



What information on contemporary terrestrial carbon dynamics can an integration of current geospatial data confidently provide?

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Abstract. The terrestrial carbon (C) cycle is a key global biogeochemical cycle, linked to climate change and regulation, provisioning and regulating ecosystem services and underpinning human livelihoods. To understand climate risks and to support the development of effective climate mitigation strategies requires rigorous, uncertainty bounded, systemic information on C-dynamics and their underpinning ecological processes. Significant effort has been invested into attempting to quantify current C stocks and exchanges of C. These data are often incomplete in space and time, contain poorly characterised errors, and lack internal consistency checks, making the construction of a reliable global C budget a significant challenge. Here, we ask what information on contemporary terrestrial carbon dynamics can an integration of current geospatial data confidently provide?

We present a global (0.5×0.5 deg), multi-decadal (2003-2024) analysis of the terrestrial C-cycle at a monthly time step. Using a Bayesian model-data fusion framework (CARDAMOM) we calibrate a model of terrestrial ecosystems (DALEC) integrating diverse ecological spatio-temporal observations (leaf area, absorbed photosynthetically active radiation, gross primary production, woody biomass, soil C), and forcing (meteorology, atmospheric CO₂, burned area and forest loss). CARDAMOM propagates observational uncertainties through to the retrieved DALEC parameters (i.e. ecosystem properties) and simulates C states and fluxes for each of 55,246 pixels across the vegetated land surface. The resulting analysis is systemic (i.e. consistent between states and fluxes) and can support national and international policy development (e.g., Global Carbon Project).

Our analysis shows that current global multi-decadal datasets are inadequate to provide >95 % confidence on the sign of net exchange across 91 % of the vegetated land surface. At this confidence level we can identify 0.23 % of vegetated land is a net source, with 0.75 % a net sink and 7.3 % as neutral. Although we note that at 68 % confidence we the area identified as likely a sink increases to 30 % without change to the area identified as neutral or a source. We show that uncertainty in net C exchange is strongly correlated with the dynamics of wood ($r = 0.8$) and soil organic matter ($r = 0.7$) but poorly correlated with gross fluxes which have historically been a focus of research such as photosynthesis ($r = 0.1$). New satellite missions such as BIOMASS have more accurate wood biomass sensing, and so should enhance confidence in sink/source detection in the next five years. Soil C dynamics data remain a major challenge, with research and investment required to provide a global constraint on soil C stock changes.



25 1 Introduction

The terrestrial carbon (C) cycle plays a central role in global climate change, climate policy and delivery of ecosystem services; ultimately supporting human livelihoods. Rigorous knowledge of net C-exchange in space and time, and the underpinning gross fluxes, is essential to quantify risks to existing ecosystems, identify opportunities for effective mitigation of anthropogenic climate change, and to sustain delivery of ecosystem services. In response, there has been a huge effort to quantify terrestrial ecosystems across spatial (leaf-plant-ecosystem-globe) and temporal (seconds-decades) scales (e.g., Avitabile et al., 2016; Bloom et al., 2016; Arora et al., 2020; Jung et al., 2020; Butler et al., 2017; Tyukavina et al., 2022; Santoro and Cartus, 2025; Friedlingstein et al., 2023). However, observations have gaps and errors. Often observations are not directly made of the target variable (e.g., measure net fluxes rather than gross fluxes, aboveground biomass rather than total biomass) and many components are challenging to observe (e.g. fine root biomass and root depth). Current observation-based estimates of C-cycle components are generated independently of each other, are inconsistent with one another and underestimate their uncertainty (Seiler et al., 2022). These gaps make constructing a reliable global budget from observations a significant challenge. The lack of a data-informed systemic analysis with rigorously quantified uncertainties creates over-confidence, preventing reliable monitoring, and undermines effective decision-support from individual land owners through to international policy making. In this paper, we will address this challenge at global scale.

Statistical and process-based (mechanistic) models have been constructed to interpret ecosystem behaviour but with contrasting challenges. Statistical, including machine learning / artificial intelligence based approaches, are often perceived as being ‘close’ to data, ingesting information across space and time, and offer some quantification of their uncertainty (though often an underestimate) (e.g., Zhao et al., 2020; Jung et al., 2020). These approaches represent a single ecosystem component (the target variable) and different estimates often differ by more than their estimated uncertainty (e.g., GPP, Zheng et al., 2020). The result is estimates of components of the C-cycle which are spatially and temporally incomplete, and inconsistent (biased) with respect of one another. In contrast, process-modelling provides a systemic representation built on theory bridging gaps in space and time. However, process-models are often perceived as ‘distant’ from observations due to their theoretical basis. Due to a historical lack of calibration data land surface models have typically been calibrated at a few sites, then rely on plant functional types (PFTs) to distribute these parameters uniformly in space. The result is a lack a realistic representation of ecological variation (biodiversity) at the scale of analysis (e.g., Cranko Page et al., 2024). Over recent decades land surface models have instead focused on attempting to increase the ‘realism’ through the addition of new processes and thus increasing complexity and computational requirements (e.g., Fisher and Koven, 2020). However, this focus on structure contrasts with studies which have highlighted that parameter uncertainty is as large or greater source of uncertainty than model structure (e.g., Caen et al., 2021; Smallman et al., 2021). Furthermore, increasing complexity has been shown to only increase predictive skill if adequate observational constraint is provided for calibration, which is difficult to achieve (Famiglietti et al., 2021), particularly at global scale.

Both statistical and process-based approaches struggle to quantify uncertainties and propagate these into their estimates of ecosystem state and function. Neither approach alone can maximise the information value of the growing ‘ecosystem’ of



observations available from collaborative databases or global spanning satellite-based Earth Observation. Model-data fusion (MDF), also known as data assimilation, seeks to maximise the benefits of statistical and process-based model approaches by directly updating the parameters (not states as done in numerical weather forecasting) of the process-models with diverse observations spanning space and time. Furthermore, Bayesian MDF approaches support direct propagation of uncertainties through to the final systemic analysis of ecosystem state and function, varying in space and time.

Here we present a global (0.5 x 0.5 degree), systemic, data-informed and uncertainty-bounded analysis of the terrestrial ecosystem spanning 22 years (2003-2024) at a monthly time step. We use the CARDAMOM MDF framework to train DALEC, an intermediate complexity C-cycle model, assimilating location-specific, time series information on absorbed photosynthetically active radiation (APAR), leaf area index, C stored in biomass and soils, and information on plant traits. DALEC is forced with information on meteorology, burned area and deforestation / degradation.

We summarise C-budgets and ecosystem properties to support comparisons with existing estimates and to provide novel data-informed evaluation of existing land surface models that underpin large-scale intercomparison activities.

Specifically we will:

- 1) Report global and regional C budgets aligned to the RECCAP2 regions.
- 2) Diagnose the main determinants of net C exchange at global and regional scales aligned to the RECCAP2 regions.
- 3) Characterise sources of uncertainty from across ecosystem components to the overall net exchange.
- 4) Determine allocation of photosynthate to plant tissues, and their respective C residence times.

Our analysis will address the question "*what information on contemporary terrestrial carbon dynamics can an integration of current geospatial data confidently provide?*"

2 Methods

2.1 CARDAMOM

CARDAMOM is a Bayesian model-data fusion (MDF) framework, it uses an Adaptive Proposal - Markov Chain Monte Carlo algorithm (AP-MCMC; Haario et al., 2001) to estimate ensembles of parameters for a process-model (DALEC). The retrieved parameters are consistent with available observational constraints, their uncertainties and ecological theory encapsulated in the ecological and dynamical constraints (Sect. 2.1.1) (Bloom and Williams, 2015; Smallman et al., 2021). CARDAMOM analyses are conducted independently for each pixel / location and repeated three times (each repeat is known as a chain). Each chain assesses 100 million parameter proposals, drawn from uniform prior ranges and then assessed against the local observational constraints. From each chain a sub-sample of 1000 accepted parameter vectors are stored to support forecasting, diagnosis of between-parameter correlations and parameter covariance with the simulated outputs. The presented output comes from 100 parameter combinations drawn from the second half of each chain (i.e. 300 combinations per pixel). These parameter combinations are used to evaluate whether the three chains to have converged (i.e. agree) and thus represent a realistic approximation



90 of the real pixel-level uncertainty. The Gelman-Rubin convergence criterion is used to determine whether the chains in any given pixel have come to a consistent solution (Gelman and Rubin, 1992). Any location which did not achieve convergence is re-run.

Pixel-level uncertainties are estimated directly from the retrieved parameter ensembles and the resulting ensemble of simulations of C stocks and fluxes. As we lack a robust understanding of how uncertainties are correlated in space, propagat-
95 ing uncertainties from individual pixels to the global-scale is challenging. Assuming an intermediate correlation length-scale would lead to an arbitrary estimate of uncertainty while assuming either fully-correlated or uncorrelated uncertainties leads to either an over- or underestimate in global uncertainties respectively. To be conservative, here, we assume uncertainties are fully-correlated when propagating from pixel to global estimates. To allow for non-Gaussian distributions in the pixel-level ensembles we assume that the fully correlated assumption is approximated by aggregating the pixel-level 2.5 % and 97.5 %
100 quantiles across the globe as previously done (Exbrayat et al., 2018b).

2.1.1 Ecological and dynamic constraints

The goal of the ecological and dynamic constraints (EDC) is to enforce ecologically plausible retrieval and reduce equifinality (Bloom and Williams, 2015). EDCs allow CARDAMOM to include prior ecological knowledge and ecological theory in the assimilation that cannot easily be defined as a numeric prior with an uncertainty. EDCs fall into two broad categories (i)
105 relational and (ii) dynamic. Relational constraints ensure the relationships between two or more parameters are within plausible bounds. For instance, the turnover rate of fine root C must be faster than turnover of structural C despite their plausible uniform prior ranges overlapping. Dynamic constraints reject parameter combinations which lead to inappropriate behaviours over time, such as exponential changes in C pools in the absence of a disturbance event (e.g. fire/deforestation). For further details on EDCs used in CARDAMOM see Bloom and Williams (2015); Bloom et al. (2016); Famiglietti et al. (2021).

110 2.2 DALEC

We use one of the DALEC (Data Assimilation Linked ECosystem model) suite of intermediate complexity terrestrial ecosystem models, DALEC-4 (Bloom and Williams, 2015; Smallman et al., 2019, 2021). DALEC-4 has previously been described as M3 in Smallman et al. (2021) and C7 Famiglietti et al. (2021). DALEC-4, hereafter referred to as DALEC, represents the states and fluxes of C and water in terrestrial ecosystems and their exchanges with the atmosphere. C uptake, via gross primary production
115 (GPP), is allocated to autotrophic (plant) respiration (R_a) and plant tissues based on fixed fractions which are calibrated by CARDAMOM. DALEC simulates four live C pools; labile (which supports seasonal foliage growth), foliage, wood (above + below), and fine roots. The turnover of these pools feed two dead organic matter pools (DOM), comprised of litter and soil organic matter (Soil). Decomposition of litter to Soil and heterotrophic respiration (R_{het}) resulting from the mineralisation of both litter and Soil follow parametrisable 1st order kinetics with an exponential temperature response function. Each C
120 stock and flux within the DALEC model is controlled by one or more parameters which are estimated probabilistically by CARDAMOM (Table A1).



Foliar dynamics are controlled by a day-of-year model which determines the timing of labile turnover to support foliage growth, and senescence of the foliar pool to litter (Bloom and Williams, 2015). Plant photosynthesis and ecosystem water cycling in DALEC is simulated by the ACM-GPP-ET sub-model (Smallman et al., 2019). Photosynthesis is calculated as a function of leaf area index (LAI), meteorology, and available water supplied by fine roots from the soil. Soil water supply is determined as a function of root surface area (a function of fine root C), simulated rooting depth (linked to below ground wood), and soil moisture content within the rooting zone. The soil water dynamics across 3-soil layers are a function of precipitation, interception and evaporation by the canopy, surface run-off, evaporation, drainage and transpiration by vegetation.

DALEC can be forced with disturbance information on fire and deforestation / degradation. The resultant fire C emissions are determined by imposing a burned area fraction and assuming a fraction of the biomass contained in the burnt pixel fraction is combusted or converted to litter based on tissue specific combustion-completeness factors, following Exbrayat et al. (2018b). Fire resilience and combustion completeness parameters are calibrated on a per-pixel basis. Deforestation / degradation follows a similar approach to fire but uses fixed fractions which are not calibrated due to lack of information on the variability of different management regimes. All biomass is assumed to be subject to the imposed removal fraction except fine roots which remains in the ecosystem supporting regrowth. A fraction of removed biomass is assumed to be transferred to the litter and soil C pools.

2.3 Forcings

DALEC is forced by monthly meteorological and disturbance information. Meteorology are air temperature, short-wave radiation, atmospheric CO₂ concentration, vapour pressure deficit, precipitation and wind speed. These are drawn from the CRU-JRAv3.5 dataset, a 6-hourly 0.5×0.5° reanalysis (University of East Anglia Climatic Research Unit; Harris, 2023). Atmospheric CO₂ is taken from the Mauna Loa global CO₂ concentration dataset (www.esrl.noaa.gov/gmd/ccgg/trends/, accessed: 22/08/2023).

Disturbance by fire and forest biomass removal is imposed using EO datasets. Fire is imposed using burned area extracted from GFEDv5 which itself is derived from the combination of MODIS burned fraction product (Giglio et al., 2018), corrected for missing small fire using a range of datasets including MODIS radiative power product (for details see Chen et al., 2023). Forest biomass removal (deforestation / degradation) is imposed using a forest fraction loss extracted from the global forest watch (GFW) forest cover loss product (Hansen et al., 2013). The specific product version used here attempts to remove forest losses due to fire in order to reduce double counting disturbances (Tyukavina et al., 2022). GFW provides the year in which a forest area is removed, with biomass losses assumed to occur evenly across the year.

The DALEC hydrology sub-model requires information on soil sand and clay fractions to calculate the local hydraulic properties (i.e. porosity, field capacity, conductivity) using the Saxton et al. (1986) pedotransfer functions. These data are extracted from the SoilGrids database version 2 (Hengl et al., 2017). SoilGrids uses field inventories of soil properties and interpolates these across a 250 × 250 m grid using a machine learning (ML) approach (Hengl et al., 2017).



2.4 Assimilated time series observations

155 Diverse ecologically relevant time series observations are assimilated in this study. These are spatially explicit, time varying information on LAI (2003-2024), the fraction of absorbed photosynthetically active radiation (fAPAR; 2003-2024), GPP (2003-2024) and woody biomass (2007, 2010, 2015-2019). LAI, fAPAR and GPP are all extracted from MODIS products which share a processing workflow and common reflectance bands in their creation and thus a greater likelihood of consistent information content. Alternate data products could be used and would provide further information on the analysis uncertainty - but this is
160 out of scope for this study.

The 8-day LAI and fAPAR were extracted from the MODIS product MCD15A2H.061 (Yan et al., 2016). These data were filtered to remove lower quality information, e.g., excluding LAI gap-filled using the NDVI approach which gives an inconsistent estimate of LAI when compared with the main processing chain. LAI and fAPAR were then aggregated in space from 500 x 500 m to 0.5 x 0.5 deg and to a monthly time step. The provided spatially and temporally explicit uncertainties were
165 aggregated using a sum-of-squares approach. A minimum uncertainty estimate of 0.05 was used for fAPAR (expert opinion). LAI uncertainty estimates used a minimum of $0.25 \text{ m}^2 \text{ m}^{-2}$ to prevent unrealistically low LAI uncertainties, see Zhao et al. (2020) for details on EO LAI uncertainty and bias.

Annual estimates of GPP were extracted from MOD17A3HGF.061 (Running and Zhao, 2021). An annual time step was selected due to the additional quality controls applied to this product, removing unrealistic high-frequency variation in monthly
170 GPP. This product does not come with an uncertainty estimate. As this product is largely calibrated and evaluated using eddy covariance derived GPP estimates we use eddy covariance estimates of uncertainty as our basis and inflate to account for additional model error giving a value of $1 \text{ gC m}^{-2} \text{ d}^{-1}$ averaged across the year (for details see Famiglietti et al., 2021).

Annual total woody biomass (TWB, i.e. above + below ground) estimates covering 7-years were extracted from a combination of two datasets (Xu et al., 2021; Santoro and Cartus, 2025). Xu et al. (2021) combined EO lidar and optical information
175 to estimate global maps of annual TWB at 10 x 10 km spatial resolution (2000-2019). However, these maps have a relatively high uncertainty ($\sim 80\%$) due to the greater uncertainty inherent in the allometric relationships between vegetation height and C storage. The ESA CCI above ground biomass (AGB) dataset version 6 (2007, 2010, 2015-2022; Santoro and Cartus, 2025) uses a combination of synthetic aperture radar wavelengths and C storage $\sim$ backscatter relationships to estimate biomass. These data have a relatively lower uncertainty ($\sim 33\%$), but mask areas not classified as 'woody' with zero biomass ($\sim 40\%$ of
180 vegetated land area). This creates unrealistic 'cliff-edges' for TWB and would introduce a significant bias in a MDF analysis. Therefore we combine these datasets, filling the ESA CCI v6 maps with the equivalent location values from Xu et al. (2021). The AGB estimates from ESA CCI v6 were upscaled to total woody biomass following an allometric relationship reported in Saatchi et al. (2011). These data were spatially aggregated to our analysis resolution; the TWB estimates themselves were aggregated assuming a spatial mean, while uncertainties were aggregated assuming a sum-of-squares propagation.



185 2.5 Assimilated priors

We include temporally invariant priors on three DALEC model parameters. These are initial soil C storage, the leaf C per unit area (LCA) and the ratio of R_a to GPP (R_a :GPP).

A location specific prior estimate on the initial soil C pool is extracted from the SoilGrids database version 2 (Hengl et al., 2017). SoilGrids uses field inventories of soil C and interpolates these across a 250×250 m grid using a machine learning
190 (ML) approach (Hengl et al., 2017). SoilGrids includes a ML derived estimate of pixel uncertainty. These uncertainties are propagated to the analysis resolution.

A location specific estimate and uncertainty for the LCA (also known as the leaf mass area but typically with different units) is extracted at 0.5×0.5 deg from Butler et al. (2017). This dataset was created from an interpolation of in-situ estimates and provides valuable complementary information with LAI on the leaf life span and C investment requirements that DALEC
195 parameterisations must accommodate.

A global prior for the R_a :GPP = 0.56 ± 0.12 was used (Collalti and Prentice, 2019). Collalti and Prentice (2019), derived this global estimate from a meta-analysis of in-situ estimates.

2.6 Independent evaluation

Independent evaluation is achieved by comparing CARDAMOM estimated fire C emissions and net biome exchange of CO_2
200 ($\text{NBE} = -\text{GPP} + R_a + R_{het} + \text{Fire}$) in space and time.

We use multiple estimates for each variable to estimate a plausible independent range for each location and time. We compare the overlap between the independent estimate ensemble and CARDAMOM's uncertainties on a per-pixel, per-time step basis. These interactions are then aggregated in space and separately in time to provide a probabilistic quantification of the 'overlap' between CARDAMOM and independent estimates. The range comparison means that overlap statistics replace
205 classic metrics of the root mean square error (RMSE) and regression based R^2 . We provide maps of the pixel-level temporal bias between the ensemble median from CARDAMOM and independent estimates to highlight any systemic differences. For the main manuscript we focus on whether CARDAMOM is consistent with independent estimates or not, defined as $>5\%$ overlap. The supplementary materials contain the pixel-level overlaps.

Independent fire C emissions (2003-2022) estimates are extracted from the Global Fire Emissions Database version 5
210 (GFEDv5; Chen et al., 2023) and Global Fire Assimilation System (GFAS; Kaiser et al., 2012). GFEDv5 (0.5×0.5 degree, monthly) uses fixed parameters on a per vegetation type in combination with the CASA ecosystem C-cycle model to provide fuel loads. We note that CARDAMOM uses burned area forcing provided by GFEDv5 but that CARDAMOM's fire model is independently calibrated. GFAS (0.1×0.1 degree, daily) uses satellite-based radiative power observations which are translated into a C emissions based on vegetation type coefficients. We note that GFAS was itself partially trained on an earlier
215 version of GFED and is not fully independent. However, we know of no other long-term global estimate of fire C emissions at a comparable resolution. GFAS estimates are first aggregated to a monthly value and then aggregated in space to match CARDAMOM.



Independent estimates of NBE (2015-2020, 1 x 1 degree, monthly) are extracted from the OCO2MIPv10 (Byrne et al., 2023). We evaluate against the mean and standard deviation of an ensemble of 14 atmospheric inversion models which assimilated a combination of surface atmospheric measurements and total column CO₂ estimates from NASA's OCO-2 satellite. The spatial resolution varies between the MIP ensemble members but is provided as a downscaled dataset at 1 x 1 degree. For our comparison we aggregate CARDAMOM outputs to 1 x 1 degree.

3 Results

We have generated a global, multi-decadal, data-informed analysis of terrestrial ecosystem carbon (C) cycling at spatially aggregated (Fig. 1) and discrete scales (Fig. 4). We provide uncertainty-bounded, time series information on the major ecosystem fluxes and internal C flows - providing statistical confidence on ecosystem dynamics given the assimilated observations and their uncertainties (Fig. 6). Furthermore, we retrieve at pixel-scale the underpinning ecosystem properties (embedded in DALEC parameters and simulated dynamics) offering the opportunity for ecological learning.

Using our ensemble-based analysis we are uniquely able to dissect the covariances between ecosystem traits and the resultant ecosystem simulation, precisely tracking C flows and their dependencies using both spatially aggregated (Fig. A1, A2) and spatially discrete perspectives (e.g. Fig. A3).

In the following sections we outline (1) an evaluation of our analysis' ability to effectively assimilate its observational constraints and its agreement with independent estimates of NBE and C emissions from fire (Fig. 2, 3), (2) our estimates of global and regional scale (for the RECCAP domains) C budgets and temporal trends (Table 1, 2, 3, 4). Finally, (3) the spatial distribution and uncertainty of NPP allocation and C pool mean residence times (MRT) (Fig. 8, A6, A8) - which are key when forecasting terrestrial ecosystem C dynamics. All uncertainties are given as the 95 % confidence interval explicitly derived from the pixel level ensembles.

3.1 Calibration performance and independent evaluation

We assessed how effectively CARDAMOM has assimilated its data constraints and whether it is statistically consistent with independent (i.e. non-assimilated) estimates of ecosystem variables. Statistical consistency is assessed using the histogram overlap metric (h_o) described in Sec 2.6. We report the overall h_o for each dataset and the proportion of the land surface defined as consistent (h_c) is determined from pixel with $h_o > 5\%$. Assimilated observations are not considered the 'truth', therefore we do not expect to have a perfect overlap.

There is a high global average h_o for assimilated datasets suggesting good consistency; monthly fAPAR (44 %), monthly LAI (54 %), annual wood stocks (87 %) and annual GPP (95 %). The h_c criteria is reached for >99% of pixels across all time series constraints. Posterior parameter estimates are also consistent (high h_o) with priors for LCA (66 %), Ceff (78 %), Ra:GPP (71 %) and initial soil C (81 %).

On global scales CARDAMOM is highly consistent with independent NBE (OCO2-MIP v10) with a h_o of 60% and h_c achieved across 97% of the land surface. Similarly, fire emission (GFEDv5; GFAS) have h_o of 92% and h_c achieved across all

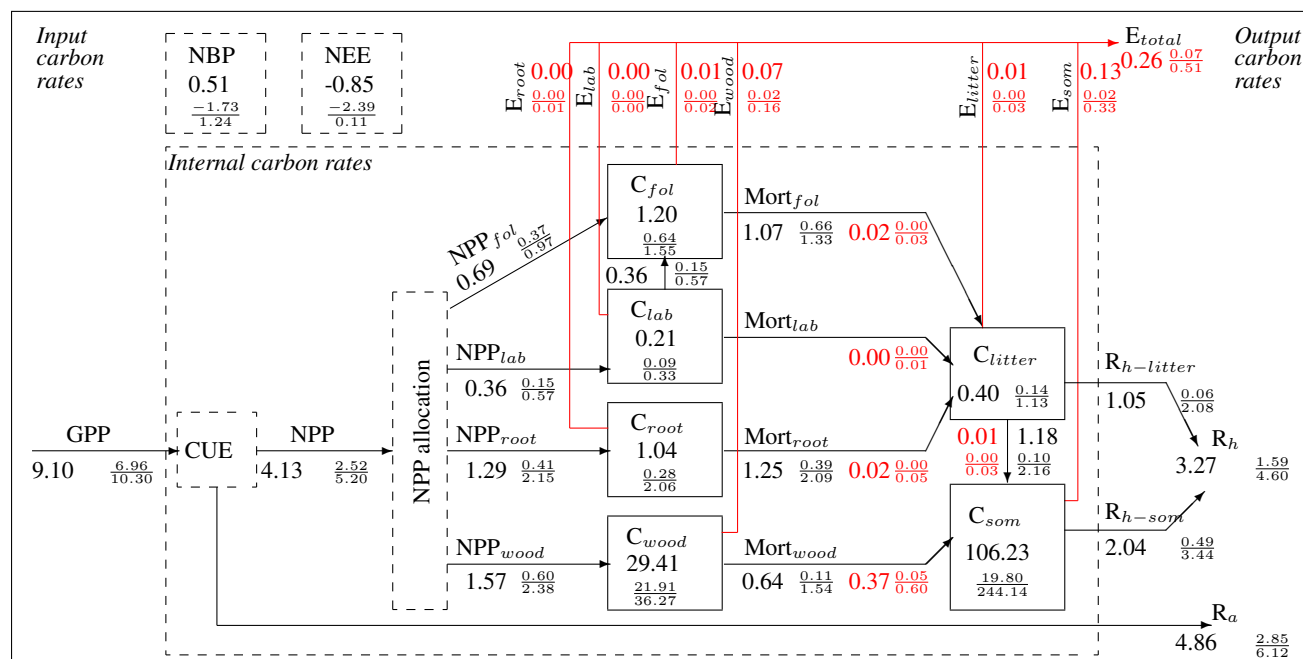


Figure 1. Global terrestrial ecosystem C-budget (2003-2024). Numbers shown are the median estimate of fluxes (alongside arrows) and of stocks (in boxes). Units are MgC ha^{-1} for stocks and $\text{MgC ha}^{-1} \text{y}^{-1}$ for fluxes. 95% confidence intervals are shown as fractions with 2.5 and 97.5 percentiles as numerator and denominator. Black fluxes are biogenic, including net primary production (NPP), mortality (Mort), autotrophic respiration (R_a) and heterotrophic respiration (R_h). $NEE = R_a + R_h - GPP$. $NBP = -NEE - E_{total} - \text{Forest}_{loss}$ (not shown). Red fluxes are fire-driven emissions (E).

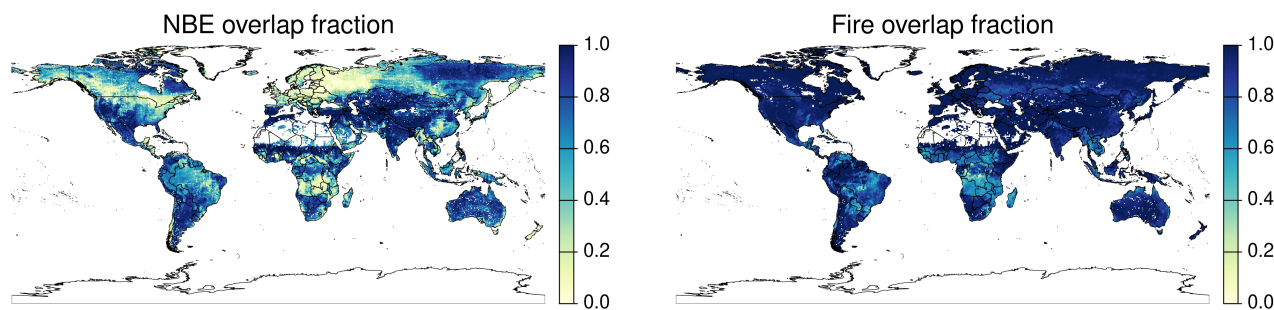


Figure 2. Maps of the pixel-level histogram overlaps for independent estimates of NBE (from OCO2-MIPv10) and fire C emissions (GFEDv5 and GFAS).

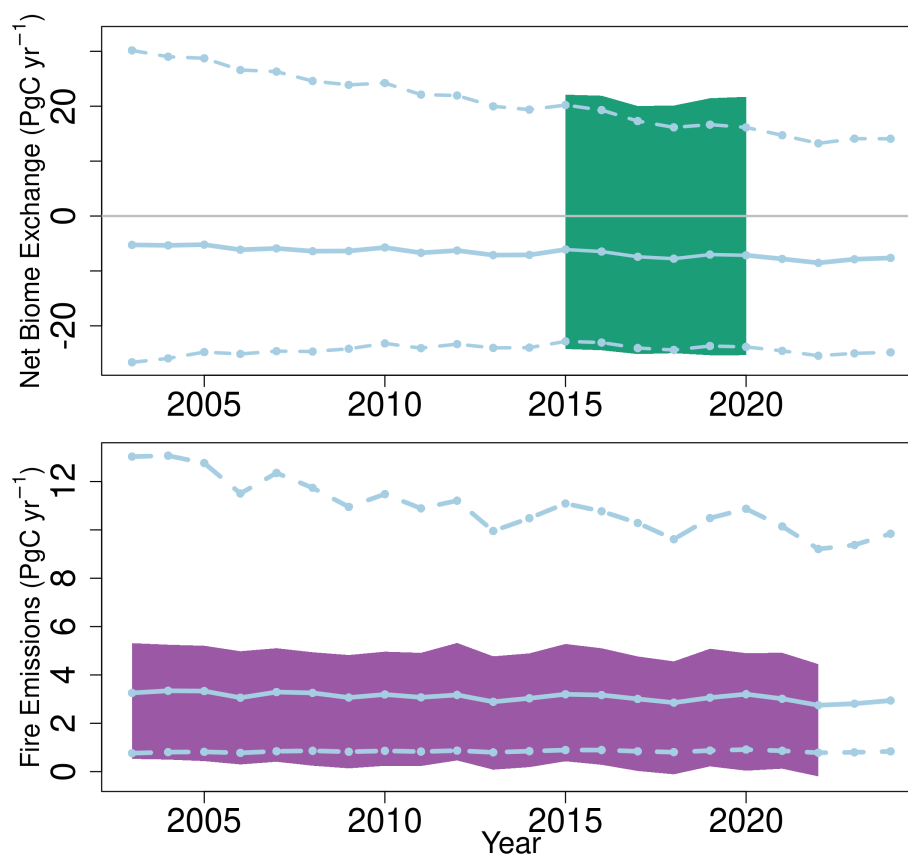


Figure 3. Time series of global NBE and fire C emissions from CARDAMOM and independent estimates. The solid line represents the global average of the CARDAMOM's pixel-level medians while the dashed lines show CARDAMOM's pixel-level averages of the 2.5 % and 97.5 % quantiles delineating the 95 % confidence interval. The green coloured area delineates the range of of the OCO2-MIPv10 ensemble of atmospheric inversions. The purple coloured area delineates the range of the GFEDv5 and GFAS fire C emissions.

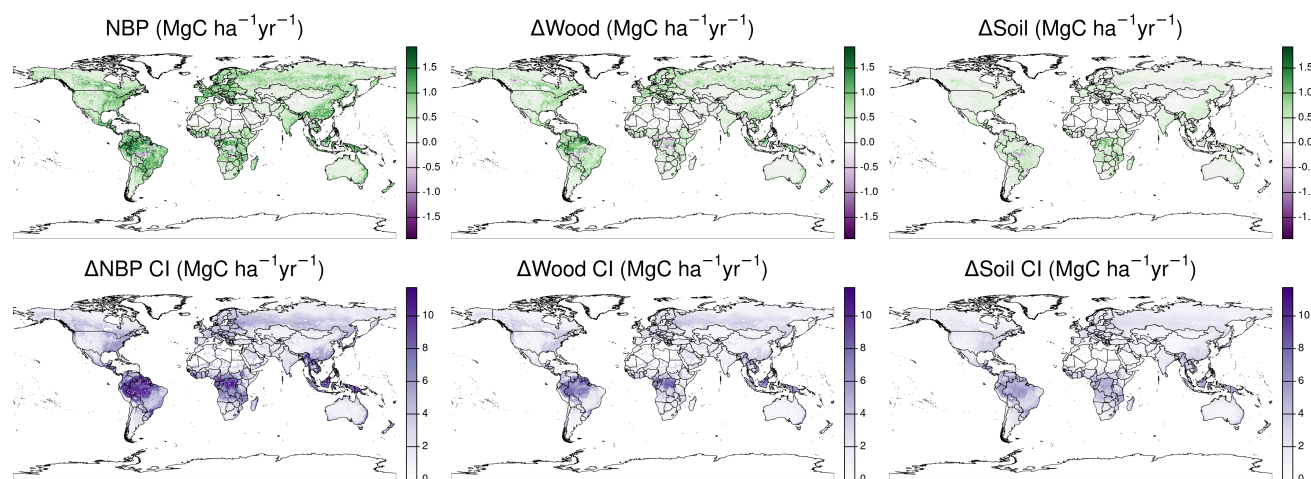


Figure 4. Top row shows the mean annual estimates of NBP, biomass (ΔWood) and dead organic matter (ΔSoil) change. The bottom row shows the corresponding mean 95 % CI. Note that the uncertainty is not temporally fixed and varies over time, here only the temporal average is shown.

250 pixels (Fig. 2). However, h_o is lower for NBE across regions dominated by needleleaf forests (e.g. Canada, western Russia and Scandinavian countries) and complex managed landscapes (e.g. Eastern USA and central and north western Europe). Despite localised disagreement (discussed later) the global picture indicates robust consistency across the regions of greatest global importance (wet and dry tropics) and consistent across two decades (Fig. 3).

3.2 Global C Budget

255 Our analysis indicates that global terrestrial ecosystems are most likely a net C sink, but with significant uncertainty crossing the source / sink boundary ($\text{NBP} = 6.0 \text{ } (-22/24) \text{ PgCy}^{-1}$; Table 1). NBP is most likely increasing, but also with significant uncertainty ($0.8 \text{ } (-5.1/7.2) \text{ gCm}^{-2}\text{y}^{-1}$; Table 3). Underpinning the changes in NBP is a long-term trend of declining emissions from fire ($-0.2 \text{ } (-3.0/1.9) \text{ gCm}^{-2}\text{y}^{-1}$). Areas with the greatest increase in NBP correspond to those of greatest declines in fire emissions both in space and magnitude (Fig. 5). Furthermore, declining fire emissions across African savannas corresponds
260 with declining R_h , due to declining litter inputs from fire-induced mortality. The geographically discrete changes in fire occur along side a geographically broad trend of increasing C removal by GPP ($4.9 \text{ } (-5.3/14.0) \text{ gCm}^{-2}\text{y}^{-1}$), partially balanced by increasing emissions from respiration; primarily from R_a (a fixed fraction of GPP) and R_h (except African savanna ecosystems where R_h declines). However, there remains substantial uncertainty in our analysis given the uncertainties contained within and propagated from the assimilated observations. Therefore, we cannot be >95 % confident in the sign of global NBP or
265 trends of net and gross ecosystem C fluxes across much of the world (Table 1, 3).

We also quantified the spatially-aggregated but temporally evolving behaviour of C exchanges. Fire emissions have declined in a largely consistent way over the last 20 years which contrasts the more variable time series of the magnitudes of C extracted

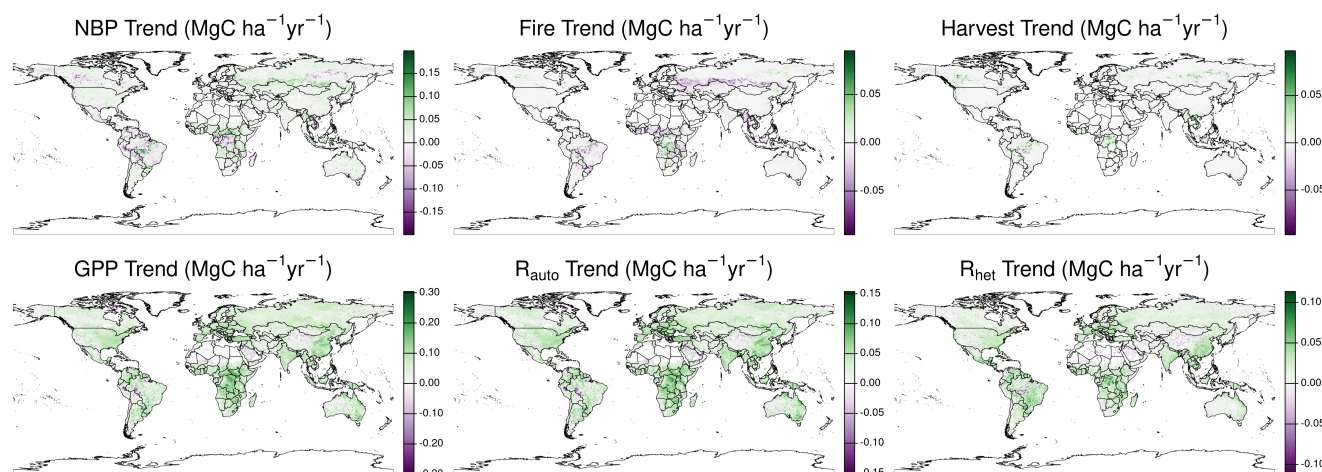


Figure 5. Maps of the pixel-level temporal trends for NBP and its component gross fluxes. Note the different axes scales on each map.

due to land use change (i.e. deforestation and degradation). The global LUC flux is estimated to have been largely flat between 2003 and 2011 ($\sim 0.5 \text{ PgCy}^{-1}$) before rapidly increasing to a peak of $\sim 1.1 \text{ PgCy}^{-1}$ by 2016 and subsequently declining again (Fig. 6). However, this globally-averaged signal is composed of various contrasting regional temporal patterns (Fig. A4). The rapid increase in LUC emissions post 2010 is driven largely by the Southern African ecosystems, while the peak in 2015-16 is driven by emissions from South America. LUC fluxes have not declined to their pre-2010 magnitude in either region. Other regions display greater relative inter-annual variability but without significantly impacting the global magnitude, with one exceptions. In 2023, LUC fluxes in North America approximately double but subsequently returned to their long-term average.

Uncertainty remains a dominant challenge in constraining the land C sink. The average pixel-level NBP uncertainty is 5.2 times that of the magnitude of the estimated flux - i.e. the uncertainty is larger than the estimated flux (Fig. 4). NBP is dominated by changes in the large C pools, i.e. wood (ΔWood) and soil organic matter (ΔSoil) which are highly uncertain. The uncertainty:flux ratio of ΔSoil (11.4 times) is roughly double that of ΔWood (5.2 times). The uncertainty imbalance is even greater when considering the current C stocks rather than their dynamics. The ratio of uncertainty to total ecosystem C is 2.7; dominated by the uncertainty ratio of soil C at 3.0, while wood C is relatively well constrained with an uncertainty ratio of 1.2.

As a result of these uncertainties, only 1 % of the vegetated land surface can be reported as either a net source or sink with >95 % confidence. A further 7.3 % are estimated to be C neutral - defined as locations where the absolute magnitude of mean NBP $< 10 \text{ gCm}^{-2}\text{y}^{-1}$ and its uncertainty crosses source~sink boundary. Confidence over source-sink-neutral is greater for ΔWood - unsurprising given the large amount of observational constraint - with 2.5 % of vegetated land being confidently a net sink, 0.2 % as a net source and a further 17.3 % estimated as neutral. For ΔSoil only 0.2 % of vegetated land can be confidently determined to be a net sink, 0.1% as a net source though 42 % as estimated to be neutral. We note that the above definition of 95 % confidence aligns with the *Very Likely* definition. If we were to consider the *likely* quantification at 68 %

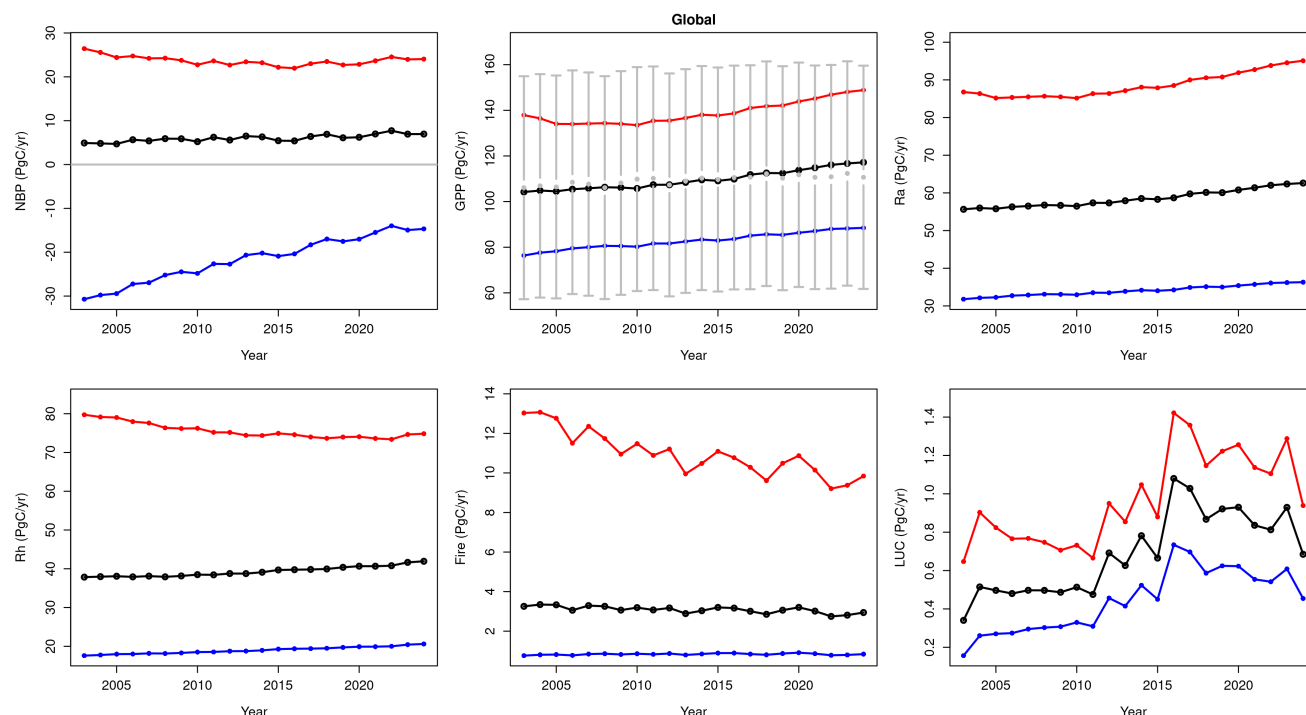


Figure 6. Time series of the global total fluxes for NBP, GPP, R_{eco} , R_h , Fire, LUC. The solid black line shows the aggregate of the pixel-level median estimates. The coloured lines show the aggregate of the pixel-level 2.5 % (blue) and 97.5 % (red) quantiles - defining the 95 % confidence bounds. Grey points show the assimilated GPP estimates, where the error bars are the assimilated uncertainties aggregated following fully correlated error assumption (to be comparable with the CARDAMOM uncertainty propagation).

confidence (or 1 standard deviation) shows that we have a greater ability identify sinks than sources. For example, 30 % of the vegetated surface is estimated to be a net sink under the *likely* definition with less than 1 % as a net source, and no change in the identification of neutral areas (Fig. A5).

The pixel-level NBP uncertainty is strongly correlated with that of ΔWood ($|r| = 0.82$) and ΔSoil ($|r| = 0.71$). However, NBP uncertainty is weakly correlated with the current size of wood and soil C pool ($|r| = 0.32$ and 0.15 respectively, Figure 7), showing a clear contrast between the value of information on the size versus dynamics of C pools. Furthermore, the absolute size of the ΔSoil CI is ~ 2 times that of ΔWood CI. There are also some unexpected results. There is little correlation between NBP uncertainty and the uncertainty of GPP or LAI ($|r| < 0.15$), despite both often being suggested as key observational targets needed to constrain the terrestrial C balance. However, there is a strong correlation with uncertainty for R_h ($|r| = 0.55$), likely linked to R_h being correlated with both ΔWood CI ($|r| = 0.45$) and ΔSoil CI ($|r| = 0.42$). This result suggests the more significant knowledge gap is ecosystem C losses rather than inputs.

South America is estimated to have the largest contribution to the terrestrial NBP ($\sim 20\%$, Table 1) but also has the largest uncertainty range (11 PgCyr^{-1}). Southern Africa has the next largest uncertainty (7.3 PgCyr^{-1}) and contributes jointly (with

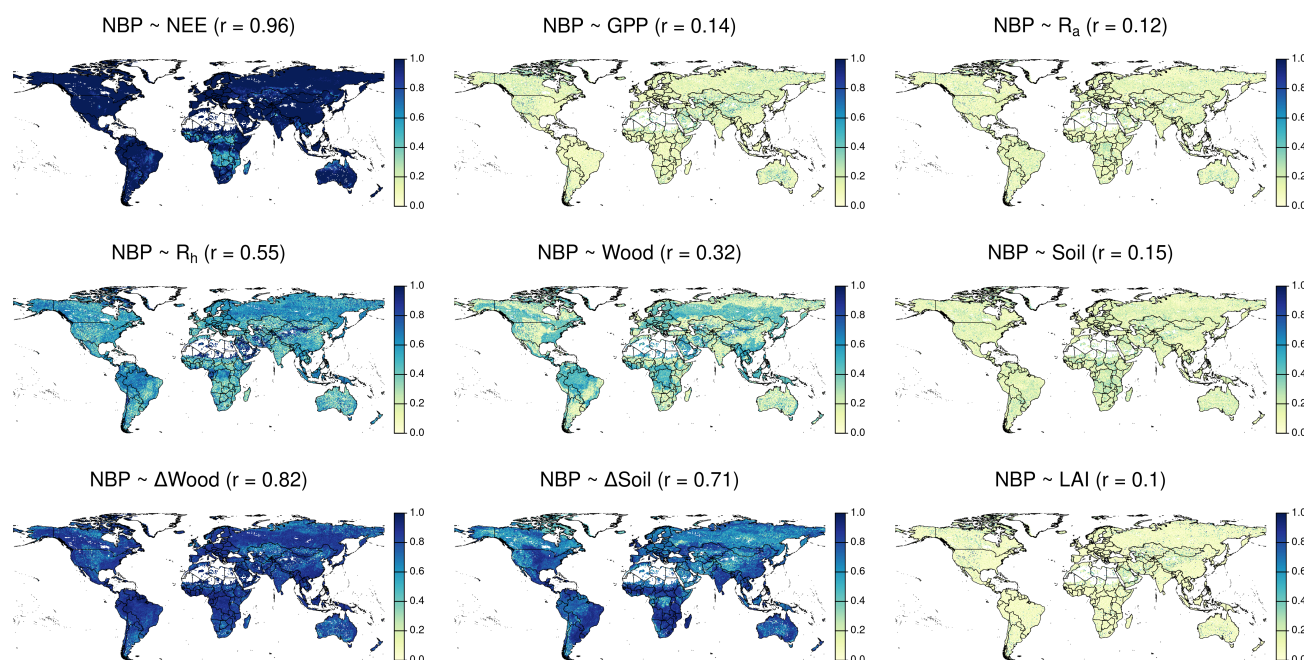


Figure 7. Maps of the absolute magnitude of the pixel-level correlations between NBP and gross ecosystem fluxes or observable states. The spatial average is reported in the title of each map.

North Asia) the third most to global NBP ($\sim 11\%$). The large uncertainties across these RECCAP regions is underpinned, in absolute and relative terms, by C loss fluxes; in order of $R_{h_{som}}$, $R_{h_{litter}}$ and fire, potentially reflecting that these regions have large scale and intensive disturbance activities (both natural and anthropogenic).

305 The importance of disturbance fluxes (fire and LUC) on global scales is widely accepted; LUC and fire emissions combined are equivalent to 62 % of NBP (Table 1). But the RECCAP regions make highly variable contributions to global disturbance fluxes - particularly when contrasting absolute versus relative impacts. In absolute terms, Southern Africa has the largest C emission from fire, accounting for half of the global total, followed by South America, North Africa and South East Asia. Whereas, South America is responsible for roughly a third of global LUC, and twice that of the next regions which contribute
310 approximately equally (North America, Southern Africa, South East Asia and North Asia). In proportionate terms, Southern Africa is the most disturbed with LUC and fire equivalent to 68 % of its NEE (i.e. disturbance changes the C balance from sink to source).

3.3 Carbon allocation and residence times

On global scales NPP is allocated in roughly equal, but uncertain, fractions between foliage (0.29 (0.18/0.47)), fine roots
315 (0.33 (0.12/0.57)) and wood (0.36 (0.16/0.62)) (Table 5). Furthermore, these fractions are highly variable in space (Fig. 8).



Table 1. Global mean and RECCAP region terrestrial ecosystem fluxes for C averaged over 2003-2024. Values in the parenthesis are the (2.5%/97.5 % quantiles). All fluxes are in units of PgCy^{-1} . To calculate the global aggregate values the simulated land area used is $120,530,825,704,344 \text{ m}^2$. Note that reconstructing budgets from the global medians of the gross fluxes is not always possible due to non-Gaussian distributions and covariance structures between pixel-level ensemble members. As such new variable calculations should be carried out through processing the full parameter ensembles. For clarity all values are rounded to 2 significant figures or 1 decimal place, as a result a zero value may not be precisely zero. See example codes in SI. RECCAP region codes are: NA = North America, SA = South America, EU = Europe, Naf = Northern Africa, Saf = Southern Africa, NAs = North Asia, CA = Central Asia, EA = East Asia, SAs = South Asia, SEA = South East Asia, Oce = Oceania. For RECCAP region areas see Table A2

Fluxes	Mean	NA	SA	EU	Naf	Saf	NAs	CA	EA	SAs	SEA	Oce
GPP	110 (83/139)	16 (11/20)	27 (22/33)	5.4 (4.0/7.0)	4.0 (2.8/5.6)	18 (14/22)	11 (8.0/14)	2.9 (1.8/4.6)	7.2 (5.2/9.5)	3.4 (2.5/4.4)	8.0 (6.4/9.5)	4.5 (3.2/6.1)
R_a	59 (34/56)	8.3 (4.7/13)	15 (8.8/21)	3.0 (1.7/4.5)	2.1 (1.2/3.5)	9.3 (5.5/14)	5.6 (3.1/8.8)	1.6 (0.8/2.9)	3.8 (2.2/6.0)	1.9 (1.1/2.9)	4.3 (2.6/6.1)	2.6 (1.5/4.0)
$R_{h-litter}$	13 (0.7/38)	2.1 (0.1/5.8)	3.0 (0.2/9.1)	0.7 (0.3/1.9)	0.4 (0.03/1.5)	1.7 (0.1/5.5)	1.5 (0.1/4.1)	0.3 (0.01/1.1)	1.0 (0.1/2.8)	0.4 (0.02/1.2)	0.9 (0.05/2.5)	0.4 (0.02/1.4)
R_{h-som}	25 (5.9/63)	3.5 (0.8/8.9)	6.6 (1.7/16)	1.2 (0.3/2.9)	0.8 (0.2/2.8)	3.6 (0.8/9.6)	2.6 (0.6/6.4)	0.6 (0.1/2.2)	1.6 (0.4/4.2)	0.7 (0.2/1.8)	1.9 (0.5/4.6)	0.9 (0.2/2.4)
R_h	39 (19/76)	5.8 (3.0/11)	10 (5.0/19)	1.9 (1.0/3.6)	1.4 (0.5/3.3)	5.7 (2.3/11)	4.3 (2.3/7.8)	1.0 (0.4/2.6)	2.7 (1.4/5.2)	1.2 (0.6/2.2)	2.9 (1.4/5.4)	1.4 (0.6/2.9)
R_{eco}	100 (49/139)	14 (9.9/20)	25 (18/34)	5.0 (3.5/6.9)	3.6 (2.2/5.8)	15 (10/21)	10 (6.7/14)	2.7 (1.6/4.7)	6.7 (4.5/9.5)	3.1 (2.1/4.3)	7.2 (5.2/9.6)	4.1 (2.7/5.9)
Fire	3.0 (0.8/11)	0.1 (0.03/0.5)	0.4 (0.1/1.8)	0.03 (0.01/0.1)	0.3 (0.1/0.9)	1.6 (0.4/5.0)	0.2 (0.1/0.6)	0.03 (0.01/0.1)	0.04 (0.01/0.2)	0.06 (0.02/0.2)	0.3 (0.1/0.9)	0.1 (0.02/0.4)
LUC	0.7 (0.4/1.0)	0.1 (0.1/0.2)	0.2 (0.1/0.3)	0.02 (0.02/0.04)	0.003 (0.002/0.01)	0.1 (0.08/0.2)	0.09 (0.06/0.1)	0.0004 (0/0.0007)	0.02 (0.01/0.03)	0.005 (0.003/0.01)	0.1 (0.07/0.2)	0.004 (0.003/0.006)
NPP	50 (30/76)	7.1 (4.3/11)	12 (7.4/18)	2.4 (1.5/3.7)	1.9 (1.1/3.0)	8.3 (5.1/12)	5.3 (3.4/8.0)	1.2 (0.6/2.2)	3.3 (1.9/5.2)	1.5 (0.9/2.3)	3.6 (2.2/5.3)	1.8 (1.0/3.0)
NEE	-10 (-30/17)	-1.3 (-3.8/2.3)	-2.0 (-6.5/4.4)	-0.5 (-1.3/0.7)	-0.5 (-1.4/1.0)	-2.5 (-6.4/1.9)	-1.0 (-3.1/1.7)	-0.2 (-0.8/1.0)	-0.6 (-1.7/1.2)	-0.3 (-0.8/0.4)	-0.7 (-2.2/1.2)	-0.4 (-1.1/0.6)
NBE	-6.7 (-24/21)	-1.2 (-3.6/2.5)	-1.5 (-5.8/5.0)	-0.4 (-1.2/0.8)	-0.2 (-0.9/1.4)	-0.8 (-3.6/3.7)	-0.8 (-2.9/2.0)	-0.2 (-0.8/1.1)	-0.5 (-1.7/1.3)	-0.2 (-0.7/0.5)	-0.3 (-1.7/1.5)	-0.3 (-0.9/0.7)
NBP	6.0 (-22/24)	1.0 (-2.7/3.5)	1.3 (-5.2/5.6)	0.4 (-0.8/1.2)	0.2 (-2.4/0.9)	0.7 (-3.8/3.5)	0.7 (-2.1/2.8)	0.2 (-1.1/0.8)	0.5 (-1.3/1.6)	0.2 (-0.5/0.7)	0.3 (-1.6/1.6)	0.3 (-0.8/0.9)

Fractional NPP allocation to foliage is the largest component across much of the northern hemisphere. Fine root allocation is lowest across the Boreal latitudes and the Congo Basin, while allocation to wood is lowest in dryer areas. Foliage allocation is the least uncertain - consistent with the order-of-magnitude greater information available about canopies (assimilated LAI, fAPAR and LCA) than either wood or fine roots.

320 The trade-off between NPP allocation to each tissue is highly variable preventing a straight-forward empirical relationship being derived at global scales. Linear regression between the analysis forcing (meteorology and disturbance), and allocation fractions explains 46 %, 16 % and 18 % of spatial variability for foliage, fine root and wood respectively. However, there is a clear bounding to the retrieved combination of allocations (Fig A7). Typically no more than ~ 0.6 is allocated to any component,



Table 2. Global mean and RECCAP region terrestrial ecosystem C stocks averaged over 2003-2024. Values in parentheses are the (2.5%/97.5 %). All stocks are in units of PgC. To calculate the global aggregate values the simulated land area used is 120,530,825,704,344 m². As such new variable calculations should be carried out through processing the full parameter ensembles. For clarity all values are rounded to 2 significant figures or 1 decimal place, as a result a zero value may not be precisely zero. RECCAP region codes are: NA = North America, SA = South America, EU = Europe, Naf = Northern Africa, Saf = Southern Africa, NAs = North Asia, CA = Central Asia, EA = East Asia, SAs = South Asia, SEA = South East Asia, Oce = Oceania. For RECCAP region areas see Table A2.

Stocks	Mean	NA	SA	EU	Naf	Saf	NAs	CA	EA	SAs	SEA	Oce
Labile	2.5 (1.0/5.8)	0.5 (0.2/1.1)	0.2 (0.1/0.7)	0.2 (0.1/0.4)	0.1 (0.03/0.2)	0.2 (0.1/0.6)	0.7 (0.4/1.3)	0.1 (0.04/0.2)	0.2 (0.1/0.4)	0.1 (0.03/0.2)	0.1 (0.02/0.2)	0.05 (0.01/0.1)
Foliage	14 (7.6/23)	1.8 (0.9/2.9)	4.2 (2.2/6.5)	0.6 (0.3/0.9)	0.4 (0.2/0.8)	2.0 (1.1/3.1)	2.1 (1.1/3.2)	0.3 (0.1/0.6)	0.6 (0.3/1.0)	0.3 (0.2/0.6)	1.3 (0.7/2.1)	0.5 (0.3/0.9)
Fine roots	12.5 (3.4/44)	1.8 (0.5/6.5)	3.2 (1/11)	0.5 (0.1/2.0)	0.6 (0.1/1.9)	1.9 (0.6/6.4)	1.0 (0.3/3.7)	0.4 (0.01/1.3)	1.0 (0.2/3.3)	0.5 (0.1/1.6)	0.8 (0.3/2.9)	0.5 (0.1/1.8)
Wood	353 (247/584)	48 (32/71)	109 (84/140)	14 (9.3/21)	7.4 (2.3/44)	58 (54/78)	44 (30/62)	6.2 (1.3/52)	16 (9/44)	4.4 (2.1/12)	34 (26/42)	6.7 (4.0/12)
Biomass	386 (276/620)	52 (36/76)	117 (91/150)	16 (11/22)	8.6 (3.3/46)	63 (48/83)	48 (34/66)	7.1 (2.0/53)	18 (11/46)	5.5 (3.0/13)	36 (28/45)	8.0 (5.0/13)
Litter	4.8 (1.7/51)	0.9 (0.3/12)	0.8 (0.3/6.1)	0.3 (0.1/3.4)	0.1 (0.05/1.2)	0.5 (0.2/3.3)	1.0 (0.3/13)	0.2 (0.05/1.8)	0.4 (0.1/5.3)	0.1 (0.04/1.2)	0.2 (0.1/1.5)	0.2 (0.1/1.3)
Soil	1280 (237/5266)	235 (43/910)	264 (38/1382)	60 (16/143)	38 (5.4/219)	159 (26/800)	210 (54/483)	46 (7.3/191)	93 (21/250)	26 (4.5/132)	71 (11/346)	50 (6.9/284)
DOM	1290 (244/5277)	237 (44/913)	265 (39/1384)	61 (16/144)	38 (5.6/219)	160 (26/801)	212 (56/485)	46 (7.5/191)	94 (22/251)	26 (4.7/131)	71 (12/346)	50 (7.0/284)

though very high allocations to foliage occurs at a small number of locations. Neither foliage or fine roots have allocation fractions <0.1 , but allocation to wood can be near zero. These combination may provide a hypothesis on the ecologically plausible range of NPP allocation combinations - for example supporting the evaluation of land surface models or targeting field campaigns to test and refine the hypothesis.

The spatial patterns in mean residence times (MRT) also remain challenging to explain. The controls on MRT are dependent on additional factors not considered here or inherently non-linear in nature. We estimate the MRT of each of the six C pools simulated by DALEC and aggregate to an ecosystem level, i.e. biomass + dead organic matter (Fig. 8). Ecosystem MRTs broadly increase towards the poles. This latitudinal pattern is driven by litter and soil MRT, while the spatial distribution of live C MRTs are more variable. More than half of spatial variation in foliage (72 %) MRT can be explained as a linear function of its own mean C pool size (i.e. itself) with <20 % explained by other C pools. Mean annual meteorology and disturbance forcing can explain through linear regression a substantial amount of spatial variability of MRT for soil C (33 %) and litter (56 %) - most likely due to their close dependency on temperature for decomposition as well as indicating a greater degree of convergence in the baseline decomposition and litter mineralisation parameters (i.e. they are more similar in space) and those estimated or soils.



Table 3. Temporal trends for Global and RECCAP regions terrestrial ecosystem C stock and flux trends for C and H₂O cycles averaged over 2003-2024. Trends are all in units of gCm⁻²y⁻¹. Trends were calculated as the difference between the final and first time steps divided by the number of years simulated. This approach is used rather than fitting a linear regression due to the lack of a linear trend across much of the globe leading to non-representative statistical fits. Values with > 95 % confidence are shown in **bold**. For clarity all values are rounded to 2 significant figures or 1 decimal place, as a result a zero value may not be precisely zero. To calculate the global aggregate values the simulated land area is 120,530,825,704,344 m². RECCAP region codes are: NA = North America, SA = South America, EU = Europe, NAF = Northern Africa, SAF = Southern Africa, NAs = North Asia, CA = Central Asia, EA = East Asia, SAs = South Asia, SEA = South East Asia, Oce = Oceania. For RECCAP region areas see Table A2.

Fluxes	Mean trend	NA	SA	EU	NAf	SAf	NAs	CA	EA	SAs	SEA	Oce
GPP	4.9 (-5.3/14)	3.5 (-5.3/11)	4.6 (-11/15)	6.8 (0.4/12)	4.7 (-6.8/17)	8.4 (-0.7/19)	4.8 (-1.2/9.4)	3.0 (-9.9/13)	5.1 (-10/14)	6.7 (-0.5/13)	7.2 (-0.3/14)	5.4 (-2.4/17)
R _a	2.7 (-2.5/7.5)	1.9 (-2.3/5.7)	2.5 (-6.1/8.0)	3.7 (0.2/6.9)	2.4 (-3.4/8.1)	4.4 (-0.4/9.9)	2.4 (-0.5/4.9)	1.7 (-5.1/7.2)	2.8 (-4.9/7.8)	5.8 (-0.6/11)	3.9 (-0.3/13)	3.1 (-1.3/9.3)
R _{h-litter}	0.5 (-1.0/1.9)	0.4 (-1.0/1.7)	0.5 (-0.8/1.7)	0.9 (-0.1/2.0)	0.2 (-3.1/2.0)	0.8 (-0.2/2.0)	0.6 (-0.4/1.8)	0.1 (-1.9/1.4)	0.5 (-2.5/2.3)	0.7 (-0.2/1.8)	0.8 (-0.1/1.7)	0.4 (-0.3/1.7)
R _{h-som}	1.0 (-0.5/4.4)	0.8 (-0.2/3.5)	1.7 (-3.0/5.9)	1.4 (0.03/3.4)	0.4 (-0.9/2.7)	1.7 (-0.8/6.6)	0.6 (-0.1/1.9)	0.3 (-0.3/1.6)	0.8 (-0.1/3.6)	1.4 (-0.003/4.4)	1.9 (-2.3/6.6)	0.9 (-0.2/4.0)
R _h	1.4 (-2.4/5.4)	1.1 (-2.3/4.5)	2.1 (-3.1/6.6)	2.3 (-0.01/4.6)	0.6 (-5.2/4.2)	2.6 (-0.3/7.7)	1.1 (-1.1/2.9)	0.3 (-3.2/3.1)	1.2 (-4.0/5.2)	2.2 (-0.7/5.3)	2.6 (-1.7/7.3)	1.3 (-0.7/5.0)
R _{eco}	4.0 (-4.7/11)	2.9 (-4.3/9.5)	4.5 (-7.4/12)	6.0 (0.3/11)	3.0 (-7.5/11)	6.9 (-0.2/16)	3.5 (-1.1/7.3)	2.0 (-8.0/9.7)	4.0 (-9.0/12)	5.8 (-0.6/11)	6.2 (-0.2/13)	4.3 (-1.7/12)
Fire	-0.2 (-3.0/1.9)	0.03 (-0.8/1.2)	-0.2 (-4.1/2.5)	-0.1 (-1.3/0.2)	-0.1 (-2.5/1.7)	0.04 (-4.5/4.7)	-0.4 (-4.0/1.2)	-0.2 (-1.8/0.2)	-0.02 (-1.1/1.0)	0.1 (-1.5/1.5)	-0.9 (-7.1/3.2)	-0.05 (1.5/1.2)
LUC	0.2 (-0.5/2.3)	0.1 (-1.1/2.0)	0.3 (-1.3/3.1)	0.2 (-0.04/1.4)	0.04 (-0.003/0.3)	0.5 (-0.1/4.5)	-0.4 (-4.0/1.2)	0.004 (0.00/0.04)	0.1 (-0.1/0.9)	0.06 (-0.004/0.6)	0.7 (-2.4/5.1)	0.2 (-0.02/1.5)
NPP	2.2 (-2.4/6.6)	1.6 (-2.5/5.0)	2.0 (-5.3/7.2)	3.0 (0.2/5.5)	2.2 (-3.1/8.9)	3.9 (-0.3/9.5)	2.2 (-0.5/4.6)	1.3 (-4.1/6.1)	2.3 (-4.4/6.4)	2.9 (-0.3/5.9)	3.3 (-0.2/6.4)	2.3 (-0.9/8.4)
NEE	-0.8 (-4.5/2.9)	-0.5 (-2.9/2.5)	0.1 (-6.4/6.0)	-0.7 (-2.4/0.9)	-1.4 (-6.5/1.3)	-1.1 (-6.3/3.9)	-1.1 (-3.2/0.9)	-1.0 (-4.9/1.5)	-1.1 (-3.5/1.6)	-0.7 (-3.3/2.1)	-0.7 (-5.9/4.4)	-0.9 (-6.1/1.7)
NBE	-1.0 (-7.2/3.6)	-0.5 (-3.6/3.4)	-0.4 (-11/8.0)	-0.9 (-3.5/0.9)	-1.6 (-7.4/4.5)	-1.4 (-9.7/6.0)	-1.6 (-7.2/1.9)	-1.2 (-5.7/1.5)	-1.1 (-4.1/1.8)	-0.7 (-4.7/2.2)	-2.1 (-12/6.7)	-1.0 (-6.8/2.2)
NBP	0.8 (-5.1/7.2)	0.4 (-5.0/4.3)	0.12 (-10/12)	0.7 (-1.6/3.5)	1.6 (-1.6/7.4)	0.9 (-8.8/9.4)	1.4 (-3.8/7.4)	1.2 (-1.5/5.8)	1.0 (-1.9/4.1)	0.6 (-2.4/4.2)	1.4 (-9.5/12)	0.8 (-3.0/6.7)

Soil and wood have the longest residence times while litter has the shortest. These are the pools with the largest uncertainties both relative (6.0, 4.3 and 11 times respectively) and in absolute terms (Table 5). The pixel-level MRT uncertainty is largely proportional for foliage, litter and soil, where the pool magnitude explains 66-77 % of the uncertainty, but <33 % for other pool.



Table 4. Temporal trends for Global mean and RECCAP region terrestrial ecosystem C stock trends for C cycles averaged over 2003-2024. Trends are all in units of $\text{gCm}^{-2}\text{y}^{-1}$. For clarity all values are rounded to 2 significant figures or 1 decimal place, as a result a zero value may not be precisely zero. Values with > 95 % confidence are shown in **bold**. To calculate the global aggregate values the simulated land area is $120,530,825,704,344 \text{ m}^2$. RECCAP region codes are: NA = North America, SA = South America, EU = Europe, NAf = Northern Africa, SAf = Southern Africa, NAs = North Asia, CA = Central Asia, EA = East Asia, SAs = South Asia, SEA = South East Asia, Oce = Oceania. For RECCAP region areas see Table A2/

Stocks	Mean trend	NA	SA	EU	NAf	SAf	NAs	CA	EA	SAs	SEA	Oce
Labile	0.08	0.1	-0.02	0.2	-0.1	0.07	0.2	-0.04	0.1	0.1	0.05	-0.03
	(-0.9/0.6)	(-0.9/0.5)	(-0.4/0.2)	(-0.1/0.6)	(-2.1/0.6)	(-0.3/0.4)	(-0.6/0.7)	(-1.2/0.5)	(-1.0/0.7)	(-1.0/0.6)	(-0.09/0.4)	(-1.0/0.4)
Foliage	0.3	0.04	0.4	0.5	-0.1	0.5	0.5	-0.1	0.2	0.5	0.8	0.3
	(-1.7/2.3)	(-2.1/1.5)	(-1.7/1.9)	(-0.5/2.0)	(-3.5/1.3)	(-0.6/2.1)	(-1.2/3.9)	(-2.4/1.0)	(-2.1/1.5)	(-0.7/1.5)	(-1.0/2.7)	(-1.0/1.4)
Fine roots	0.5	0.3	0.6	0.6	0.6	0.9	0.4	0.3	0.5	0.9	0.85	0.7
	(-0.7/2.1)	(-0.8/1.5)	(-1.1/2.4)	(-0.04/1.4)	(-0.9/2.6)	(-0.2/2.6)	(-0.4/1.3)	(-1.3/2.0)	(-2.3/2.2)	(-0.1/2.7)	(-0.1/2.3)	(-0.4/4.0)
Wood	30	32	49	46	13	14	32	16	29	29	40	19
	(-37/115)	(-30/103)	(-43/145)	(1.8/126)	(-49/62)	(-112/106)	(-31/99)	(-24/63)	(-11/99)	(0.05/87)	(-66/141)	(-4.4/89)
Biomass	31	32	50	47	13	15	32	16	29	30	41	20
	(-38/116)	(-32/103)	(-43/146)	(3.1/126)	(-56/62)	(-111/106)	(-32/101)	(-25/63)	(-15/63)	(-1.2/86)	(-62/141)	(-4.8/89)
Litter	0.1	0.1	0.1	0.2	0.06	0.2	0.3	0.03	0.2	0.2	0.2	0.1
	(-0.7/0.7)	(-1.3/0.7)	(-0.3/0.4)	(-0.1/0.5)	(-0.9/0.6)	(-0.1/0.5)	(-0.8/0.9)	(0.8/0.5)	(-1.5/0.9)	(-0.1/0.5)	(-0.1/0.4)	(-0.2/0.6)
Soil	9.7	8.0	13	18	2.3	22	4.9	0.01	10	22	11	10
	(-57/83)	(-43/64)	(-119/104)	(-25/63)	(-41/50)	(-64/141)	(-45/55)	(-32/30)	(-32/63)	(-24/74)	(-95/119)	(-46/80)
DOM	10	8.1	13	18	2.4	22	5.4	0.2	11	22	11	10
	(-57/83)	(-44/64)	(-118/104)	(-26/64)	(-41/50)	(-64/142)	(-46/56)	(-31/31)	(-32/63)	(-24/78)	(-96/120)	(-46/78)

4 Discussion

In this study we address our overall research question ‘*what can existing datasets confidently tell us about current C-dynamics in space and time?*’. To answer this question we generated a systemic, uncertainty bounded analysis of the global terrestrial C cycle, informed by state-of-the-art satellite-based remote sensing and geospatial datasets of statistically upscaled in-situ observations. Furthermore, we have used independent estimates of net biome exchange and fire C emissions to demonstrate the robustness of the analysis.

The novelty of this analyses arises from its systemic representation (Fig. 1), spatial specificity, and uncertainties propagated from diverse observations to model parameters and the resultant simulated ecological traits and dynamics (Fig. 4,5). In addition, our analysis provides observationally-informed ‘*targets*’ for evaluating land surface models to inform their parameterisations and simulated ecosystems (e.g., Caen et al., 2021).

4.1 Global and regional C budgets

Our results show that current global datasets for terrestrial ecosystems are not adequate to understand global C dynamics - in particular a critical lack of knowledge on the dynamics of soils. Between 2003 and 2024 terrestrial ecosystems were more



Table 5. Global average NPP allocation fractions to foliage, fine roots and wood, and the mean residence time (MRT, years) for each C stock (labile, foliage, fine roots, wood, litter, soil). The values reported are the averages of the pixel-level medians while parenthesis provide uncertainty quantification from the average of the 2.5 % and 97.5 % pixel-level quantiles. Note that reported NPP fractions will not equal 1 from reported global medians due to non-Gaussian distributions and covariance structures between pixel-level ensemble members.

NPP (0-1)	Global
Foliage	0.29 (0.18/0.47)
Fine roots	0.33 (0.12/0.57)
Wood	0.36 (0.16/0.62)
MRT (years)	
Labile	0.48 (0.24/1.1)
Foliage	1.2 (0.55/2.3)
Fine roots	0.84 (0.34/1.8)
Wood	27 (6.9/123)
Litter	0.19 (0.08/2.2)
Soil	69 (16/431)
Biomass	9.9 (4.4/30)
DOM	53 (10/280)
Ecosystem	41 (11/180)

likely than not to be a net sink of C (Table 1) - given the currently assimilated observations. Furthermore, our analysis suggests that the net C sink strength has increased over time (Table 3). However, this global picture is underpinned by significant uncertainty and spatial variability (Fig. 4). At the global scale uncertainties are likely to be smaller that we report due to variable correlation of uncertainties in space. But lacking a understanding of these uncertainty correlations we maintain a conservative assessment. CARDAMOM propagates the observation uncertainties into DALEC's systemic representation - thus the pixel-level uncertainties accurately reflect the combined information content of the assimilated data given their uncertainties. Despite assimilating diverse and state-of-the-art information the 95%CI remains large, meaning that we can only confidently determine whether a given location is a net source, sink or neutral across ~8% of the land surface. The magnitude of pixel-level 95 %CI may appear large, but is consistent across the majority of the world with the pixel-level spread of an ensemble of atmospheric inversions informed by the latest in-situ and OCO2 observations (OCO2-MIPv10, Fig. 2, 3). Our study is consistent with others which have concluded that current global datasets for terrestrial ecosystems are not adequate to diagnose global C dynamics (e.g., Seiler et al., 2022).

Our global estimate of NBE and its evolution over time closely aligns with the OCO2-MIPv10 ensemble (Fig. 3), though we recognise that our median estimate is higher than globally integrated estimates of NBE based on O2/N2 ratios (2003-2016, -1.0 -> -2.8 PgCy⁻¹; Tohjima et al., 2019). However, the OCO2-MIPv10 atmospheric inversions offer spatial detail supporting a regional comparison with our analysis and allow us to generate hypotheses to explain disagreement. Low pixel-level overlaps,

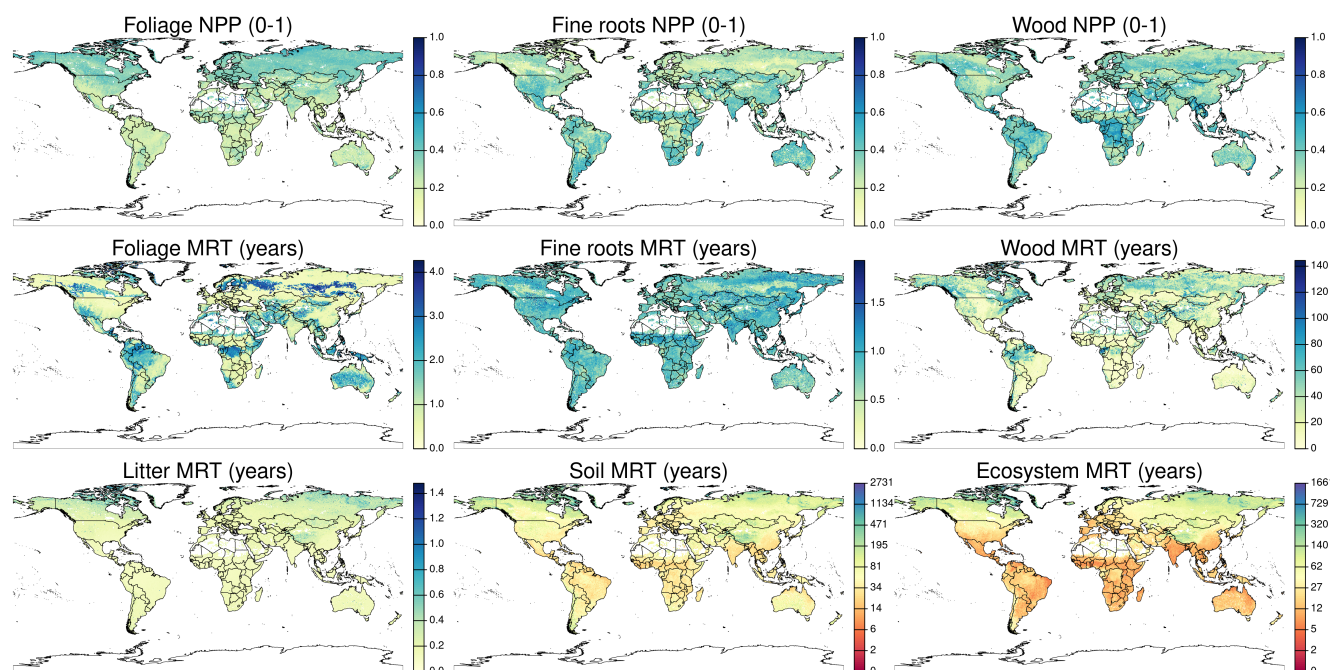


Figure 8. Maps of the pixel-level median estimates of NPP allocation fractions to foliage, fine root and wood (top row) and the mean residence times (MRT, years) for foliage, fine roots, wood (middle row), litter, soil organic matter and total ecosystem C (bottom row). Note that the legend scales colour is different for the soil and ecosystem maps to visually indicate the use of a logarithmic rather than linear scale.

i.e. biases, between CARDAMOM and the OCO2-MIPv10 ensemble are found on the USA-Canada border, and across Europe and western Russia (positive bias). These areas are dominated by intensive agriculture and complex land cover composition which may not be well resolved at the 0.5 deg spatial resolution of our analysis (Milodowski et al., 2023). However, we note that our analysis resolution is the finest resolution typically used by global land surface modelling activities, suggesting that strategies to better represent sub-grid dynamics must be well understood and reflect real-world management and disturbance regimes. Furthermore, the bias shown here is consistent with UK-focused studies which suggested CARDAMOM's estimates of NBE (and that of the UK's JULES land surface model) were biased over areas with intensive arable agriculture (e.g. south east England) (White et al., 2019). Agro-ecosystems are dominated by large lateral flows (e.g., harvest). While these can be managed in site scale analyses (Revill et al., 2021; Myrgeiotis et al., 2022, e.g.,), approaches integrating detailed location-specific and observation-informed land management have not yet been applied, to our knowledge, for regional or global simulation or data assimilation based analyses. Similarly, complex land cover compositions will contribute to a systemic bias due to the mismatch of scales between the analysis (degrees) and scales of management (ha). We have demonstrated how to overcome this through a modified tiling approach but have yet to apply global analyses due to a lack of sufficiently high confidence, high resolution



land cover, leaf area and biomass datasets (Milodowski et al., 2023), though this is an area of active research effort for future
385 studies.

4.2 Determinants of net carbon balance

Net C balance is driven by varied contributions from mostly far larger gross fluxes (photosynthesis, autotrophic and heterotrophic respiration, fire C emissions and lateral transfers from LUC) which in turn are variable in magnitude, space (Fig. 5) and time (Fig. 6). For example, only across one RECCAP region (Europe) is our analysis >95% confident in the trend of GPP
390 (Table 3). The large uncertainties reported in this study are consistent with the large differences between EO-derived estimates reported elsewhere (e.g., Seiler et al., 2022; Zheng et al., 2020). Net C balance is unsurprisingly dominated by the dynamics of the large C pools, wood and soil - both in terms of their correlation with net exchange in space but also the within-pixel uncertainties (Fig. 7). But the dynamics of wood and soil themselves are not always strongly correlated. For example, the Congo is estimated to be a small sink or neutral in terms of woody dynamics but there is a relatively strong C accumulation
395 estimated for its soils. What is consistent is that the dynamics of wood and soil C pools remain uncertain (Fig. 4).

Uncertainties remain significant, but there are coherent spatial and temporal patterns in our analysis which can be independently substantiated. For example, declining NBP within the Congo Basin (Democratic Republic of Congo) is associated with increasing LUC, while increasing NBP north of the Congo region (Central African Republic, South Sudan) is correlated with (i) declining emissions from fire, which is driven by EO burned area used as a forcing, and (ii) declining heterotrophic
400 respiration, due to reduced fire-mediated litter inputs in the same areas (Fig. 5). Our fire C emissions and associated declines are supported by comparable independent data products (Fig. 2, 3). The interconnectedness of fire, biomass and litter dynamics has also been highlighted by a southern African woodland focused analysis (Williams et al., 2025).

4.3 Characterising uncertainty on net carbon balance

Characterising and reducing uncertainty are key challenges which must be overcome in order to identify where current global
405 sources and sinks are located and what biotic and abiotic factors are impacting them. This information is needed to provide credible decision-support to policymakers and land managers - but this information has been lacking with persistent divergence in estimates of sources and sinks between analyses (e.g., Mitchard, 2013; Exbrayat et al., 2018a; O'Sullivan, 2022; Seiler et al., 2022; Sitch et al., 2024). The datasets used in this analysis represent the current state-of-the-art for time series of leaf area, woody biomass and soil C stocks, yet their collective information content results in pixel-level uncertainties for NBP, Δ Wood
410 and Δ Soil which is several times larger than the estimated change (Fig. 4).

Current products lack the accuracy needed to reduce uncertainty in both Δ Soil and Δ Wood. Uncertainty in Δ Soil is the largest followed by Δ Wood but the pixel-level uncertainty of both are strongly correlated with pixel-level uncertainty of NBP (Fig. 7). Δ Wood remains a major driver of uncertainty, suggesting that we stand to gain significant scientific and decision-support benefit from ongoing and upcoming EO based efforts to improve our understanding of the dynamics of biomass
415 (e.g. ESA's BIOMASS and ROSE-L, NASA-ISRO's NISAR, JAXA's ALOS-PALSAR). These missions have the potential to generate more accurate maps and change detection. It is critical that these missions deliver robust uncertainty quantification on



both biomass stocks and the change of biomass stocks between time points. This information would unlock the capability for biomass change and long-term trend information to reduce overall NBP uncertainty.

We need a similar global sensing effort towards advancing understanding of the state and dynamics of soils. Soil characteristics (e.g. soil C, hydraulic properties) are not easily monitored using EO. Over recent decades there have been substantial developments in soil C cycling models but there remains little agreement on the processes being simulated and their parameterisation (e.g., Exbrayat et al., 2013; Todd-Brown and Allison, 2013; Xenakis and Williams, 2014; Le Noë et al., 2023). Thus, alternate and novel approaches must be considered, such as improving theoretical understanding of soil decomposition processes and its interconnection with the magnitude and quality of its inputs (i.e. from biomass turnover), its environment and ecological variability by leveraging efforts to harmonizes soils data into more usable formats allowing discrimination between competing hypotheses (e.g., Hashimoto et al., 2015; Todd-Brown et al., 2022; Le Noë et al., 2023). Furthermore, similar to a recent study, we argue for improved soil monitoring including long-term longitudinal studies of both stock stocks, fluxes and characteristic in order to support theoretical development and model calibration (Buchkowski and A.Bradford., 2026).

4.4 Allocation of photosynthate and ecosystem residence times

Our analysis estimates the global average fractional allocation of NPP to foliage, wood and fine roots to be approximately equal (Table 5); but underpinned by substantial geographical variability (Fig. 8). As expected we find higher allocation of photosynthate to wood in forest-dominated areas, but the trade-off with foliar and fine root allocation is geographically distinct. Across high latitude areas high wood allocation corresponds with lower allocation to fine root, while over moist tropical forests it is allocation to foliage which tends to be lower. These allocation fractions are not well predicted using linear regression with meteorology, but they do combine to delineate an ecologically plausible phase space, i.e. biomes (Fig A7). A significant body of research on NPP allocation for forest ecosystems has been developed. These suggest an average allocation to wood which is slightly higher than either foliage or fine root (e.g., Lu et al., 2025), which is consistent with our findings. These studies also broadly agree that meteorology alone is a poor predictor of allocation patterns. Lu et al. (2025) combine in-situ estimates from 131 forest sites which defines a phase space (in their Figure 2) which is remarkably similar to that shown in our analysis (Fig. A7) offering further corroboration to the robustness of our ecological analysis.

Litter and soil dominate the spatial pattern of ecosystem MRT. Ecosystem MRT (i.e. biomass + DOM) increases towards the poles, most clearly seen towards the Arctic (Fig. 8) which is consistent with previous studies Carvalhais et al. (e.g., 2014). However, our analysis explicitly disaggregates the ecosystem level estimate into its component parts; the latitudinal gradient is primarily underpinned by soil and litter MRTs with distinct spatial patterns found in the various biomass pools (Fig. 8). That dead organic matter is a dominant factor in ecosystem level MRTs strongly supports the need for a greater focus on developing understanding of soil biogeochemistry to understand the global C cycle (e.g., Buchkowski and A.Bradford., 2026).

The MRTs of the biomass pools estimated here are not well predicted using linear regression with meteorological and disturbance forcing. Thus, biomass MRTs are determined by factors which are implicitly captured in the assimilated data and not explicitly represented, such as soil condition, disease, insect infestation etc. This result is also consistent with studies that suggest soil condition and nutrient limitation play an important role in determining MRTs (e.g., Galbraith et al., 2013; Xue



et al., 2017). However, Galbraith et al. (2013) and Xue et al. (2017) estimated contrasting continental differences between the Amazon and Congo from their respective sampling networks. Large relative and absolute uncertainties in MRT remains a challenge, often of a similar magnitude to the MRT estimate itself (Fig. A8). Uncertainties possibly explain the contrasting field based estimates, alternatively the representativeness of the sampling locations in their dataset may also contribute. Our analysis suggests that sampling locations may significantly impact the wider interpretation; substantially longer wood MRTs are estimated in western Congo than central Congo, and longer wood MRTs in north west and eastern Amazon with shorter values in central areas (Fig. A8).

5 Conclusions

Existing state-of-the-art geospatial information on LAI, fAPAR, woody biomass, soil C and LCA are inadequate to confidently (>95% CI) estimate net C sources and sinks across much of the vegetated land surface. Soil C dynamics are the largest source of uncertainty - highlighting the urgent need for a greater observational and theoretical understanding of soil and litter dynamics globally. There are significant uncertainties remain in biomass stock and dynamics but also the potential for significant EO activities underway or being implemented shortly to address this. We provide, to our knowledge, the most robust global spanning estimate of ecosystem NPP allocation and tissue mean residence times to exist - complete with uncertainty covariance information. Our novel dataset can support the evaluation of existing land surface models. It can also provide a baseline to quantify the information content of new satellite missions, e.g. for biomass, and support development of observing networks or targeted field campaigns to address key knowledge gaps.

Code availability. The CARDAMOM and DALEC software are available under open-source licence from Github with the specific code version used in the study found here (<https://github.com/GCEL/CARDAMOM/releases/tag/GCB2025>). Appropriate controlling R scripts can be assessed at repository under DOI <https://doi.org/10.7488/ds/8094> (Smallman et al., 2026) to support re-running of the retrieved parameter to support extraction of additional variables.

Data availability. The interested public should reach out to Edinburgh DataShare for data access <https://doi.org/10.7488/ds/8094> (Smallman et al., 2026). Note we also make available the DALEC4 model code and appropriate controlling R scripts are also available under the following doi to support re-running of the retrieved parameter to support extraction of additional variables.

Author contributions. TLS conceived the analysis. TLS conducted the analysis and wrote the 1st draft of the manuscript. All authors reviewed the manuscript and provided edits.



Competing interests. The authors declare that there are no competing interests.

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1 Appendix A

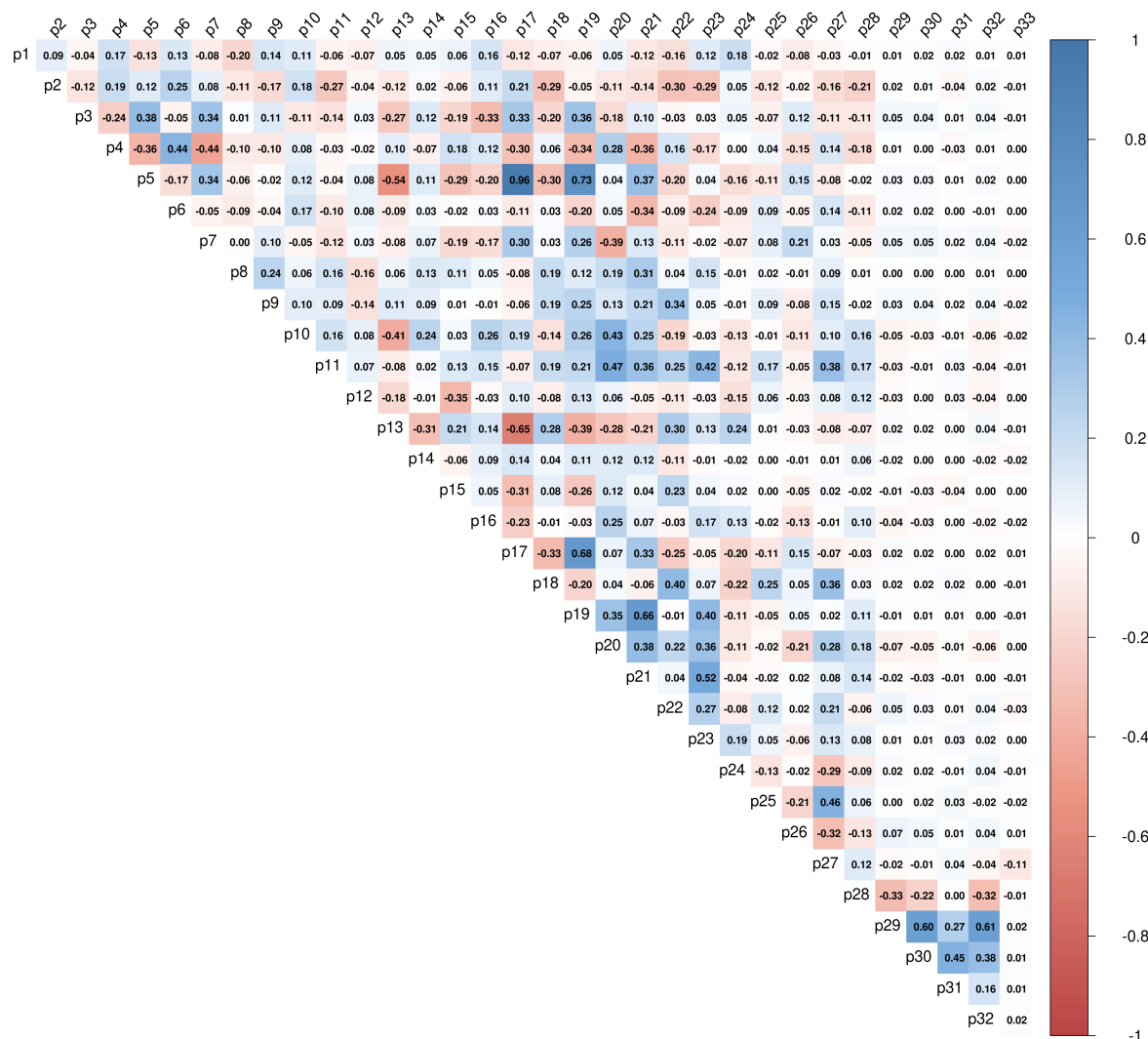


Figure A1. Spatial correlation matrix between parameter medians across the whole analysis. The 'p' numbers refer to the parameter numbers used in Table A1. Note that p33 refers to the log-likelihood scores calculated from comparisons with assimilated data.

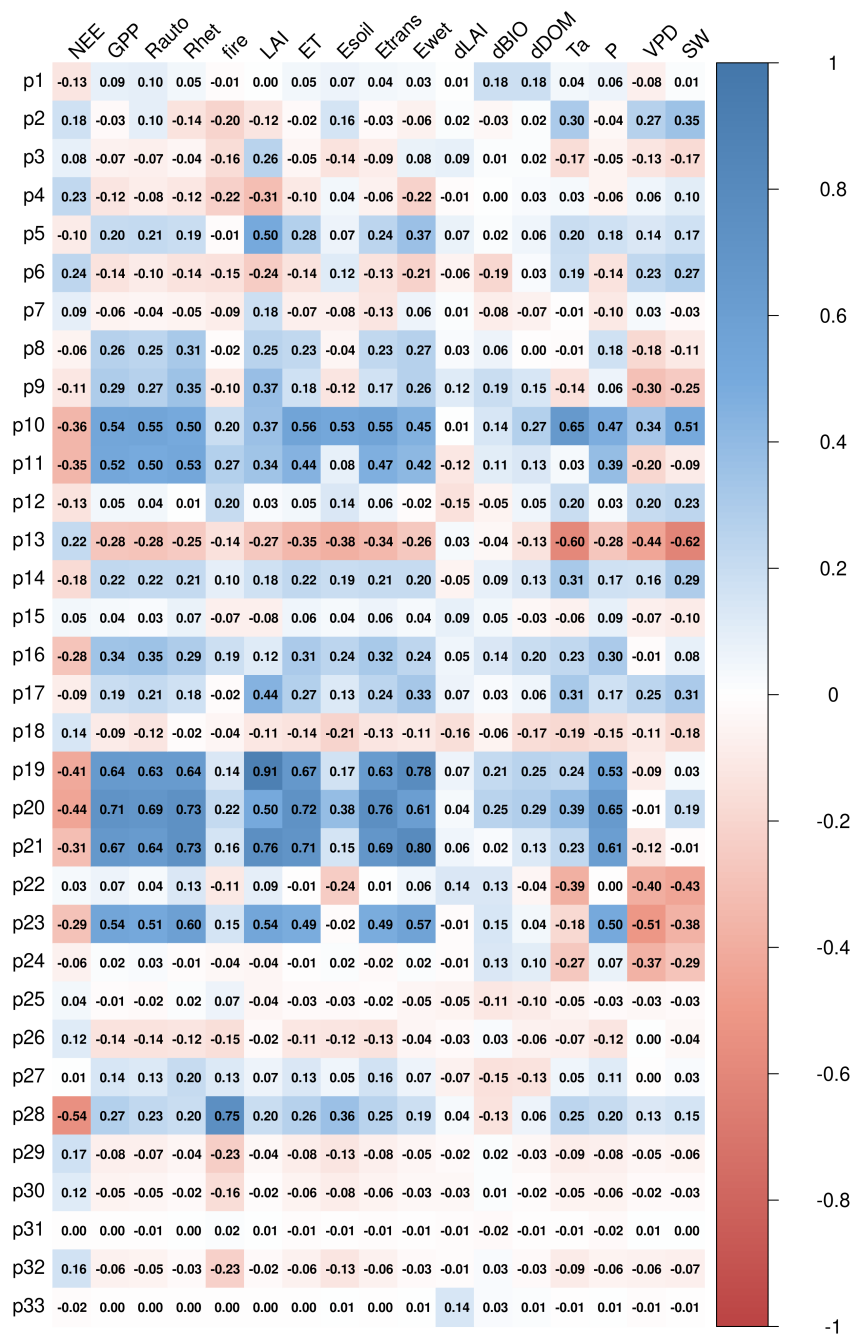


Figure A2. Spatial correlation matrix between parameter medians and median analysis outputs and forcings. The 'p' numbers refer to the parameter numbers used in Table A1. Note that p33 refers to the log-likelihood scores calculated from comparisons with assimilated data. Model outputs not described elsewhere are soil evaporation (Esoil), evaporation of canopy intercepted rainfall (Ewet), change in LAI (dLAI), biomass (dBIO) and dead organic matter (dDOM) over the analysis time period. Mean annual forcings are also correlated for air temperature (Ta), precipitation (Pa), vapour pressure deficit (VPD) and incoming shortwave radiation (SW).

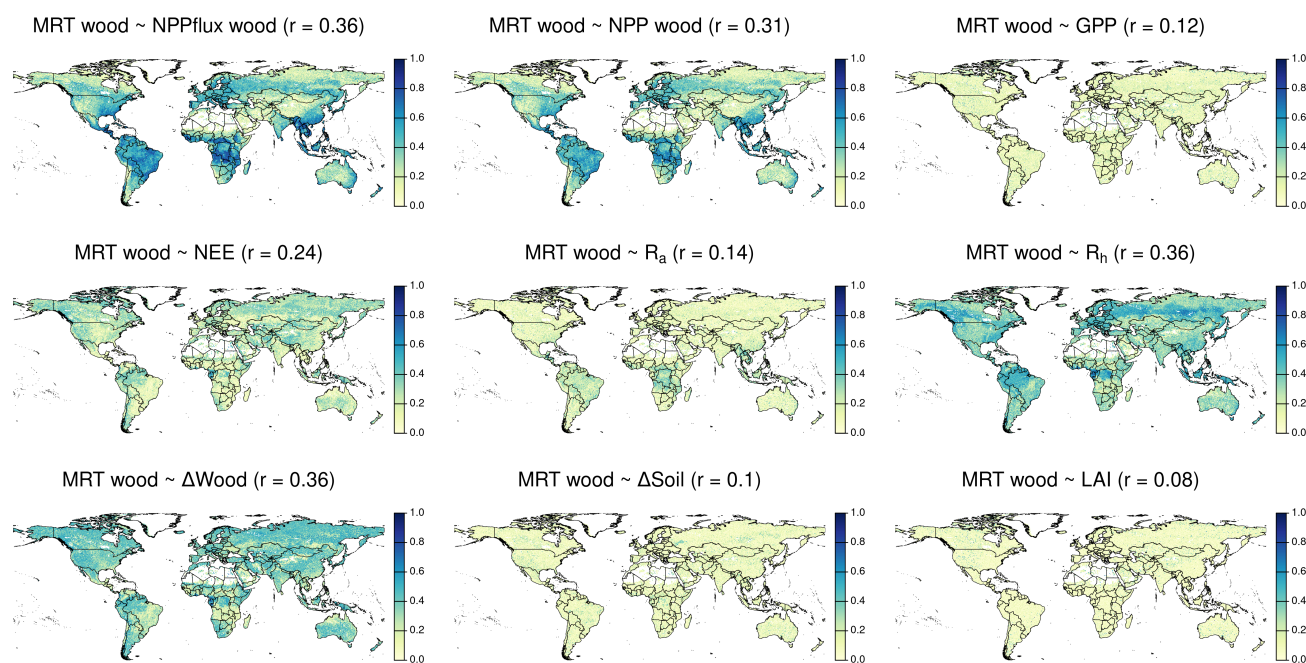


Figure A3. Maps of the absolute magnitude of pixel-level correlations between the mean residence time of wood (MRT wood) and the uncertainty in various observables (of various difficulty). High correlation is hypothesised to show a greater potential opportunity for adding additional constraint to the analysis. Therefore, the spatial variability delineates variable opportunity for different datasets to provide information. These correlations are calculated from the within-pixel parameter ensembles. Correlates not defined elsewhere are the absolute NPPflux to wood (NPPflx wood), fractional allocation of NPP to wood (NPP wood).

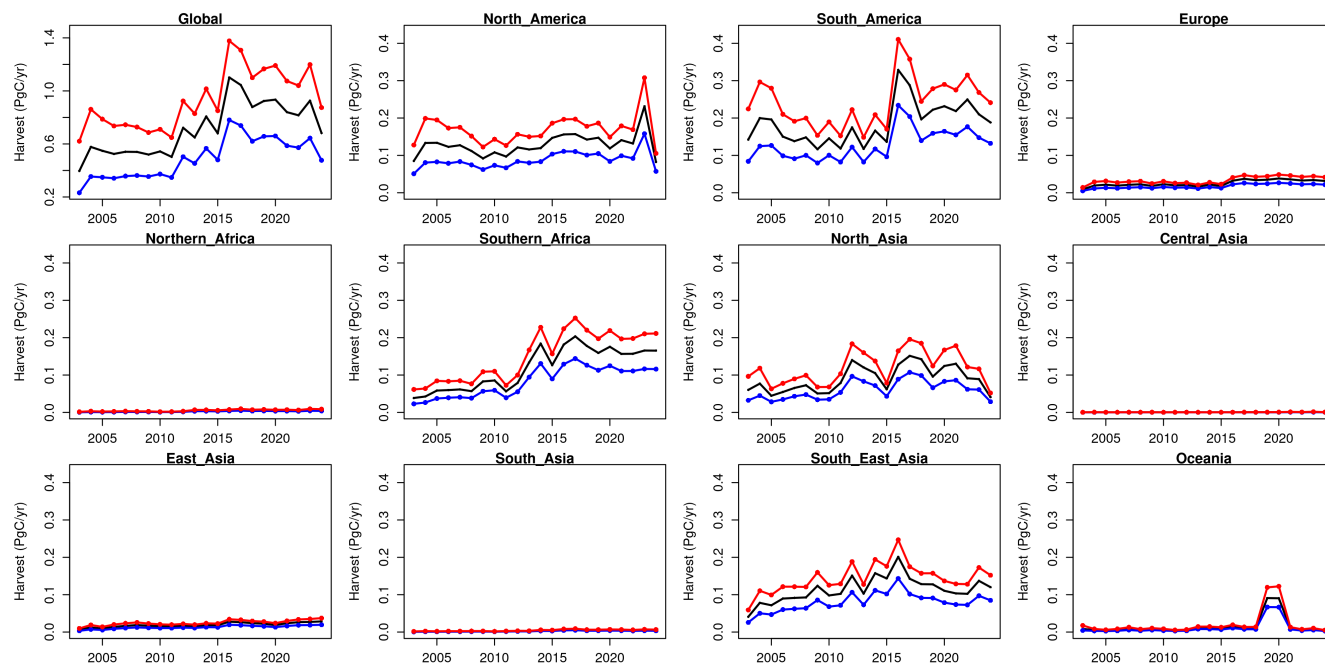


Figure A4. Time series of carbon extracted from ecosystems as the result of LUC driven harvest activity - i.e. deforestation and degradation. The top-left plot shows the global total. All other plots show one of the RECCAP regions, except 'Oceans' which is excluded due to this domain being dominated by islands many of which are smaller than the pixel size of the analysis. The black line shows the aggregate of the pixel-level medians. The red and blue lines show the aggregate of the 97.5 % and 2.5 % quantiles respectively, defining the 95 % CI.

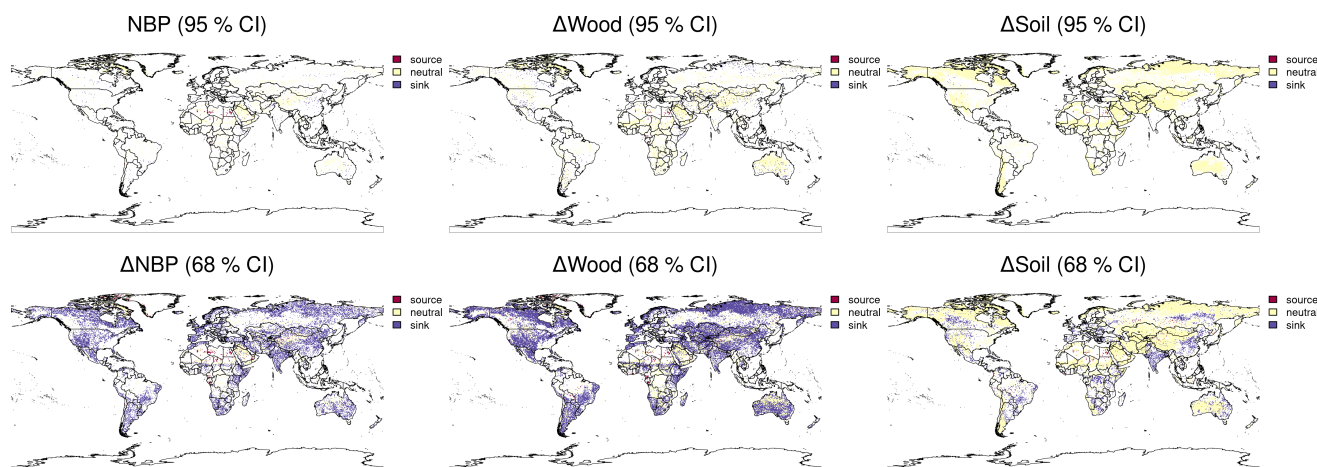


Figure A5. Maps show the areas classified as a net source / sink / neutral at the 95 % confidence level (top) and 68 % confidence level (bottom). Note the IPCC define 'likely' as > 68 % confidence and > 95 % confidence as 'very likely'.

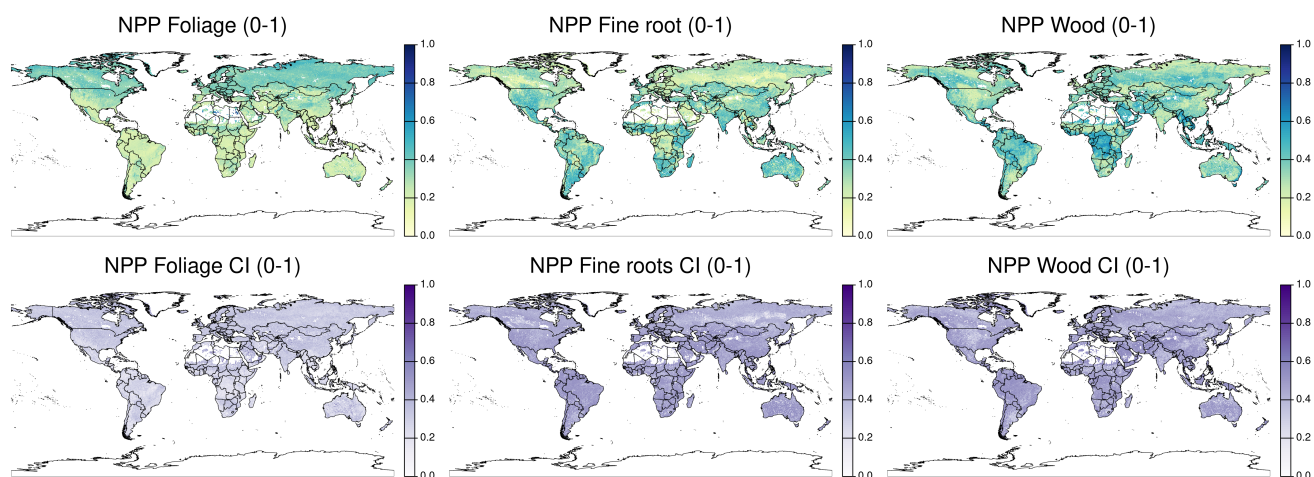


Figure A6. Maps of the pixel-level median estimates of NPP allocation fractions (top row) and corresponding 95 % confidence intervals (bottom row) for foliage, fine roots and wood.

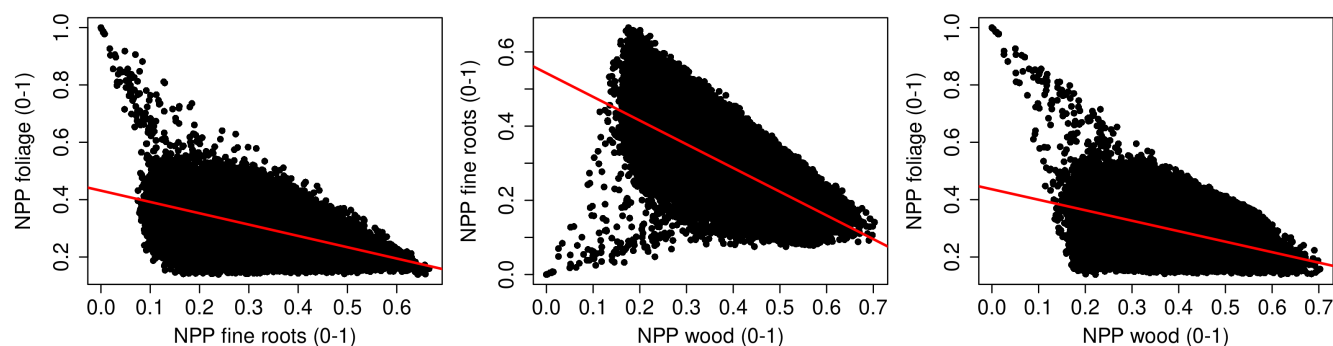


Figure A7. Trade-off between the pixel-level median estimates for NPP fractional allocations.

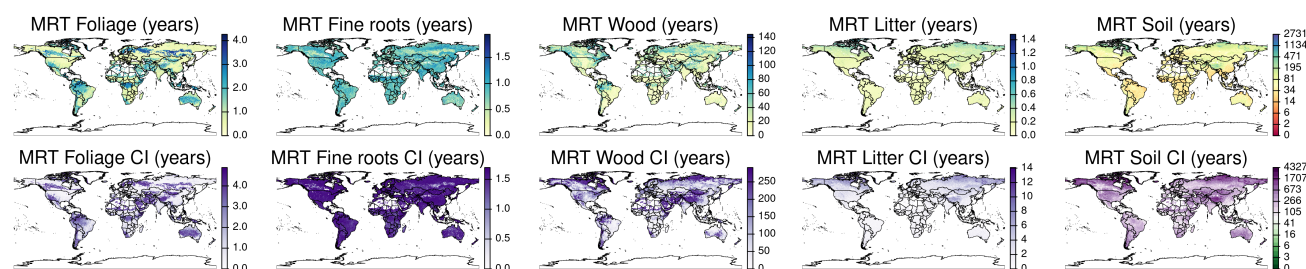


Figure A8. Maps of the pixel-level median estimates of mean residence times (MRT, years) (top row) and corresponding 95 % confidence intervals (bottom row) for foliage, fine roots, wood, litter and soil organic matter.



Table A1. A list of all DALEC4 parameters. This information includes the nominal-in code parameter number, a description, minimum and maximum prior ranges for CARDAMOM to search. The list is divided between process parameters (top section) and the initial conditions (bottom section). Our use of the in-code parameter numbering means that the numbers in the list are not sequential between the process parameter and initial conditions sections. We use the in-code numbering to support those wishing to engage with the raw parameter output or interested in conducting a CARDAMOM analysis. Note that the fractional allocation of GPP is applied sequentially, in order to R_a , foliage, labile, fine roots with the residual to wood.

	Min	Max	Units	Description
Process parameters				
1	1.141×10^{-4}	0.02	0-1	Baseline daily fractional loss of fine litter decomposition to soil organic matter.
2	0.2	0.8	0-1	Fractional allocation of GPP used for R_a , the R_a :GPP.
3	0.1	0.5	0-1	Fractional allocation of GPP to foliage.
4	0.1	0.8	0-1	Fractional allocation of GPP to fine roots.
5	1.001	6.0	years	Inverse of the annual fractional canopy loss.
6	9×10^{-6}	0.001	0-1	Daily fractional loss of the total woody pool.
7	0.00137	0.02	0-1	Daily fractional loss of the fine root pool.
8	1.14×10^{-4}	0.02	0-1	Baseline daily fractional loss of fine litter mineralisation to R_h .
9	1.37×10^{-6}	9.13×10^{-5}	0-1	Baseline daily fraction loss of soil organic matter mineralisation to R_h .
10	0.019	0.08	-	Exponential coefficient providing temperature modification to parameters 1,8 & 9.
11	10	100	$\text{gCm}^{-2} \text{leaf} \text{d}^{-1}$	Theoretical potential photosynthetic capacity per unit leaf area index.
12	1	366	day	Day of year at which max rate of labile to foliage occurs.
13	0.01	0.5	0-1	Fractional allocation of GPP to labile.
14	10	100	day	Number of days over which labile to foliage occurs.
15	1	366	day	Day of year at which max rate of foliage to litter occurs.
16	20	150	day	Number of days over which foliage to litter occurs.
17	20	180	gCm^{-2}	Leaf carbon per unit area. The inverse of the specific leaf area.
25	0.15	0.5	0-1	Fraction of wood pool assumed to be below ground, i.e. coarse root.
26	100	2500	gm^{-2}	Coarse root biomass needed to reach 50 % of max rooting depth.
27	0.35	20	m	Maximum rooting depth.
28	0.01	0.9	0-1	Biomass resilience to post fire mortality.
29	0.01	0.99	0-1	Combustion completeness of burned foliage.
30	0.01	0.99	0-1	Combustion completeness of burned fine root and wood.
31	0.01	0.1	0-1	Combustion completeness of burned soil organic matter.
32	0.01	0.99	0-1	Combustion completeness of burned foliage & fine root litter.
Initial conditions				
18	1	2000	gCm^{-2}	Initial size of the labile C pool
19	1	2000	gCm^{-2}	Initial size of the foliage C pool
20	1	2000	gCm^{-2}	Initial size of the fine roots C pool
21	1	30000	gCm^{-2}	Initial size of the total woody C pool
22	1	2000	gCm^{-2}	Initial size of the fine litter C pool
23	200	250000	gCm^{-2}	Initial size of the soil organic matter C pool
24	0.05	1	$\text{m}^3 \text{m}^{-3}$	Initial size of the soil water pool



Table A2. Global and RECCAP region simulated land areas in metre squared (m^2). Provided also are the RECCAP region codes used throughout this study.

Stocks	RECCAP code	land area (m^2)
Global	-	120,530,825,704,344
North America	NA	20,262,534,479,273.7
South America	SA	17,241,838,550,072.6
Europe	EU	5,479,103,226,878.94
Northern Africa	NAf	8,369,107,992,381.5
Southern Africa	SAf	14,086,068,596,845.6
North Asia	NAs	16,218,715,135,956.9
Central Asia	CA	9,713,044,894,410.43
East Asia	EA	11,075,033,831,550.4
South Asia	SAs	4,296,286,895,590.4
South East Asia	SEA	4,165,605,520,816.29
Oceania	OCe	7,462,147,308,660.9