumulation (~28%) of C in the structural (wood and roots) stocks (Table S4) compared to the assimilated CARDAMOM's biomass. The understanding of ecological dynamics implemented in CARDAMOM cannot fully resolve Carvalhais et al. (2014) biomass in agreement with other products of LAI and SOC.

240 On the other hand, we compared our estimates of GPP and R_h with independent datasets to evaluate the model performance (Figure 2). We found GPP to be well correlated ($R^2 = 0.81$; RMSE = 0.43 kg C m⁻²), but significantly lower (~51%) compared to Jung et al. (2017)'s GPP estimates. The areas with larger agreement, this is where FLUXCOM falls within CARDAMOM's 90% confidence interval, is in taiga regions, rather than in tundra (Figure 2). Also, we note evidence of a higher spatial variability in CARDAMOM (Figure 2). We found the R_h product from Hashimoto et al. (2015) is less 245 consistent with our estimates ($R^2 = 0.38$; RMSE = 0.09 kg C m⁻²), with a tendency towards lower values in tundra pixels, and higher values in taiga pixels. R_h falls only within the 90% confidence interval of CARDAMOM in Central Northern Canada and Eurasia as well as the grasslands in South Russia and Mongolia. Moreover, the spatial variability is considerably smaller in Hashimoto et al. (2015)'s R_h , for example in central Eurasia. This confirms the uncertainties previously noted in modelled respiratory processes (Table 1) where the upper P95 in R_h dominated NEE's uncertainties, but also the soil C stocks.

250 In order to get also a comparison with direct ground observations from the FLUXNET2015 dataset, we report here monthly aggregated P50 ± P25-75 estimates of NEE, GPP and R_{eco} to show timing and magnitudes, but also to diagnose whether CARDAMOM is in general agreement with flux tower data. Overall, CARDAMOM performed well in simulating observed NEE ($R^2 = 0.66$; RMSE = 0.51 g C m⁻² month⁻¹; Bias = 0.16 g C m⁻² month⁻¹), GPP ($R^2 = 0.85$; RMSE = 0.89 g C m⁻² month⁻¹; Bias = 0.5 g C m⁻² month⁻¹) and R_{eco} ($R^2 = 0.82$; RMSE = 0.63 g C m⁻² month⁻¹; Bias = 0.35 g C m⁻² month⁻¹) across 255 8 sub-Arctic and high-Arctic sites from the FLUXNET2015 dataset (Figure 3; Table 2). CARDAMOM NEE is 25% lower than FLUXNET2015, while GPP and R_{eco} are 30% and 10% higher, respectively. This mismatch is important in the context of the FLUXCOM GPP upscaling, as noted Some sites such as Hakasia, Samoylov, Poker Flat and Manitoba (NEE $R^2 = 0.85$, 0.87, 0.81, 0.7; GPP $R^2 = 0.98$, 0.98, 0.93, 0.93 and R_{eco} $R^2 = 0.98$, 0.89, 0.89, 0.80 respectively) represent better the seasonality and the magnitude of the C fluxes than the rest, i.e. Tiksi, Kobbefjord, Zackenberg and UCI-1998 (NEE $R^2 = 0.41$, 0.58, 0.54, 260 0.65; GPP $R^2 = 0.87$, 0.80, 0.84, 0.82 and R_{eco} $R^2 = 0.76$, 0.86, 0.86, 0.83 respectively). In general, CARDAMOM captured the beginning and the end of the growing season (Figure 3). However, the assimilation system showed bias due to difference in timing (earlier shifts of peak of the growing season in Manitoba and UCI-1998, GPP and R_{eco} or earlier end of the growing season in Poker Flat NEE) and differences in flux magnitudes (such as in Hakasia and GPP and R_{eco} and Kobbefjord NEE).

3.3 Benchmarking ISI-MIP with CARDAMOM

265 We used our highest confidence retrievals (i.e. median retrievals including LAI, biomass and soil organic C from NCSID) to benchmark ISI-MIP's NPP, C_{veg} and TT_{veg} estimates. In Table 3 we quantified the degree of agreement and bias per assessed variable, spatial domain, and forward model. Overall, ISIMIP models are more in agreement with CARDAMOM's NPP estimates (for tundra and taiga respectively RMSE = 0.3 and 0.3 kg C m⁻² yr⁻¹; Bias = 0.2 and 0.1 kg C m⁻² yr⁻¹) than C_{veg} (RMSE = 2.4 and 2.8 kg C m⁻²; Bias = 1.3 and 2.2 kg C m⁻²) and TT_{veg} (RMSE = 19.0 and 6.1 years; Bias = 270 3.0 and 4.1 years). Also, the ISIMIP models consistently estimate larger median's mean NPP, C_{veg} and TT_{veg} than CARDAMOM (36%, 53% and 45% increase respectively) across the entire pan-Arctic domain (Figure 4 and 5). Interestingly,



HYBRID overestimated CARDAMOM's NPP and C_{veg} more clearly by 70% and 75%, but only 36 % for TT_{veg} . This is a representative example of compensating errors that may reduce the apparent bias in the inner dynamics. HYBRID TT_{veg} is the result of a systematic overestimation of NPP and C_{veg} . Overall, JEDI and SDGVM are the models in closer agreement with

275 CARDAMOM (Table 3; Figure 4 and 5).

The separation between non-forested (tundra) and forested (taiga) areas also exposed some similarities and inconsistencies in model performance. For example, the ISIMIP models successfully assimilate the larger productivity, biomass and longer vegetation transit times in taiga compared to tundra (Figure 4). However, as average, the ISIMIP models are on average 56% more productive than CARDAMOM in tundra (0.16 vs 0.36 kg C m⁻² yr⁻¹ respectively), but only a 19%

280 in taiga (0.39 vs 0.48 kg C m⁻² yr⁻¹). Also, the tendency for C_{veg} and TT_{veg} coincide, estimating more biomass and transit times in tundra (55% and 46% respectively) than in taiga (51% and 44% respectively). In general, the overall agreement is closer for tundra than for taiga (Table 3).

For vegetation transit times, the pattern is more complex (Figures 4 and 5). The spatial variability patterns are similar to biomass, although larger (C_{veg} RMSE = 2.8 kg C m⁻² and TT_{veg} RMSE = 4.3 kg C m⁻²). We apportioned the error contribution

285 to TT_{veg} by applying an attribution analysis. We used CARDAMOM to calculate hypothetical TT_{veg} estimates (i.e. calculate TT_{veg} with C_{veg} from CARDAMOM, and NPP from ISIMIP models, and with C_{veg} from ISIMIP models and NPP from CARDAMOM) to calculate the largest difference with CARDAMOM's reference TT_{veg} . We estimated the hypothetical TT_{veg} for each pixel in each model, and derived a pixel-wise measure of the contribution of biases in NPP and C_{veg} to biases in TT_{veg} by overlapping their distribution functions (Figure 6). The distribution of the differences relative to CARDAMOM revealed

290 that the highest error (i.e. the lower overlapped area, and by extension the largest contributor to TT_{veg} biases) come from C_{veg} with only a 29% agreement in the distribution (Figure 6), while NPP agrees 76%.

4 Discussion

The CARDAMOM framework has been used to evaluate the terrestrial pan-Arctic C cycling in tundra and taiga at coarse spatio-temporal scale (at monthly and annual time steps for the 2000–2015 period and at 1° × 1° grid cells). The

295 sensitivity analysis suggests that the C cycle retrieved by CARDAMOM is more sensitive to differences introduced by biomass constraints compared to the differences introduced by different soil C databases (Table S4). This result indicates that data on C stocks with shorter turnover (biomass) have a higher impact in the overall pan-Arctic dynamics than stocks with slower turnover (SOC). Overall, we found that the pan-Arctic region 1) was most likely a consistent sink of C (weaker in tundra and stronger in taiga), although the large uncertainties derived from respiratory processes (Table 1) strongly increase the 90%

300 confidence interval uncertainty; 2) accumulated most of the C in the soil C stock (both fresh litter and SOM, but dominated by the latter with a contribution of about 97%); and 3) experienced longer transit times in leaves, labile, litter and SOM C stock located in tundra compared to taiga. In general, we found a good agreement between CARDAMOM and different sources of assimilated and independent data at both pan-Arctic and local scale. Finally, we used CARDAMOM as a benchmarking tool for six GVMs and we found that productivity processes are more in agreement with CARDAMOM than biomass, and

305 thus biomass is the largest contributor to the bias influencing transit times. This finding suggest that there is a need to improve simulations of vegetation C stocks in Earth System models to get the inner dynamics right.

4.1. Pan-Arctic retrievals of C cycle

CARDAMOM retrievals are in good agreement with the SOC and biomass constraints (Figure 1). The simulation of SOC turnover is also weakly constrained - our analysis adjusts turnover time to match mapped stocks, hence the strong match

310 of modelled to mapped SOC. So, independent data on SOC transit time (e.g. ¹⁴C) data is required across the pan-Arctic region to provide stronger constraint on process parameters. Further, the retrievals presented here exhibited a coherent performance



of an independent global GPP product (Jung et al., 2017), but weaker agreement with an R_h product (Hashimoto et al., 2015)(Figure 2). Indeed, uncertainties in CARDAMOM R_h are substantially larger than for GPP, and that echoes in the large uncertainty found in NEE (Table 1). One difference between these two models is the lack of moisture limitation on respiration
315 in CARDAMOM. Conversely, GPP is relatively well-constrained through the assimilation of LAI and a prior for productivity (Bloom et al., 2016). An important mismatch has been found with regards GPP though. CARDAMOM GPP is 50% lower than FLUXCOM, but 30% higher than FLUXNET2015 EC data.

The agreement between earth observation data and EC data is surprisingly good given the vast scale difference. However, direct point-to-gridcell comparison with local observations derived from the FLUXNET2015 dataset (Figure 3,
320 Table 2) is challenging and always difficult. CARDAMOM outputs C stocks and fluxes in $1^\circ \times 1^\circ$ grid cells, whereas local eddy covariance flux measurements are in the order of 1-10 hectares. Thus, for observational sites located in areas with complex terrain, such as Kobbefjord in coastal Greenland, the agreement can be expected to be low. For inland forest sites, such as Poker Flat in Alaska, there may be less differences in vegetation characteristics and local climatology between the local scale measurement footprint and the corresponding CARDAMOM grid cell. This scaling issue is likely to have a larger
325 impact on flux magnitudes compared with seasonal dynamics. In general, CARDAMOM captured the seasonal dynamics in NEE, GPP and R_{eco} well (Figure 3, Table 2). There was, however, a consistent timing-mismatch in early season flux increase, where CARDAMOM predicts earlier growing season onset compared with observations. This is likely due to the impact of snow cover, which is not explicitly included in the CARDAMOM framework.

At broader scales CARDAMOM estimates reported here are in good agreement with C flux observations and
330 estimates reported from McGuire et al. (2012) for the tundra domain, but also with the C stocks and transit times described by Carvalhais et al. (2014) in tundra and taiga, and the turnover rates (inverse of the transit times calculated here) supported by Thurner et al. (2017) in taiga regions. This performance compared to independently related C cycle components demonstrates that CARDAMOM is a robust and useful tool to assess large scale C cycle dynamics in the Arctic.

First, our NEE estimates reported in this study from Arctic tundra are inside the variability comparison of estimates
335 among field observation, regional process-based models, global-process based models and inversion models reported by McGuire et al. 2012. McGuire et al. 2012 reported that Arctic tundra was a sink of CO_2 of $-150 \text{ Tg C yr}^{-1}$ ($SD=45.9$) across the 2000-2006 period over an area of $9.16 \times 10^6 \text{ km}^2$. Here CARDAMOM's NEE estimate for the same period estimated $-125 \text{ Tg C yr}^{-1}$ over an area of $9 \times 10^6 \text{ km}^2$. For example, this exhaustive assessment of the C balance in Arctic tundra included approximately 250 estimates using the chamber and eddy covariance method from 120 published papers (McGuire et al., 2012;
340 Supplement 1) with an area-weighted mean of means estimate of $-202 \text{ Tg C yr}^{-1}$. The regional applications reported by McGuire et al., 2012 estimated NEE in $-187 \text{ Tg C yr}^{-1}$, including LPJ-Guess WHyMe (Smith et al., 2001), Orchidee (Koven et al., 2011), version 6 of the Terrestrial Ecosystem Model (TEM6) (McGuire et al., 2010) and the Terrestrial Carbon Flux (TCF) model (Kimball et al., 2009). These models also calculated GPP, NPP, R_a and R_h to be 350, 199, 151 and $182 \text{ g C m}^{-2} \text{ yr}^{-1}$, respectively. The DGVM applications included in McGuire et al., 2012 CLM4C (Lawrence et al., 2011), CLM4CN (Thornton et al., 2009),
345 Hyland (Levy et al., 2004), LPJ (Sitch et al., 2003), LPJ-Guess (Smith et al., 2001), O-CN (Zaehle and Friend, 2010), SDGVM (Woodward et al., 1995), and TRIFFID (Cox, 2001) estimated NEE in -93 Tg C yr^{-1} and GPP, NPP, R_a and R_h in 272, 162, 83 and $144 \text{ g C m}^{-2} \text{ yr}^{-1}$ respectively. For the same period CARDAMOM has estimated the gross C fluxes in 318, 161, 154 and $148 \text{ g C m}^{-2} \text{ yr}^{-1}$ respectively.

Second, Carvalhais et al. (2014) estimated total ecosystem carbon (C_{tot}) of $20.5 \begin{pmatrix} 52.5 \\ 8.0 \end{pmatrix} \text{ kg C m}^{-2}$ for tundra and
350 $24.8 \begin{pmatrix} 58.0 \\ 15.2 \end{pmatrix} \text{ kg C m}^{-2}$ for taiga, while CARDAMOM tundra was $24.6 \begin{pmatrix} 33.0 \\ 18.3 \end{pmatrix} \text{ kg C m}^{-2}$, while $28.0 \begin{pmatrix} 36.1 \\ 21.5 \end{pmatrix} \text{ kg C m}^{-2}$ in taiga (Figure 4; Table 1). Therefore, Carvalhais et al. (2014)'s C_{tot} product stored only 16.8 and 11.5% less carbon in tundra and taiga respectively than CARDAMOM. Also, we noted that the numbers are in line with Carvalhais et al. (2014) thanks to the use of the biomass constraint dataset, where C_{photo} , C_{veg} , and C_{dom} stocks decreased the C stored $\sim 78\%$, 62% and 10% respectively (Table S4). Overall, CARDAMOM estimated 20.3 and 5.7% longer transit times for tundra and taiga respectively, with average



355 values of $80.8(^{195.2}_{21.8})$ years in tundra and $51.2(^{109.3}_{22.1})$ years in taiga (CARDAMOM)(Table 1) compared to the $64.4(^{259.8}_{25.7})$ years in tundra and $48.2(^{111.6}_{24.9})$ years in taiga in Carvalhais et al. (2014). These numbers have been retrieved from the same biome classification and the confidence intervals include the 90% confidence interval of the calculated spatial variability. Both datasets agree on the fact that high (cold) latitudes, first tundra, and second taiga have the longest transit times of the entire globe (Bloom et al., 2016; Carvalhais et al., 2014).

360 Third, a recent study from Thurner et al. (2017) assessed temperate and taiga-related transit times, NPP and C_{veg} taking into consideration the current poor process understanding of decomposition dynamics. Thurner et al 2017 used of 5-year average NPP for the time period 2000-2004, applying both MODIS (Running et al., 2004; Zhao et al., 2005) and BETHY/DLR (Tum et al., 2016) products. They use a biomass product (Thurner et al., 2014) at 0.5 degree while accounting for both forest and non-forest vegetation. Our estimates of TT_{veg} for the exact same period are very close to Thurner et al. 365 (2017), where their $8.2(^{11.5}_{5.5})$ years using MODIS and $6.5(^{8.7}_{4.2})$ years using BETHY/DLR are close to the $5.2(^{17.8}_{1.9})$ years estimated by our data assimilation approach. A note of caution here, the number reported by the authors are turnover rates, which are inferred to transit times by just applying the inverse of turnover rates ($TT_{veg}=1/\text{turnover rates}$). Additionally, their estimated NPP (0.35 (MODIS) and 0.45 kg C m⁻² yr⁻¹ (BETHY/DLR), without any uncertainty reported) is only 5% more productive as average than CARDAMOM's NPP estimate of $0.4(^{0.5}_{0.3})$ kg C m⁻² yr⁻¹; while the biomass derived from Thurner et al. (2014), 370 3.0 (± 1.1) kg C m⁻², is 23% lower than our estimates of 2.3 ($^{4.9}_{1.2}$) kg C m⁻² for the same period and for the taiga region. Again, here, the presence of biomass as data constraint has helped to decrease TT_{veg} and its uncertainty significantly.

4.2. CARDAMOM as a benchmarking tool

The CARDAMOM framework has proven capable of effectively simulating Arctic C cycling dynamics in the entire pan-Arctic region, but also to partition it in its two main biomes, i.e. tundra and taiga (Table 1, Figure 1, 2, 3, Discussion 4.1).

375 Recent studies used the same GVM inter-comparison models we used here raising strong arguments about the differences in model formulations and their impact on calculations, significant uncertainties and poor representation of C stocks dynamics at global scale (Exbrayat et al., 2018; Friend et al., 2014; Nishina et al., 2014; Nishina et al., 2015; Thurner et al., 2017). Here, we have a considerably more data-constrained and data-integrated approach than GVMs to calculate C dynamics. Consequently, CARDAMOM is a good candidate to use as benchmark to pinpoint caveats of model performance. For example, 380 Exbrayat et al. (2018) found that ISIMIP models are less in agreement for NPP in boreal latitudes compared to global CARDAMOM retrievals (Bloom et al., 2016) that did not include biomass constraints in boreal regions. In this study, we incorporated two new layers of data constraints suitable for high latitudes (Carvalhais et al., 2014; Hugelius et al., 2013b) compared to their version of CARDAMOM, and we found that NPP had one of the best agreements among the assessed variables (compared to C_{veg} and TT_{veg}), but also slightly better performance in tundra than taiga (Bias = 9 and 19 g C m⁻² yr⁻¹ 385 respectively) (Figure 4 and 5; Table 3).

Also, recent studies have emphasized the significance of model comparison of turnover rates/ transit times (Ceballos-Núñez et al., 2017; Sierra et al., 2017), as diagnostic metrics independent of model internal structure. From a modelling point of view, it remains unclear why transit times differ (Figure 4 and 5) and whether NPP or C_{veg} dominates the biases. Based on Figure 4 and 5, biases in biomass C stocks likely dominate the error in turnover times. We used CARDAMOM to calculate 390 the relative contribution of productivity and biomass to the transit times bias by applying a simple attribution analysis (Figure 6). The largest bias to transit times are originated by modest understanding of the biomass component. Therefore, this study agrees with previous studies (Friend et al., 2014; Nishina et al., 2014; Thurner et al., 2017) highlighting the deficient representation of turnover dynamics, but we further suggest that GVM and ESM modellers need to focus on the vegetation C stocks dynamics calculations to improve inner dynamics.

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4.3 Outlook

CARDAMOM estimates for pan-Arctic C cycling are in good agreement with observations and data constraints; however, we have not included important components controlling ecosystem processes that could potentially improve our understanding on C feedbacks, and with emphasis for high latitude ecosystems. For example, thaw and release of permafrost
400 C is not represented in CARDAMOM, but the influence on vegetation dynamics, permafrost degradation and soil respiration is critical in high latitudes (Koven et al., 2015b; Parazoo et al., 2018). Also, Koven et al. (2017) shown that soil thermal regimes are key to getting the long-term vulnerability of soil C right. Moreover, we have not characterized snow dynamics and the insulating effect of snow affecting respiratory losses across wintertime periods either (Essery, 2015). Further, methane emissions, another important contributor to total C budget (Mastepanov et al., 2008; Mastepanov et al., 2012; Zona et al.,
405 2016), was neglected from this modelling exercise, although it is not easy to model due to its complex transport mechanisms (Kaiser et al., 2017; Walter et al., 2001).

In order to decrease uncertainties around the balance of photosynthetic inputs and respiratory outputs, future explorations on SOC decomposition by microbial activity (Xenakis and Williams, 2014), nutrient interaction with carbon (Thomas and Williams, 2014), plant traits relationships across pan-arctic regions (Reichstein et al., 2014; Sloan et al., 2013),
410 the mechanisms driving carbon use efficiency (Bradford and Crowther, 2013; Street et al., 2013) and the drivers of gross flux coupling (López-Blanco et al., 2017), or the effect of fine-scale disturbances such as moth outbreaks (Heliasz et al., 2011; López-Blanco et al., 2017; Lund et al., 2017) should be addressed at the pan-Arctic scale. From a modelling perspective, we consider that more field observations are crucial, specifically on plant and soil decomposition (C stocks turnover rates)(He et al., 2016) and respiratory processes (partitioning of R_{eco} into R_a and R_b) (Hobbie et al., 2000; McGuire et al., 2000), not only
415 across the growing season, but also during wintertime (Commane et al., 2017; Zona et al., 2016). An improved data-model integration will move towards enhanced model robustness and the decrease of its uncertainties. Field and model researchers should work on data model integration, not just driven based on data availability.

5 Conclusions

The Arctic is experiencing rapid environmental changes, which are expected to significantly influence the global C cycle. Using a data-assimilation framework we have evaluated the current state of key C flux, stocks and transit time variables for the pan-Arctic region. We successfully assimilated SOC and biomass, and showed that biomass constraints have a greater importance for contemporary C dynamics (such as C stocks and transit times) than soil C data, which suggest that short term processes are more important than the long term for monthly to annual C dynamics. However, on the longer term, the much greater stock of C in slower stocks means that e.g. the permafrost carbon-climate feedback, will likely have important
420 consequences for arctic and global carbon cycling (Koven et al., 2015b). We found that our pan-Arctic estimates of C cycling retrievals are consistent with previous studies. Comparisons with global and local scale datasets demonstrate the advantageus capabilities of CARDAMOM assessing the C cycling in the Arctic domain. Moreover, CARDAMOM is a more data-constrained and data-integrated approach than any GVMs available, thus data-assimilation systems are good candidates to benchmark a forward model's performance, and pinpoint issues that need attention. We found better agreement for NPP
425 estimates than for biomass, which is the main contributor to transit time bias. Improved mapping of vegetation C stocks and change over time is required for better analytical constraint. Moreover, future work is required with modelling of soil thermal regimes, permafrost and snow dynamics to improve accuracy and decrease uncertainties. This work establishes the baseline for more process-based ecological analyses using the CARDAMOM data-assimilation system as a promising technique to constrain the pan-Arctic C cycle.



435 Data availability

CARDAMOM output used in this study is available from Exbrayat and Williams (2018) from the University of Edinburgh's DataShare service at <http://dx.doi.org/10.7488/ds/2334>.

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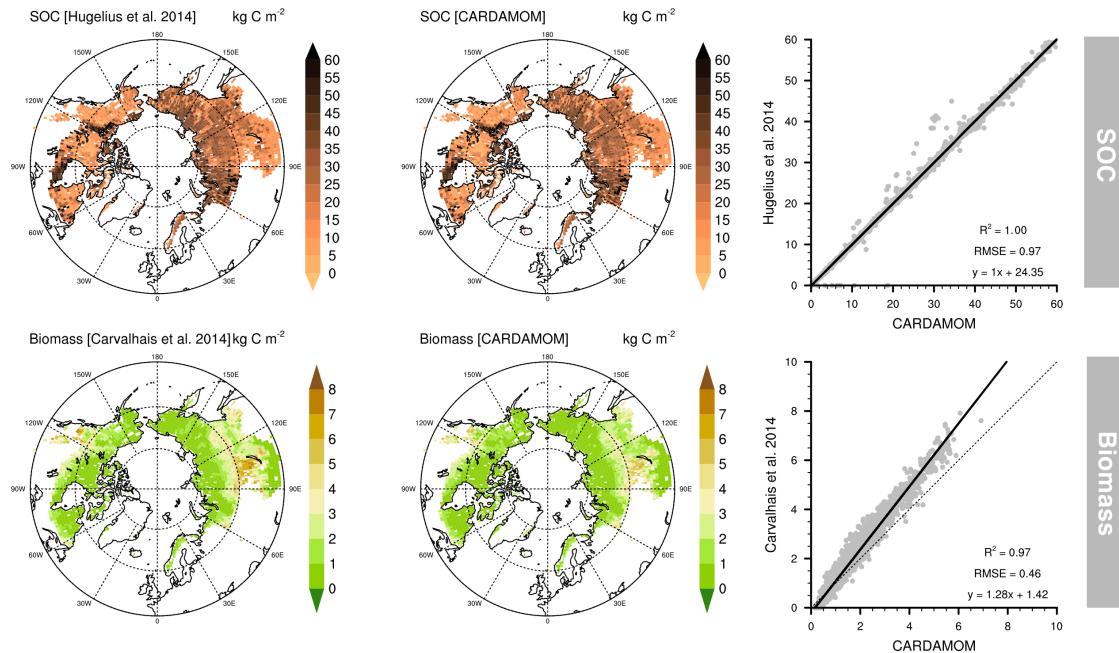


Figure 1. Original soil organic carbon [SOC; Hugelius et al., 2014] and biomass [Carvalhais et al., 2014] datasets used in the data assimilation process within the CARDAMOM framework (left hand side), assimilated SOC and biomass integrated in CARDAMOM (center), and their respective goodness-of-fit statistics between original and assimilated datasets (right hand side).

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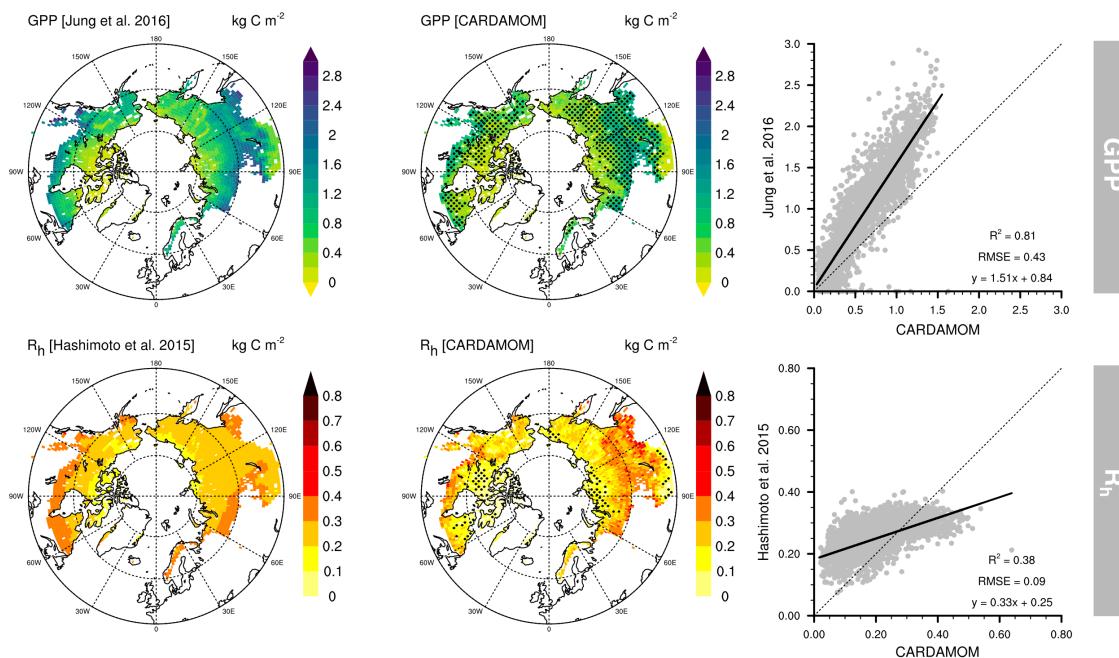


Figure 2. Original gross primary productivity [GPP; Jung et al., 2016] and heterotrophic respiration [R_h ; Hashimoto et al., 2015] datasets used in the data validation process (left hand side), estimated GPP and R_h by CARDAMOM (center), and their respective goodness-of-fit statistics between original and assimilated datasets (right hand side). Stippling indicates locations where the independent datasets are within the CARDAMOM's 5th and 95th percentiles.

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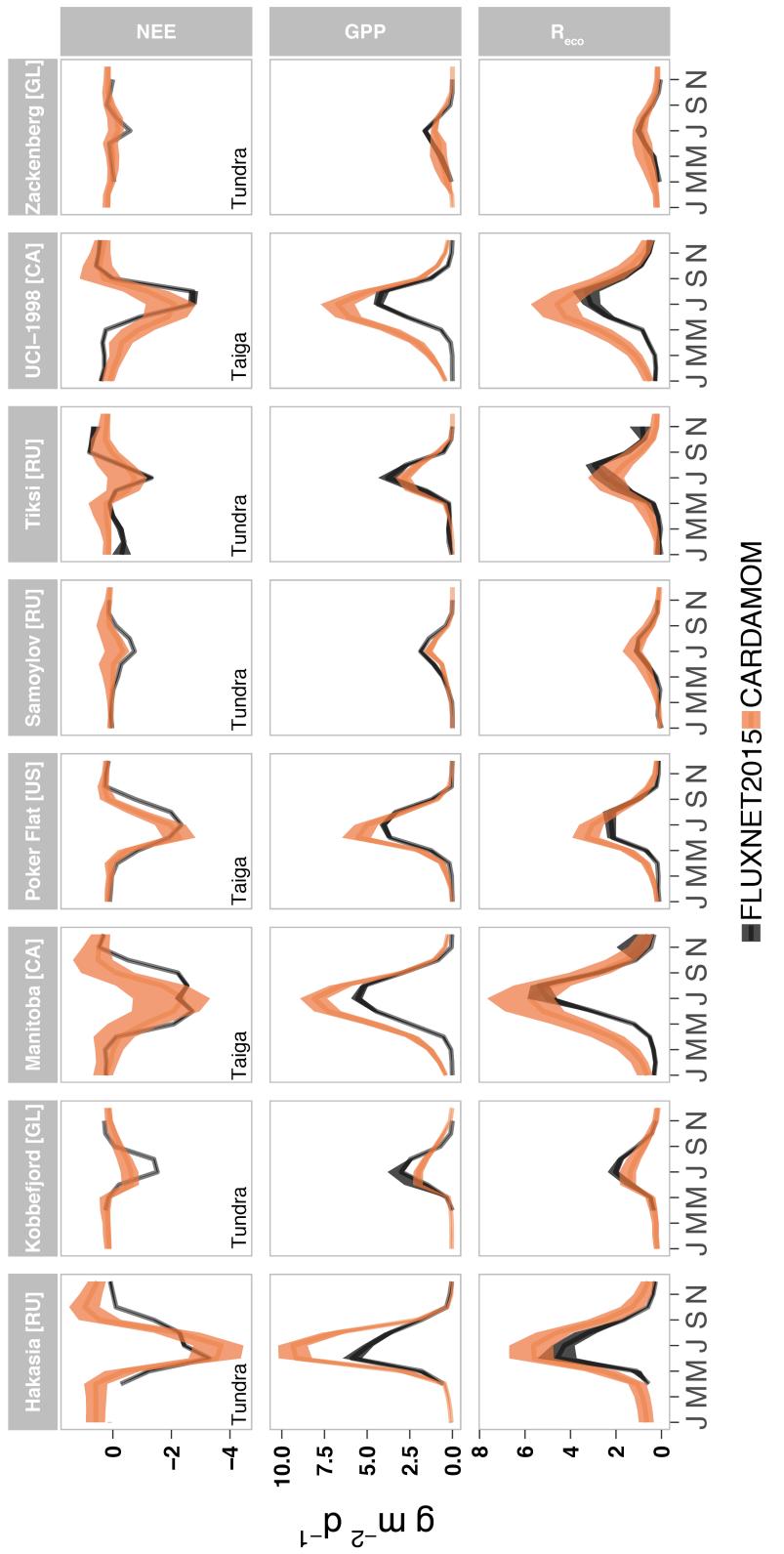
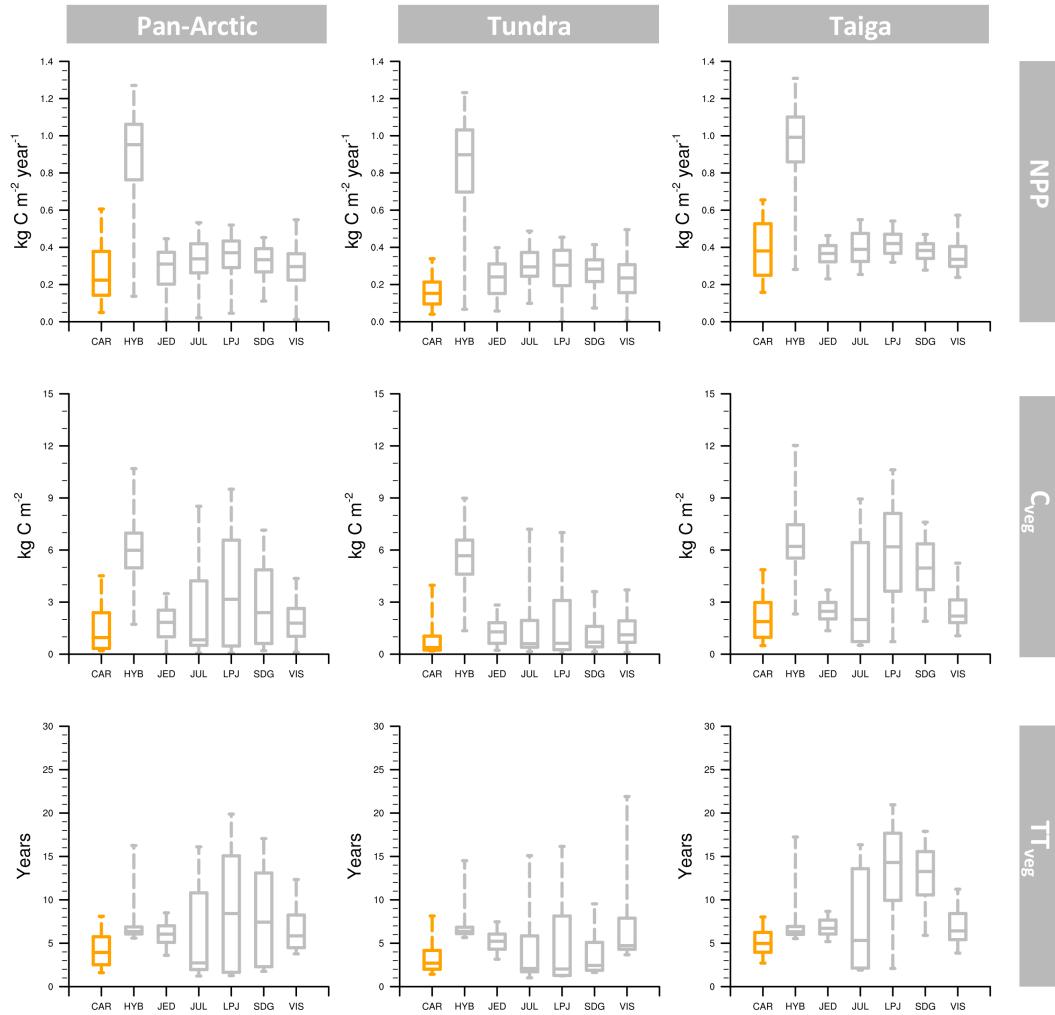


Figure 3. Monthly-aggregated seasonal variability of observed [FLUXNET2015] and modelled [CARDAMOM] C fluxes [NEE, Net Ecosystem Exchange; GPP, Gross Primary Production; R_{eco} , ecosystem Respiration] across eight low- and high-Arctic sites [Hakasia, Kobbeifjord, Manitoba, Poker Flat, Samoylov, Tundra, Taiga, Zackenberg]. Each of these sites, located in different countries [RU-Russia, GL-Greenland, CA-Canada, US-United States,] feature different meteorological conditions and vegetation types (Table S2). Uncertainties represent the 25th and 75th percentiles of both field observations and the CARDAMOM framework.



20 **Figure 4. Central tendency and variability of NPP [Net Primary Production], C_{veg} [Vegetation C pool], TT_{veg} [Vegetation transit time] in the Pan-Arctic, tundra and taiga regions. The box whisker plots comprises the estimations between the 5th and 95th percentiles, and the box encompasses the 25th to 75th percentiles. The line in each box mark the median of studied variables in each region.**

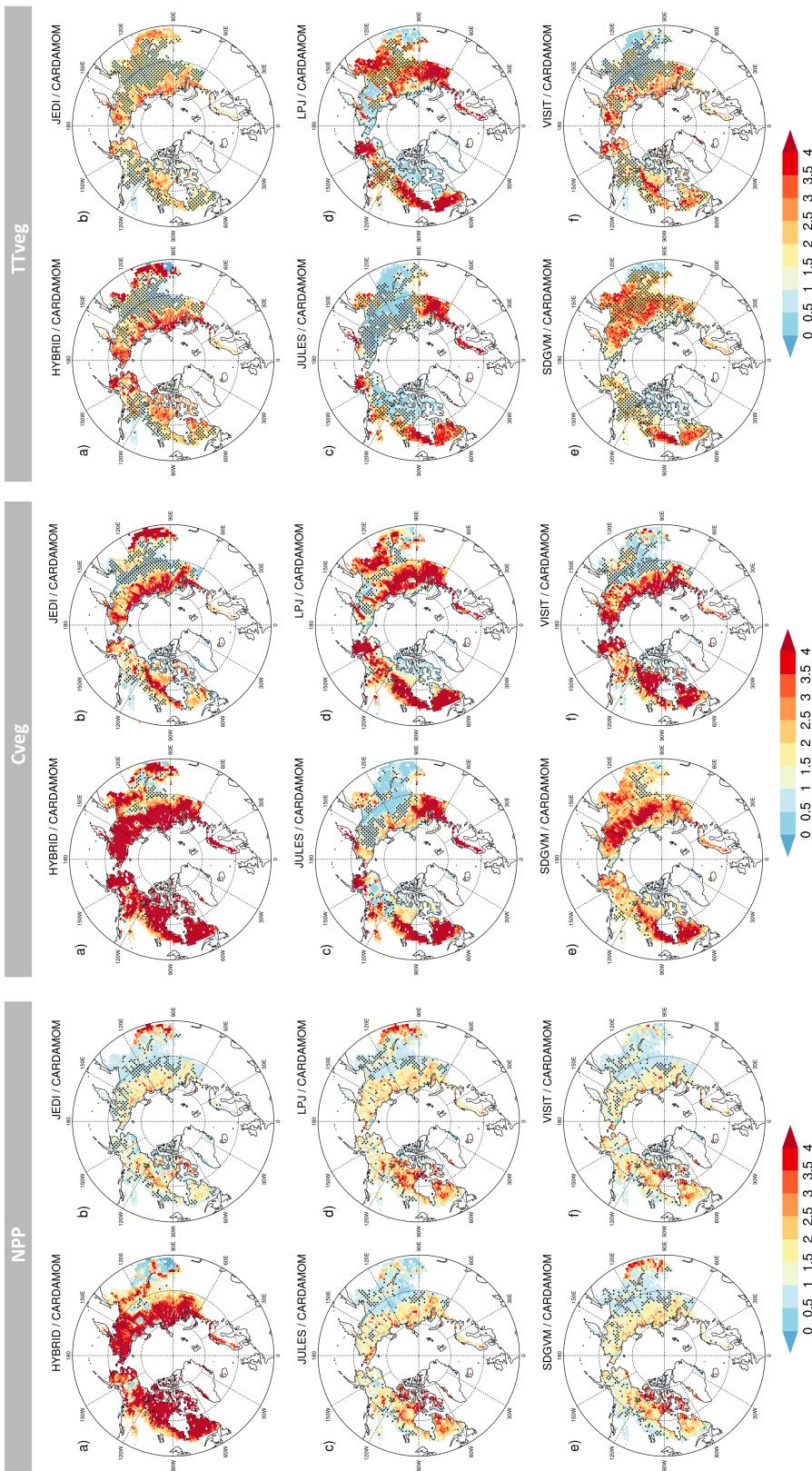


Figure 5. NPP [Net Primary Production], Cveg [Vegetation C pool] and TTveg [Vegetation transit time] ratios between ISI-MIP model ensembles [HYBRID, JEDI, JULES, LPJ, SDGVM and VISIT] and CARDAMOM. Stippling indicates locations where the ISI-MIP model mean is within the ISI-MIP's 5th and 95th percentiles.

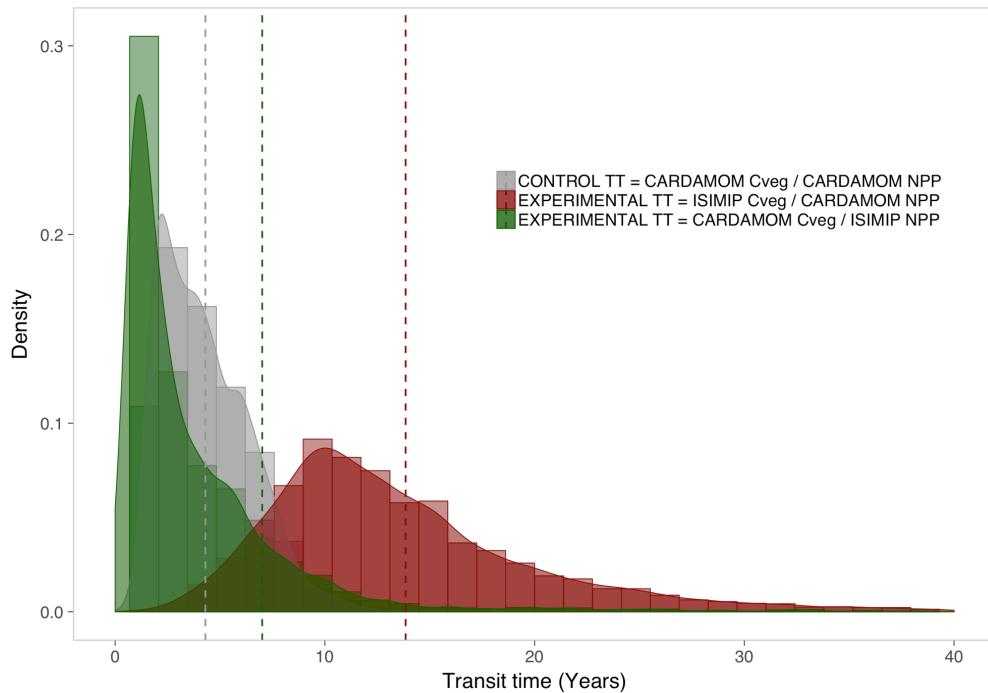


Figure 6. Distribution functions derived from the attribution analysis used to estimate the origin of vegetation transit time (TT_{veg}) bias from ISIMIP models. The control TT includes both biomass (C_{veg}) and net primary production (NPP) estimated by CARDAMOM (grey), while each of the two experimental TTs include C_{veg} (yellow) and NPP (blue) from ISIMIP models. The lower the overlapped area is between control and experimental TT, the larger the contribution for TT biases is. Dashed lines represent the average TT value for each population. For readability purposes, the scale in X-axis is delimited to 40 years.



Table 1. Multi-year (2000–2015) annual average of main ecosystem C fluxes [NEE, GPP, NPP, R_{ecos} , R_{v} , R_{h} ; g C m⁻² yr⁻¹], C pools [C_{photo}, C_{veg}, C_{dom}, C_{tot}; kg C m⁻²] and transit times [T_{T_{photo}}, T_{T_{veg}}, T_{T_{dom}}, T_{T_{tot}}; years] for the pan-Arctic, tundra (forested) and taiga (non-forested) region. The averages contain the estimations between the 5th and 95th percentiles, and the median in bold (50th percentile).

		Pan-Arctic				Tundra				Taiga				
		P05	P25	P50	P75	P05	P25	P50	P75	P05	P25	P50	P75	P95
NEE		-260.5	-152.0	-55.8	156.9	1158.1	-158.5	-81.1	-13.0	176.6	1107.7	-375.4	-232.0	134.7
GPP		385.8	456.0	513.1	578.5	681.1	226.9	273.4	315.0	367.2	450.7	564.9	736.5	816.8
NPP		177.4	224.6	263.3	307.3	376.6	104.8	133.9	159.9	192.1	243.9	259.3	326.9	379.9
C fluxes		193.2	316.3	449.9	716.6	1792.9	119.3	204.0	300.0	528.1	1515.0	276.6	442.9	619.0
R_{eco}		164.3	207.7	245.3	289.9	364.0	98.4	126.5	152.3	184.9	239.9	238.7	299.2	350.1
R_a		28.9	108.6	204.6	426.7	1428.9	21.0	77.5	147.6	343.2	1275.1	37.9	143.7	268.9
R_h		0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.3
C_{photo}		0.5	0.9	1.4	2.5	6.0	0.3	0.5	0.8	2.1	7.1	0.7	1.3	2.0
C_{veg}		10.3	18.2	24.4	32.2	47.6	10.0	17.3	23.3	30.8	46.0	10.7	19.3	25.7
C_{dom}		11.7	19.8	26.2	34.5	51.3	10.8	18.3	24.6	33.0	50.7	12.8	21.5	28.0
C_{tot}		0.9	1.1	1.4	1.7	2.2	1.0	1.3	1.6	2.0	2.8	0.7	0.9	1.1
TT_{photo}		1.6	2.7	4.3	7.2	15.3	1.4	2.3	3.5	6.0	13.0	1.9	3.2	5.2
Transit times		10.2	54.5	129.3	266.0	891.1	11.3	63.1	157.3	329.9	1096.2	8.9	44.8	97.9
TT_{veg}		11.9	59.9	142.5	297.8	1089.4	12.8	68.6	173.1	370.5	1347.4	10.8	50.0	108.1
TT_{dom}														216.2
TT_{tot}														800.1



Table 2. Statistics of linear fit between the CARDAMOM framework (independent) and the FLUXNET2015 field observations (dependent) per individual site and per C flux
 [NEE, Net Ecosystem Exchange; GPP, Gross Primary Production; R_{eco} , ecosystem Respiration]. The units for RMSE and bias are $\text{g C m}^{-2} \text{month}^{-1}$ in NEE, GPP and R_{eco} .

Flux	Site	Country	Intercept	Slope	R^2	RMSE	Bias
NEE	Hakasia	[RU]	0.89	1.40	0.85	0.67	0.49
	Kobbefjord	[GL]	-0.11	0.35	0.58	0.21	0.08
	Manitoba	[CA]	0.10	0.66	0.70	0.55	0.41
	Poker Flat	[US]	0.15	0.83	0.81	0.37	0.25
	Samoylov	[RU]	0.06	0.45	0.87	0.05	0.14
	Tiksi	[RU]	0.00	0.38	0.41	0.26	0.02
GPP	UCI-1998	[CA]	-0.26	0.59	0.65	0.50	-0.15
	Zackenberg	[GL]	0.03	0.37	0.54	0.07	0.04
	Hakasia	[RU]	-0.24	1.80	0.98	0.57	1.21
	Kobbefjord	[GL]	0.31	0.62	0.80	0.35	-0.07
	Manitoba	[CA]	0.63	1.30	0.93	0.73	1.15
	Poker Flat	[US]	0.06	1.20	0.93	0.51	0.30
R_{eco}	Samoylov	[RU]	0.01	0.70	0.98	0.06	-0.14
	Tiksi	[RU]	0.14	0.78	0.87	0.36	-0.05
	UCI-1998	[CA]	1.00	1.30	0.82	0.95	1.32
	Zackenberg	[GL]	0.22	0.57	0.84	0.14	-0.01
	Hakasia	[RU]	0.59	1.20	0.98	0.30	0.87
	Kobbefjord	[GL]	0.12	0.65	0.86	0.17	-0.22



Table 3. Statistics of linear fit between the CARDAMOM framework (independent) and the ISIMIP models (dependent) per individual model and per NPP [Net Primary Production; $\text{kg C m}^{-2} \text{yr}^{-1}$], C_{veg} [Vegetation C pool; kg C m^{-2}] and TT_{veg} [Vegetation transit time; years]. The units for RMSE and bias are $\text{kg C m}^{-2} \text{yr}^{-1}$ in NPP, $\text{kg C m}^{-2} \text{yr}^{-1}$ in C_{veg} and years in TT_{veg} .

		Panarctic				Tundra				Taiga			
		Slope	Intercept	R^2	RMSE	Slope	Intercept	R^2	RMSE	Slope	Intercept	R^2	RMSE
	HYBRID	0.80	0.30	0.03	0.30	0.61	0.66	1.00	0.09	0.30	0.66	1.00	-0.21
	JEDI	0.17	0.44	0.48	0.08	0.02	0.13	0.59	0.29	0.09	0.06	0.26	0.25
	JULES	0.25	0.36	0.29	0.10	0.07	0.19	0.68	0.33	0.09	0.13	0.33	0.17
	NPP	0.22	0.48	0.41	0.10	0.08	0.15	0.78	0.31	0.11	0.11	0.35	0.20
	LPJ	0.21	0.41	0.52	0.07	0.05	0.17	0.60	0.35	0.08	0.11	0.28	0.26
	SDGVM	0.18	0.43	0.28	0.12	0.02	0.11	0.80	0.28	0.12	0.07	0.30	0.17
	VISIT	0.18	0.43	0.28	0.12	0.02	0.11	0.80	0.28	0.12	0.07	0.30	0.17
	HYBRID	5.90	0.13	0.00	2.90	4.61	5.60	-0.05	0.00	2.40	4.60	6.80	-0.01
	JEDI	1.40	0.32	0.24	0.84	0.41	1.30	0.00	0.00	0.80	0.45	1.80	0.32
	JULES	1.80	0.55	0.08	2.80	1.07	1.60	0.15	0.01	2.40	0.85	2.20	0.57
	LPJ	2.40	0.88	0.15	3.10	2.26	1.90	0.06	0.00	2.40	0.92	4.20	0.79
	SDGVM	1.60	0.91	0.31	2.00	1.45	1.10	0.07	0.01	1.10	0.21	3.10	0.86
	VISIT	1.70	0.17	0.03	1.40	0.45	1.50	-0.06	0.00	1.20	0.45	2.40	0.10
	HYBRID	8.70	-0.07	0.00	13.00	4.14	8.80	-0.01	0.00	15.00	5.25	8.10	-0.01
	JEDI	4.80	0.29	0.18	1.30	1.80	5.00	0.07	0.01	1.30	1.93	5.40	0.29
	JULES	4.00	0.46	0.03	5.30	1.76	4.40	0.07	0.00	4.70	1.19	5.20	0.46
	LPJ	4.80	0.97	0.10	6.40	4.70	5.10	0.03	0.00	5.20	1.63	9.00	0.84
	SDGVM	2.70	1.30	0.24	4.80	3.81	3.20	0.18	0.02	2.70	0.34	6.60	1.20
	VISIT	3.00	1.40	0.01	31.00	4.85	-0.20	3.20	0.03	43.00	7.60	7.20	-0.05