→ EARTH OBSERVATION SUMMER SCHOOL

Earth System Monitoring & Modelling

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Combining models and data to quantify the terrestrial carbon cycle

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National Centre for Earth Observation
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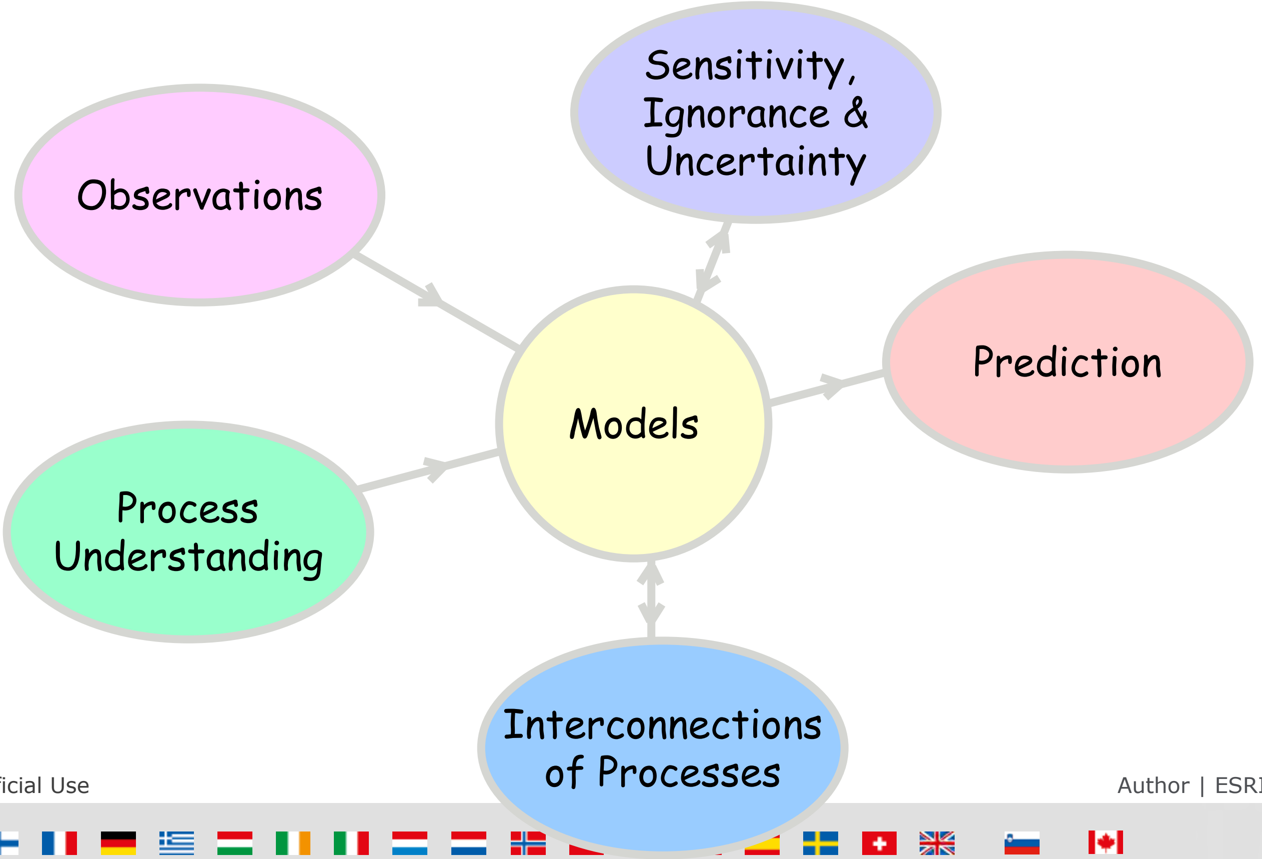
Lecture content

1. What a C model has to do
2. Types of C models
3. Interfacing data to models: concepts and examples

A Systems Approach Implies Models



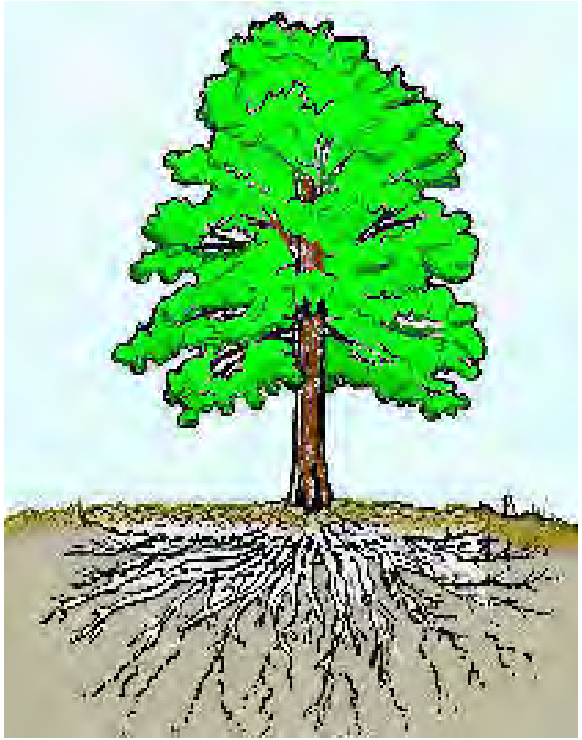
Timescale of models

Change in emphasis from prediction out to 2100 to regional & decadal prediction

Implications:

1. For century scale prediction, asymptotic behaviour matters, not initial conditions
2. For decadal prediction, initial conditions are critical. This changes totally the relation between models and data and the needs of models for data, and makes EO data an essential part of the process.

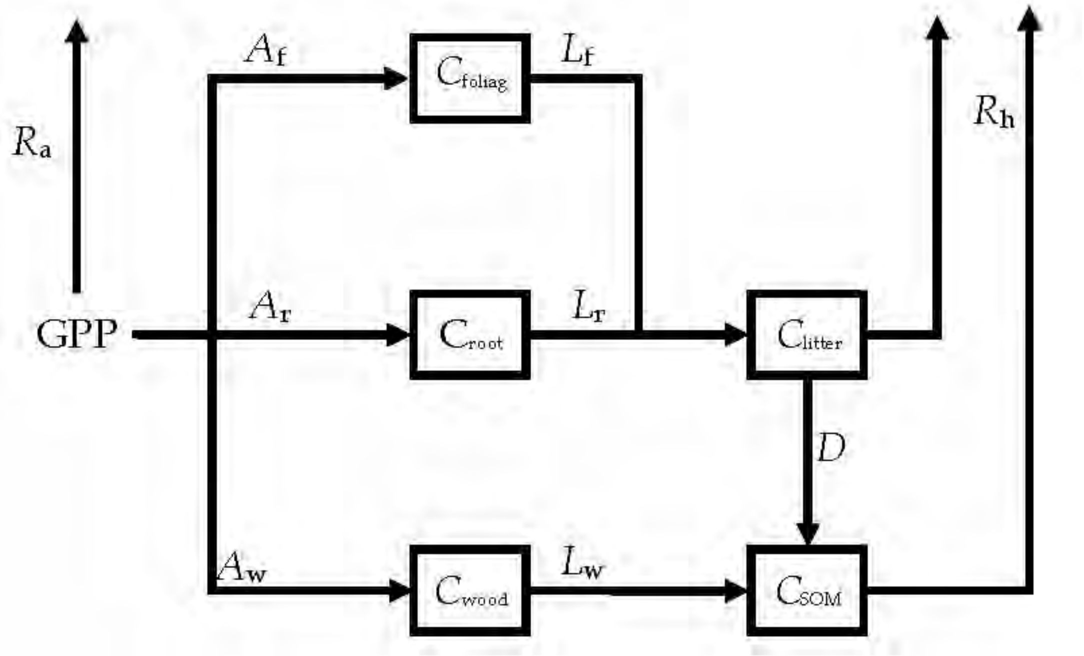
The Role of Vegetation & Soils in the C Balance



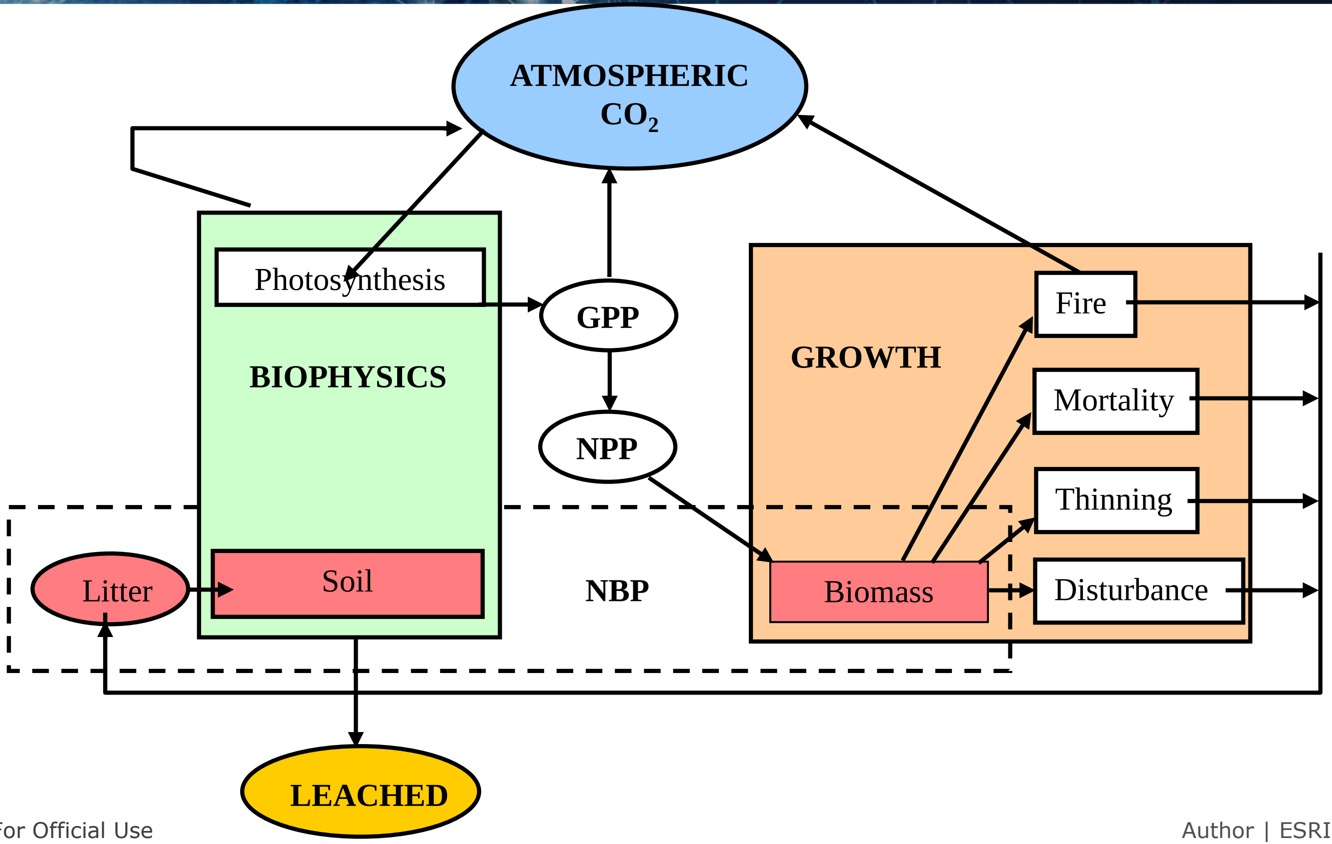
Terms:

- Above Ground Biomass (AGB)
- Above Ground Biomass (BGB)
- Litter
- Soil Carbon (Organic Matter: SOM)
- Leaves
- Fine Roots

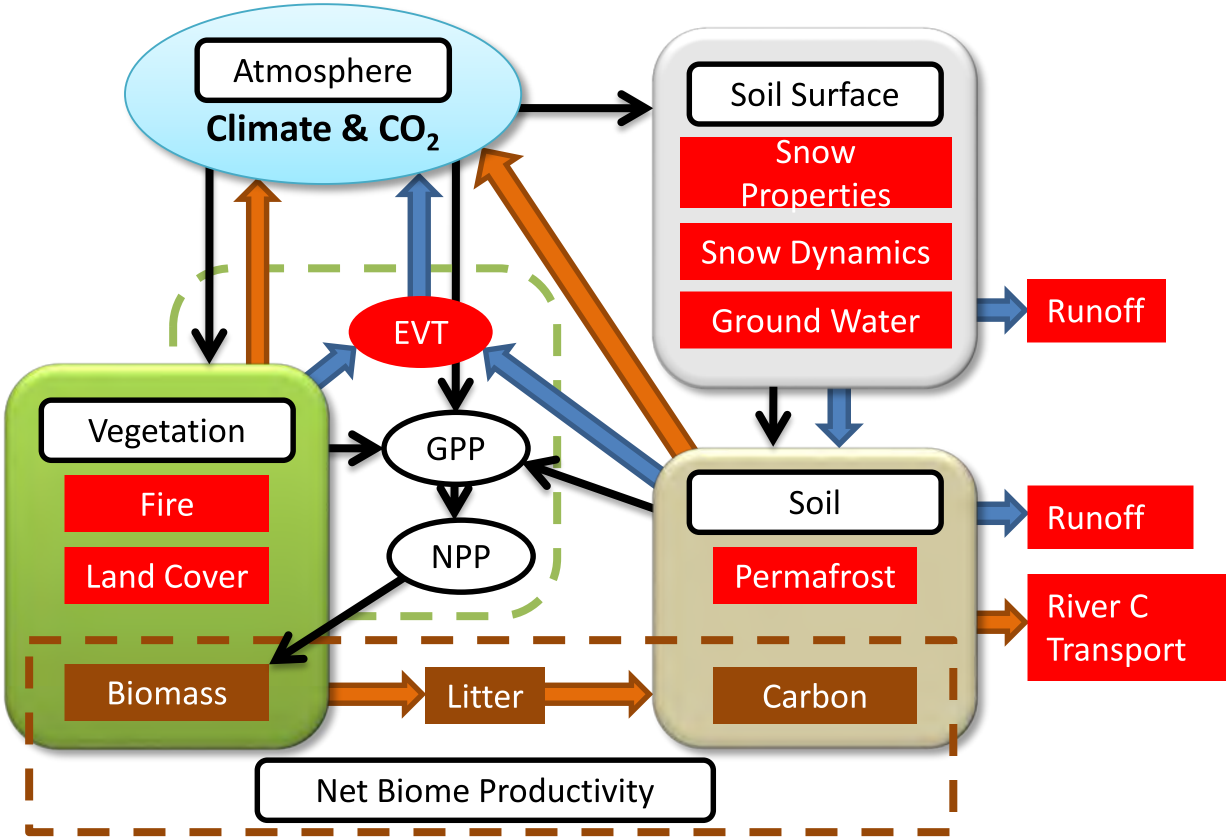
Generic model of carbon flows through an ecosystem



Dynamic Vegetation Model (DVM)



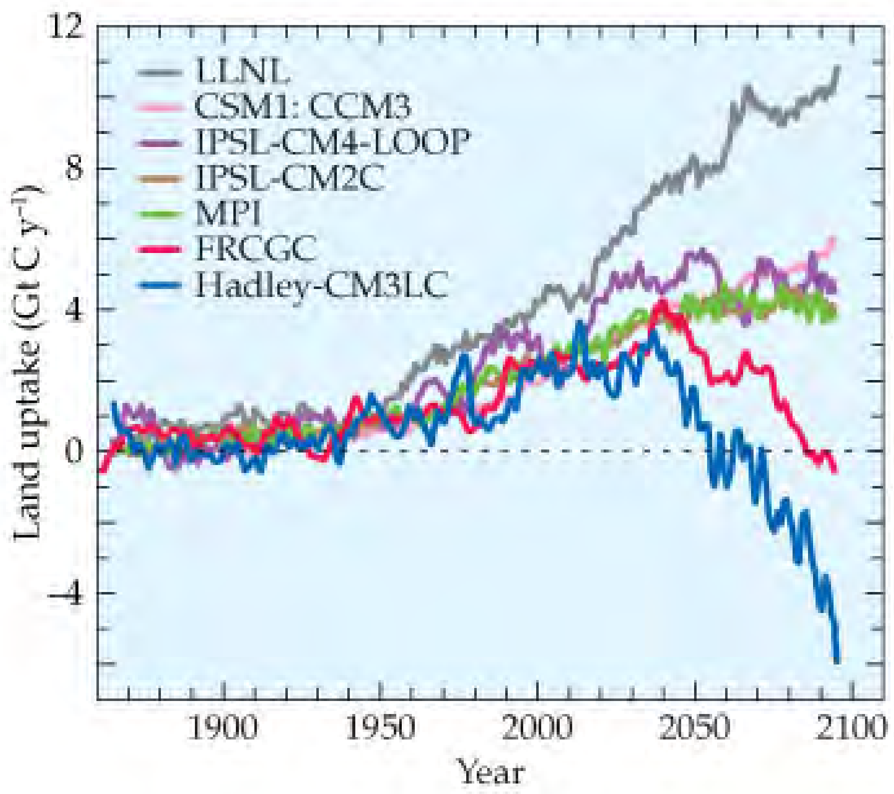
Terrestrial C-water model



Carbon flux models

- ESM carbon flux models developed mainly to investigate the response of the land and ocean to climate change.
- Intended to be **predictive**, hence parameterised rather than data-driven.
- Designed for a data-poor environment.
- Land models extended to allow full climate-land surface coupling so that climate-carbon cycle feedbacks can be taken into account.

Should carbon models worry only about fluxes?



Weaknesses of these models:

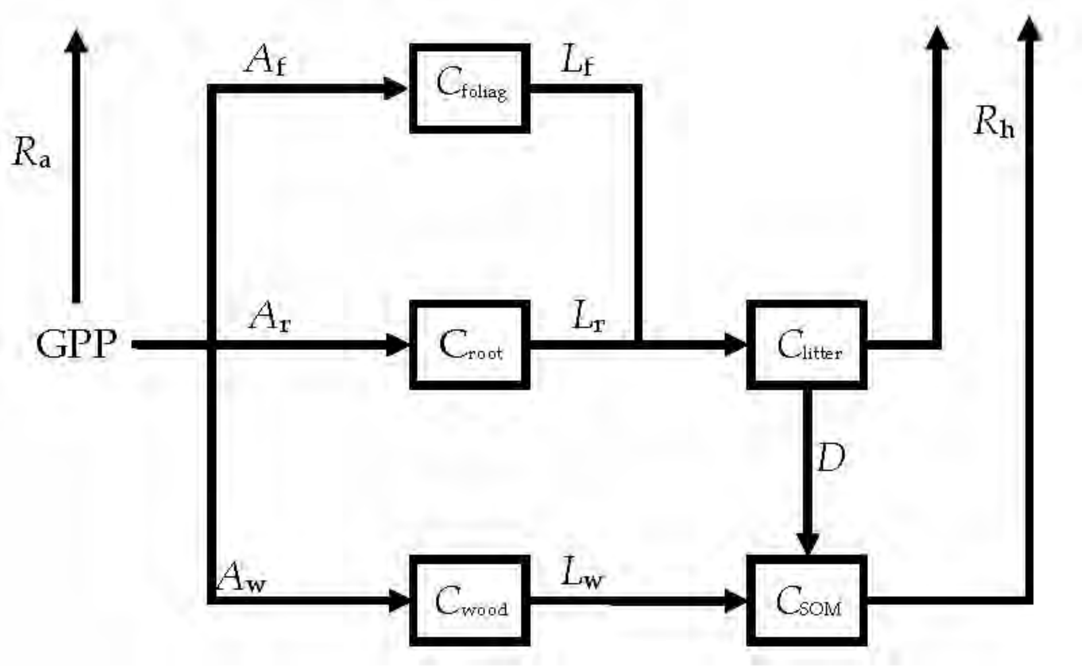
1. Not constrained by data
2. Behaviour is entirely controlled by internal parameters and climate
3. Focus on C fluxes, not C pools

Why C pools matter: C residence time is a key variable

The importance of getting the pools right becomes manifestly clear from a key finding of Friend et al. (PNAS 2014):

Carbon residence time dominates uncertainty in terrestrial vegetation responses to future climate and atmospheric CO2.

Residence time is a simple consequence of the generic model



Make the reasonable assumption that the loss rate from a pool is proportional to the size of the pool, i.e.

$$L = C/\tau$$

where τ is the residence (turnover) time. Then the equilibrium size of the pool is τP, where P is the mean input into the pool.

Estimating residence time

For the biomass pool, *B*, then in steady state,

$$B = \tau_B P_B$$

where P_B is mean production of biomass = NPP.

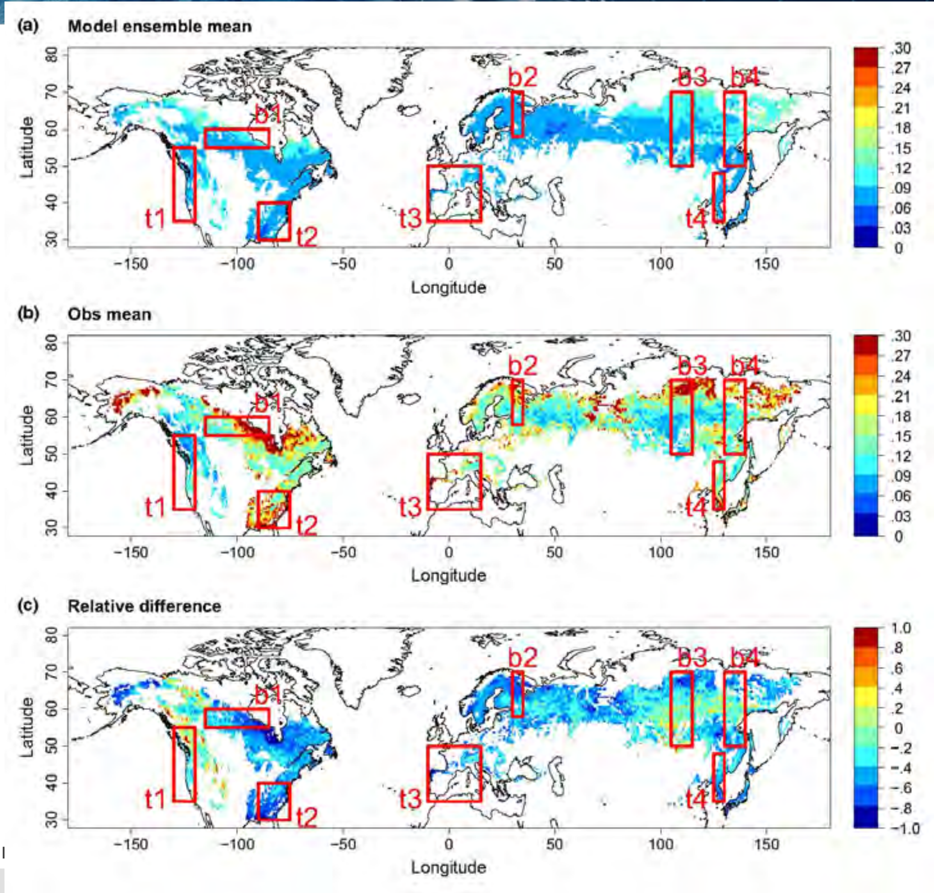
So we would expect: biomass $\propto$ NPP

If the fraction of NPP allocated to **above-ground biomass** (AGB) is constant and known (= f_B) we would then expect

$$AGB \propto f_B \, NPP$$

Then C residence time = $AGB/(f_B \, NPP)$

Carbon turnover rate (NPP/biomass)



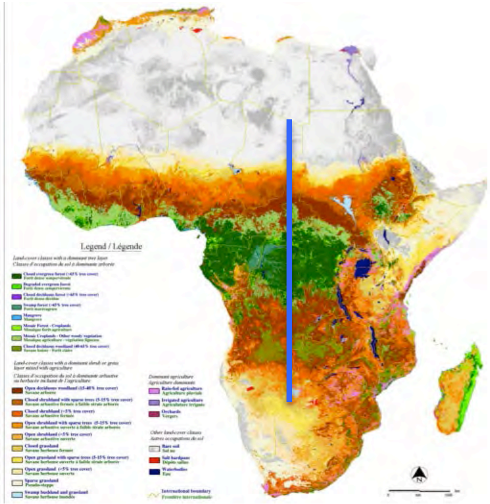
Modelled

"Observed" = NPP (MODIS)/ biomass (Envisat)

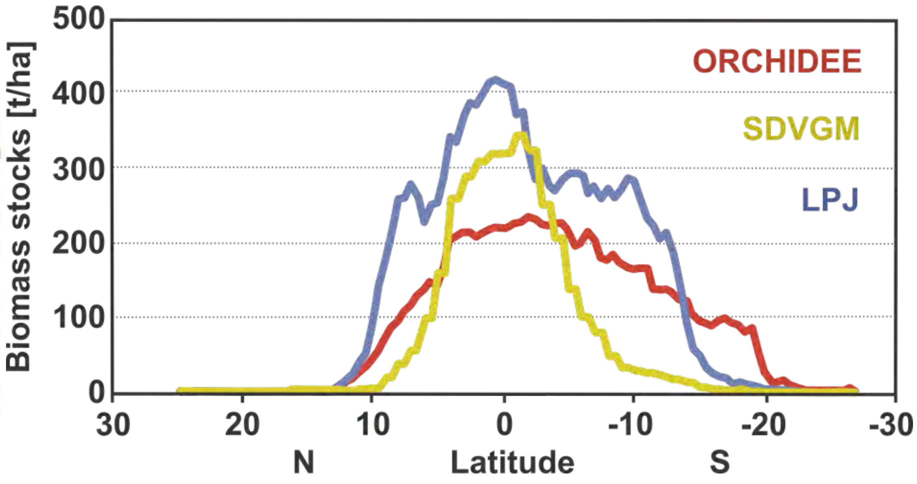
Relative difference

Thurner et al. 2017

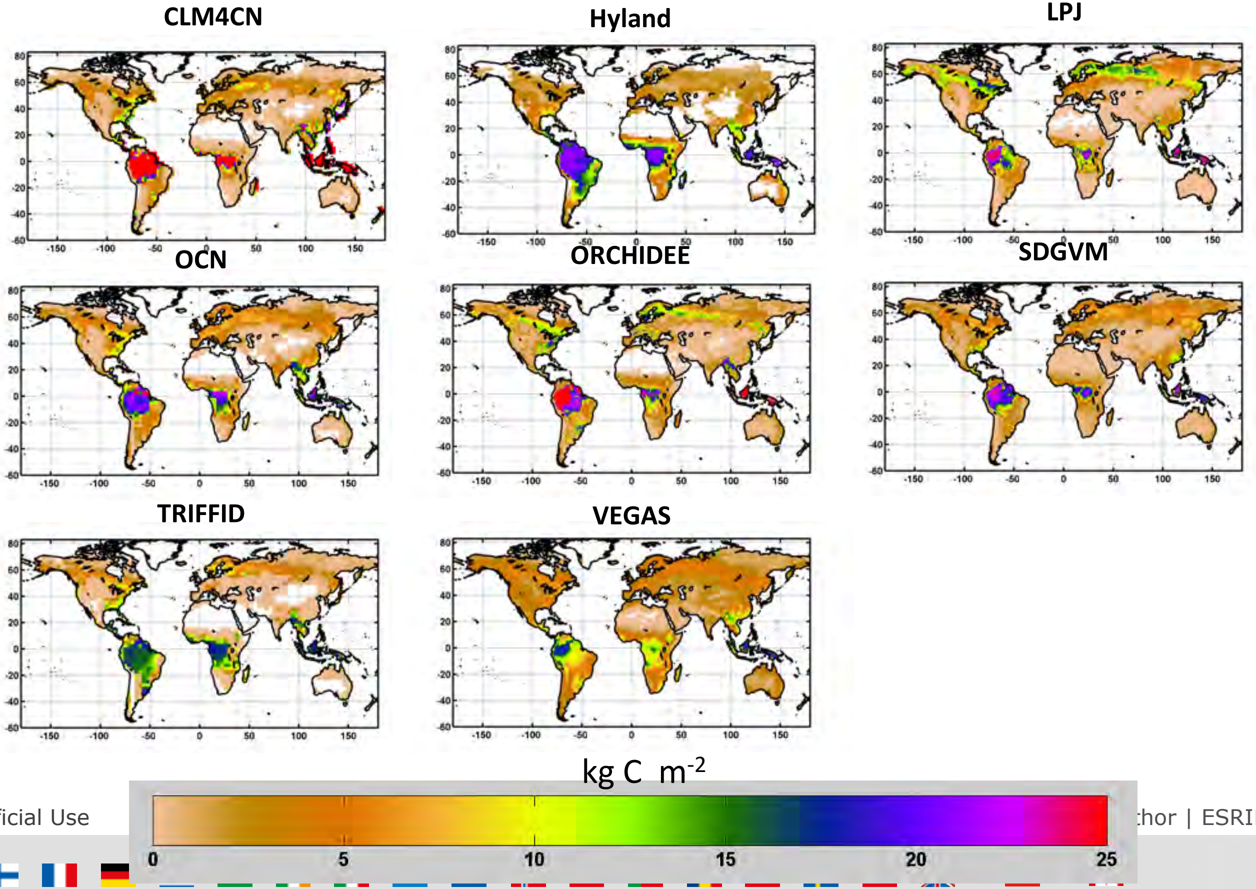
Models disagree sharply on biomass distribution ……



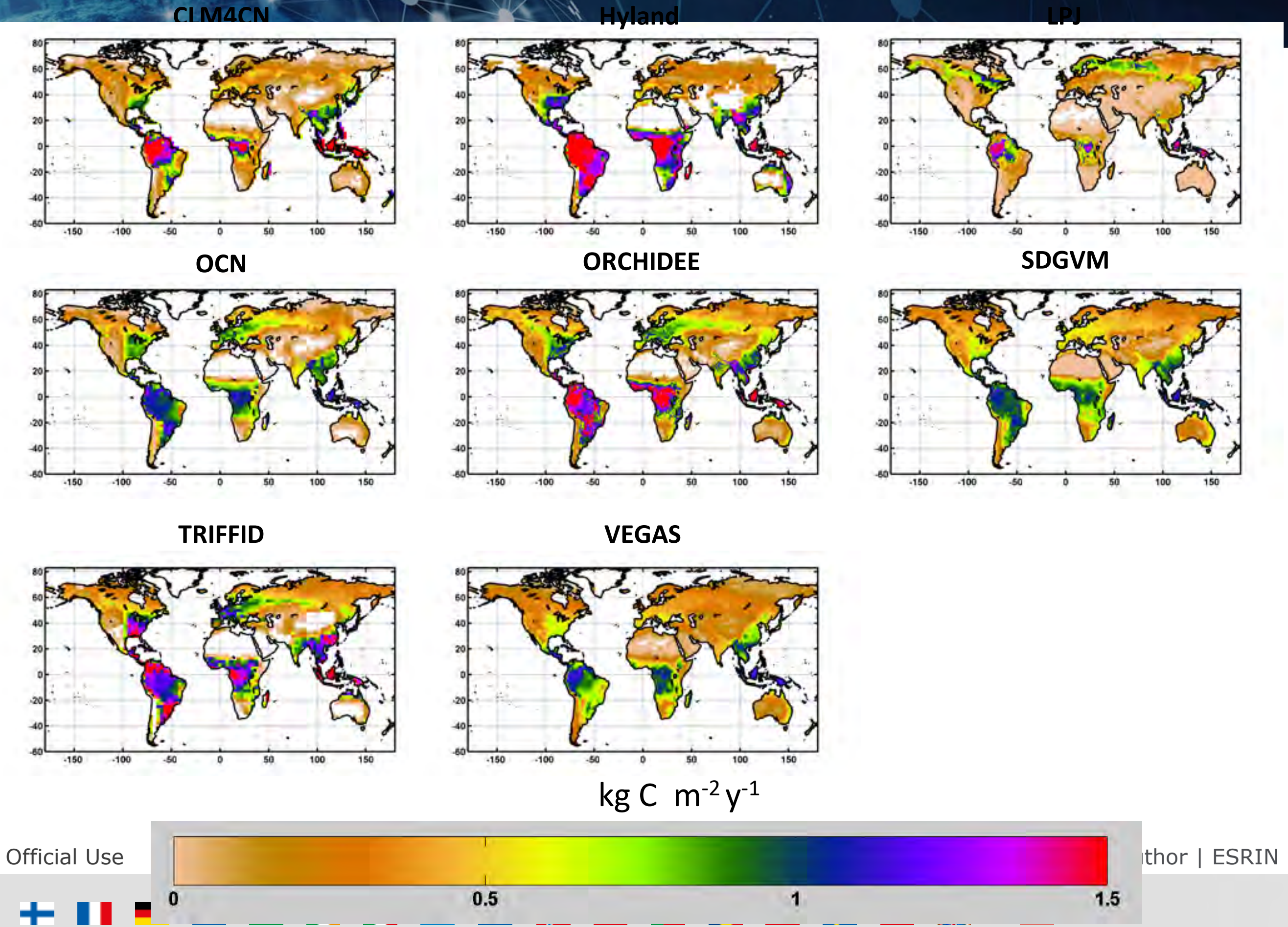
Biomass estimates from 3 state-of-the-art Dynamic Vegetation Models



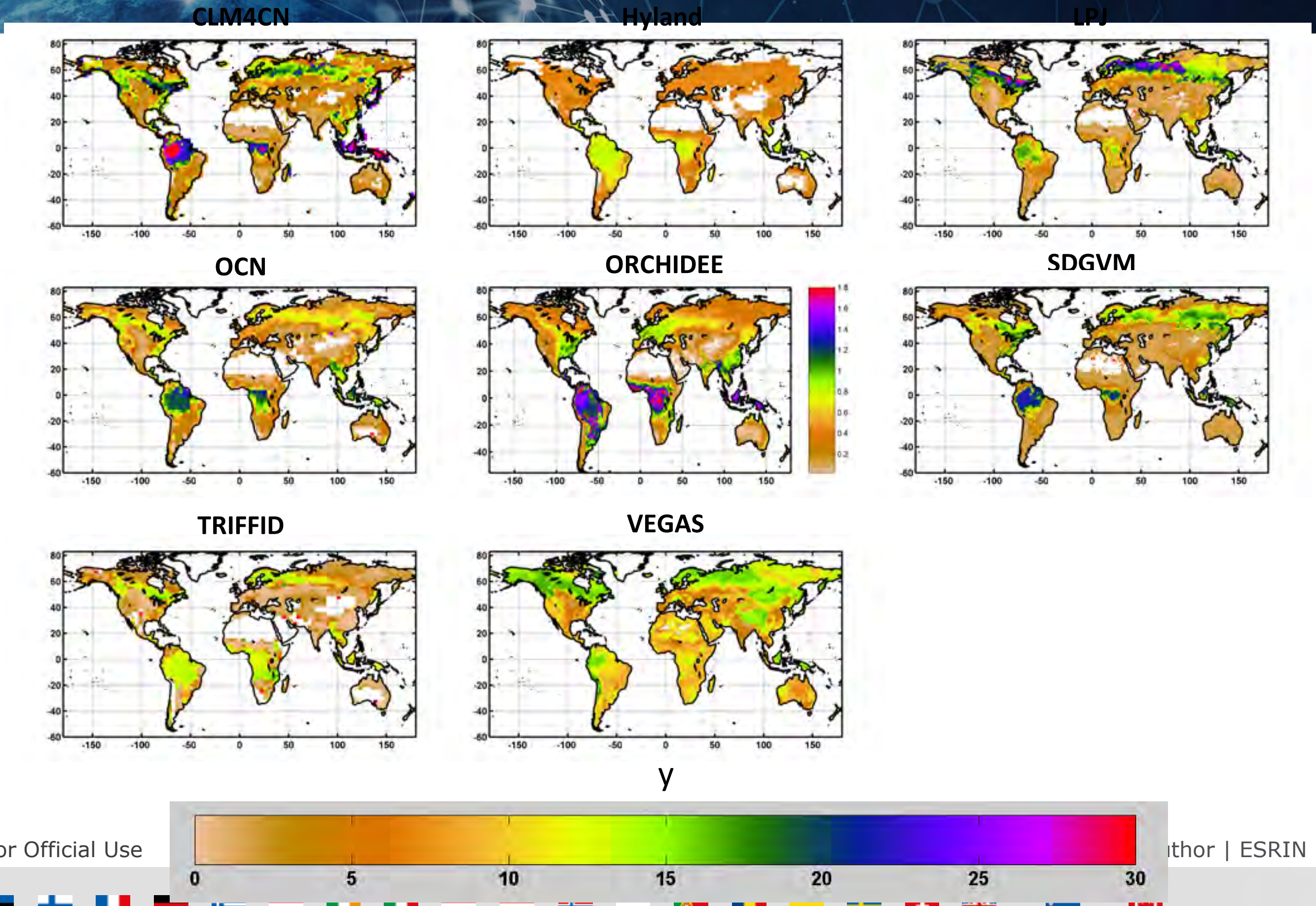
Carbon cycle models need to be evaluated against independent biomass maps


CLM4CN
Hyland
LPJ
OCN
ORCHIDEE
SDGVM
TRIFFID
VEGAS
kg C m-2
0
5
10
15
20
25

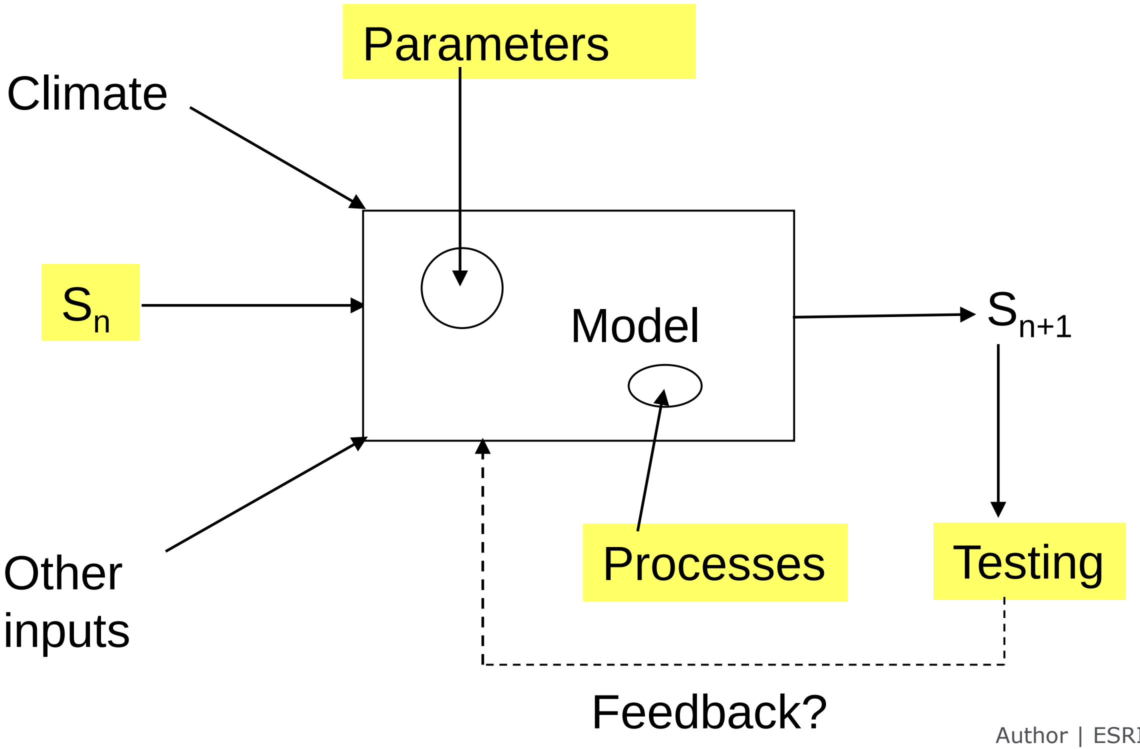
NPP


CLM4CN
Hyland
LPJ
OCN
ORCHIDEE
SDGVM
TRIFFID
VEGAS
kg C m-2 y-1
0
0.5
1
1.5

TRENDY estimates of C_{veg} / NPP (residence time)

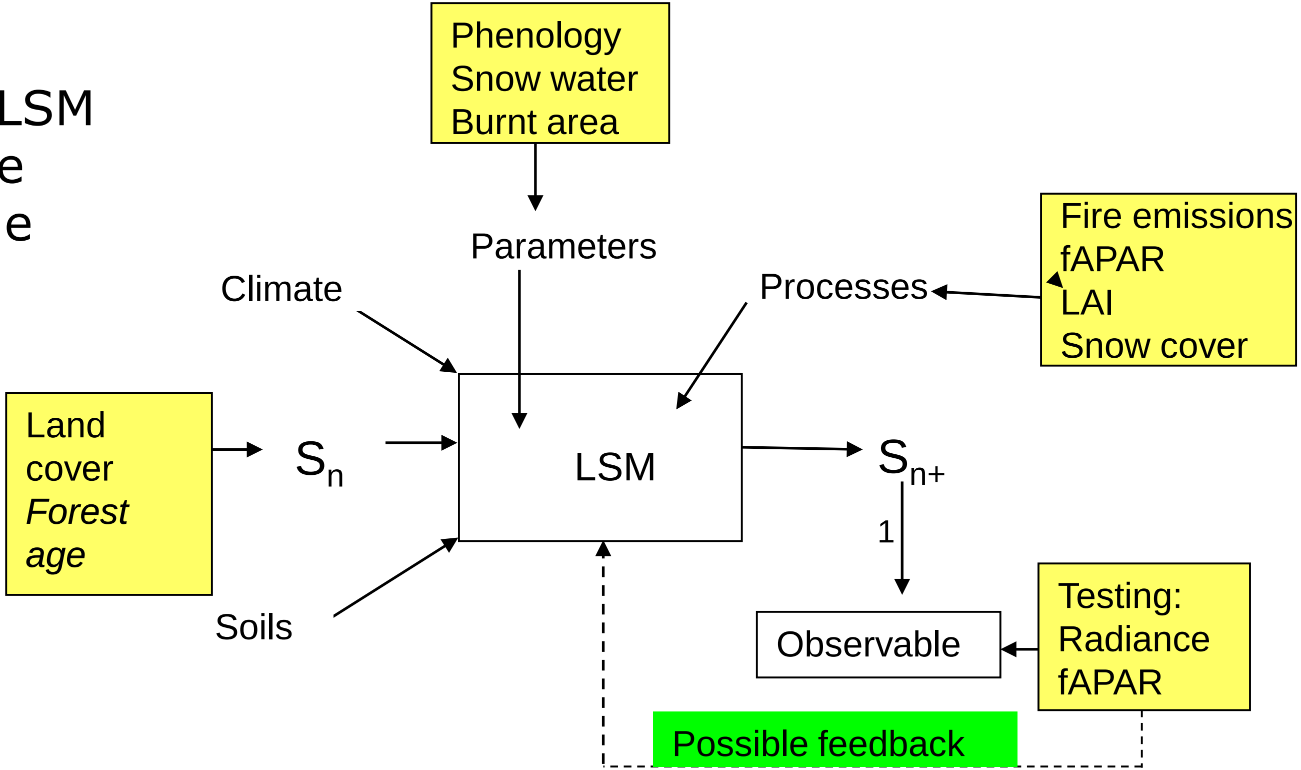


How can data affect a carbon flux model?

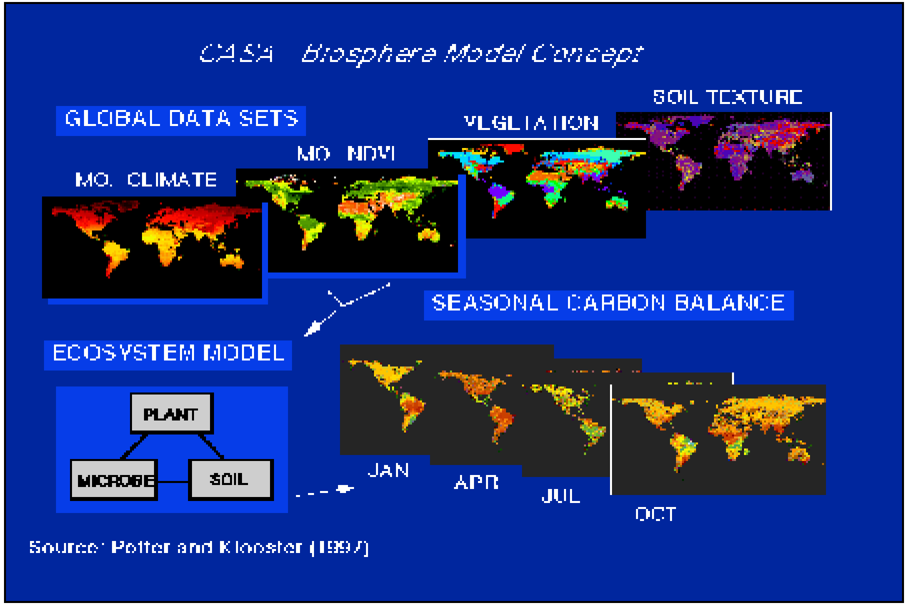


EO interactions with a Land Surface Model

Basic spatial scale of the LSM is the climate grid-cell scale



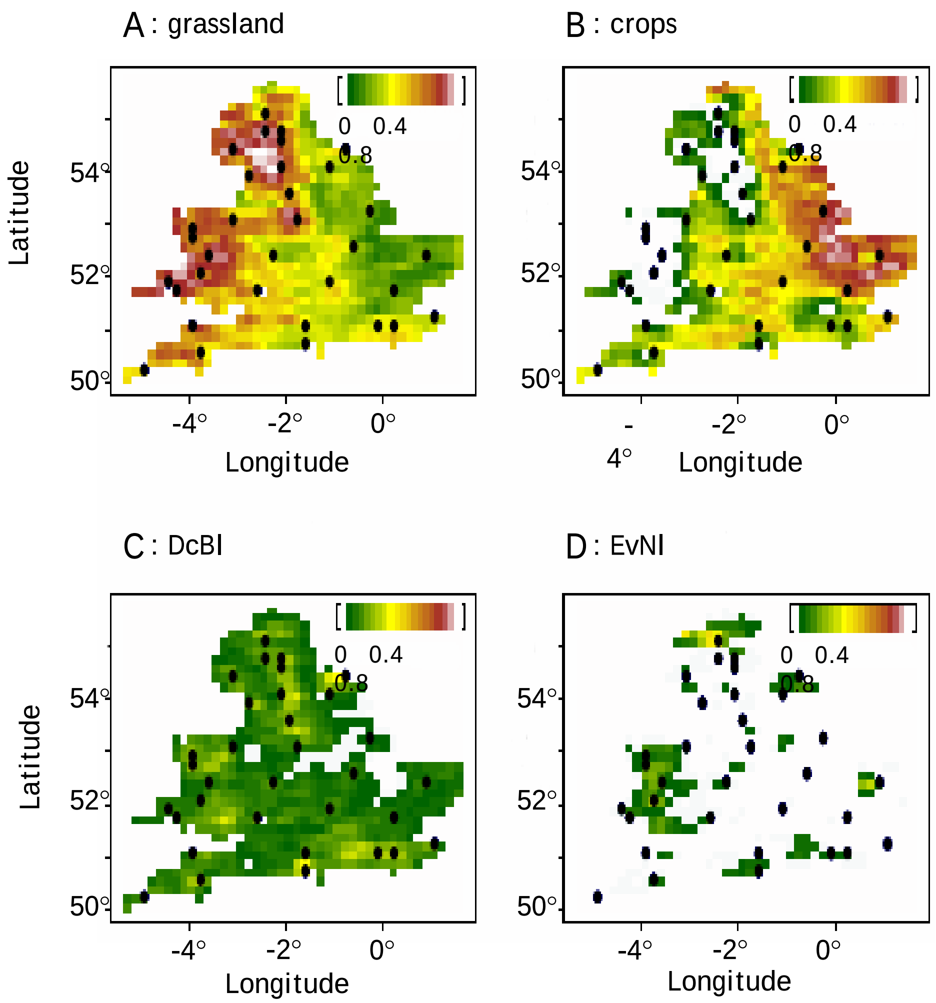
CASA: a Light Use Efficiency Model



Light Use Efficiency:

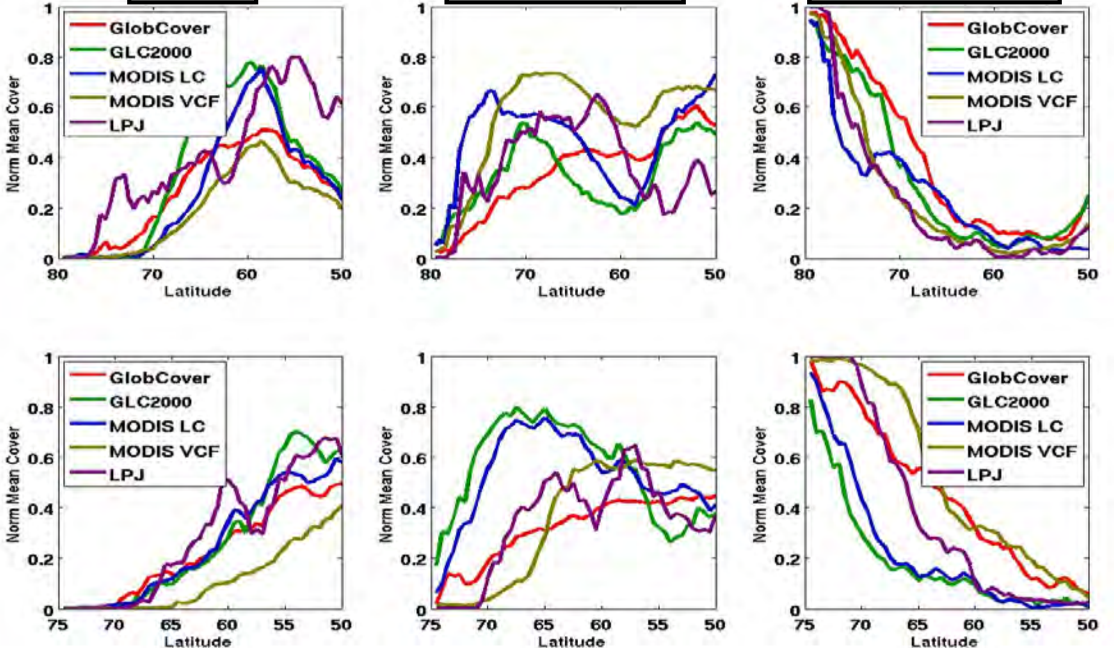
$$GPP = \varepsilon \times PAR \times fAPAR$$

$$\varepsilon = \varepsilon_{max} \times f_t \times f_w$$


A : grassland
B : crops
C : DcBl
D : EvNl
0 0.4 0.8
Latitude
Longitude
54°
52°
50°
-4°
-2°
0°

Land Cover by Latitude Bands

Trees | **Herbaceous** | **Bare Ground**

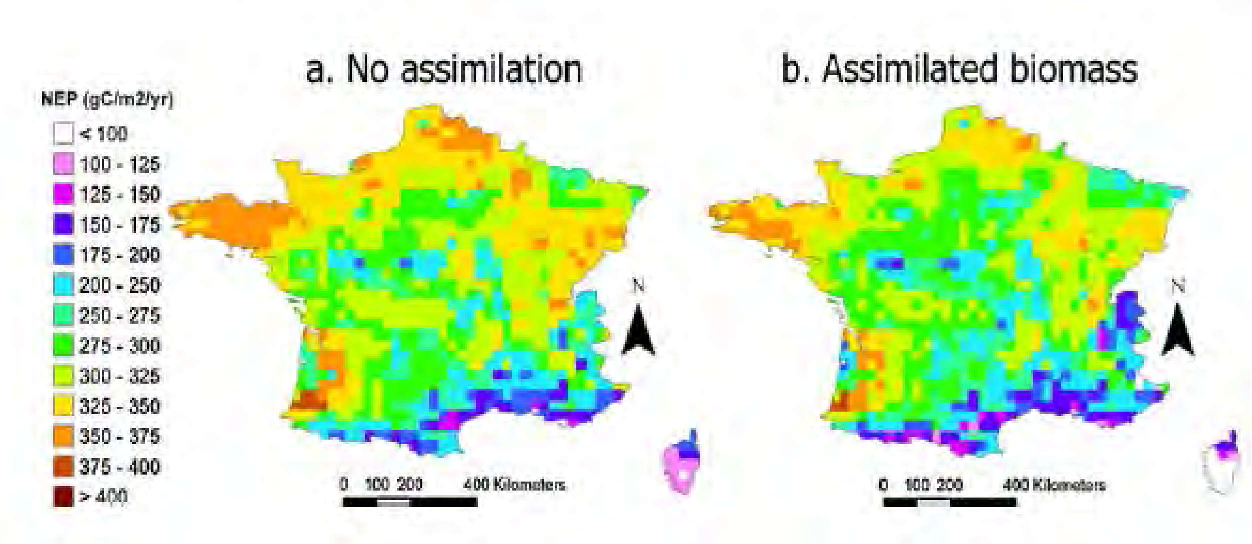


Eurasia

N. America

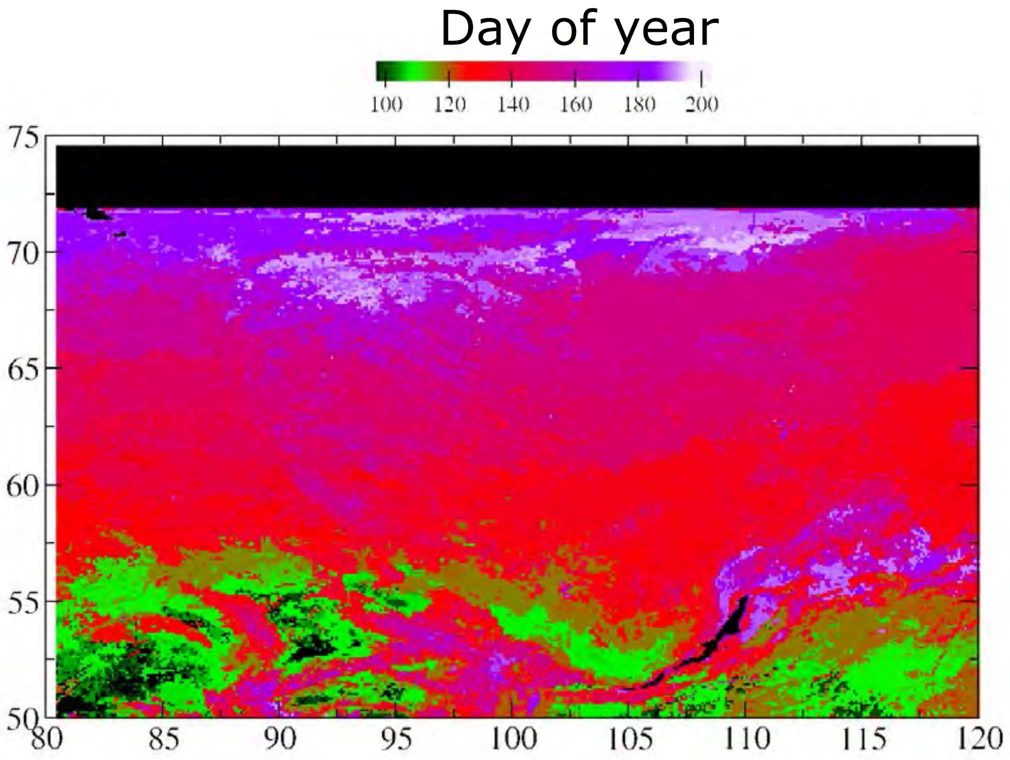
Key Messages:	•Driving the models with different land cover data sets causes the NBP to differ by up to 30%. •Water fluxes remained largely unchanged.

Initialising models using biomass data



NEP simulated by ORCHIDEE-FM with (b) and without (a) input age maps reconstructed from biomass data (Bellassen 2012)

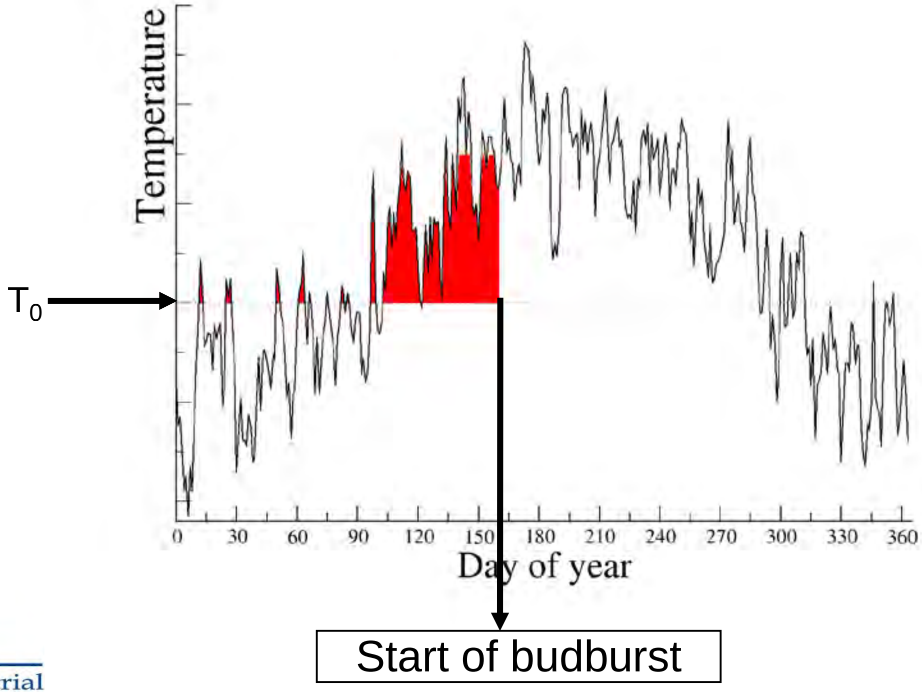
The Date of budburst derived from minimum NDWI (VGT sensor, 2000)



The spring warming budburst algorithm

When $\sum_{days} \min(0, T - T_0)$ > Threshold, budburst occurs.

The sum is the red area. Optimise over the 2 parameters, Threshold and T_0 (minimum effective temperature).



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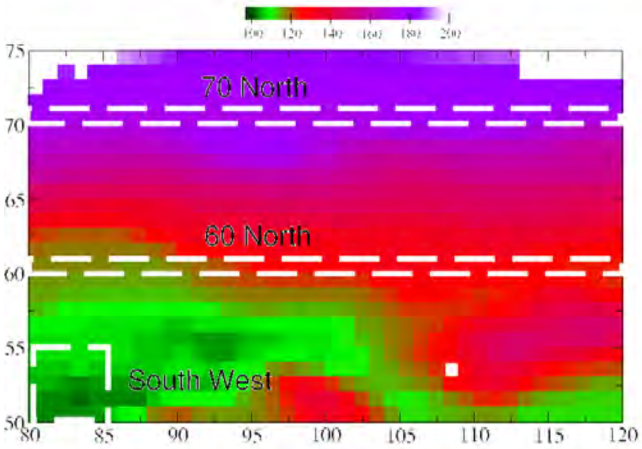
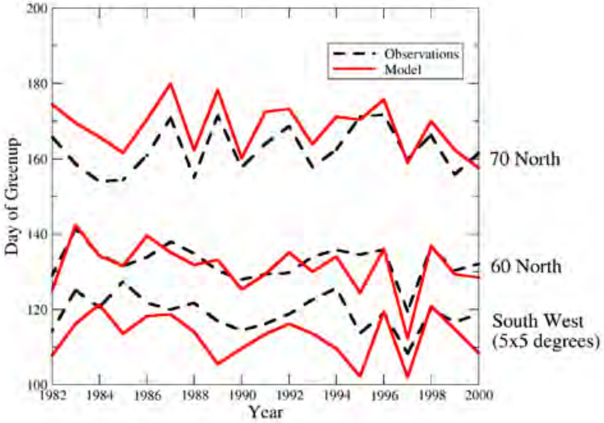
Spatial variation of model-data fit





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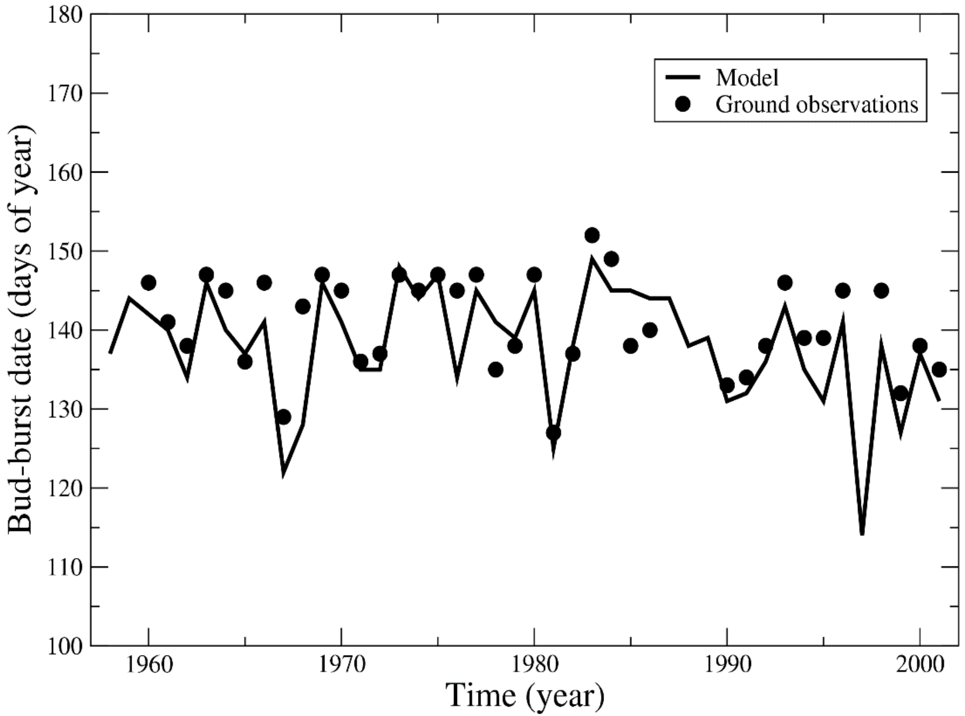
Comparison of ground data with calibrated model



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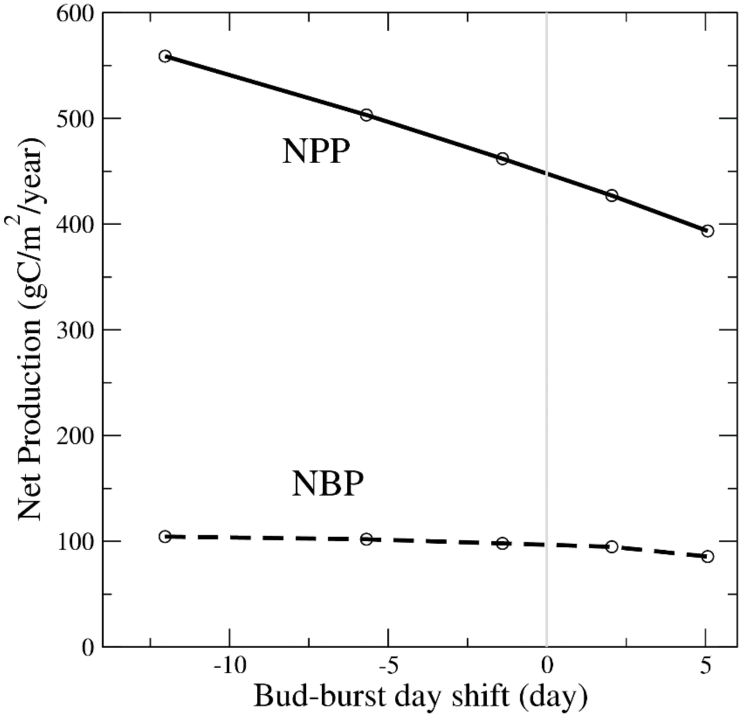
Effects of bias on NPP



1 day earlier BB => NPP increases by 10.1 gC m^{-2} y^{-1} (~2.2%)
Growing season ~100 days

Without adaptation, 5^{o} C increase =>BB occurs 16 days earlier => 34% increase in NPP.

Biases in NDVI can be up to 15 days due to snow effects => errors in NPP of 32%

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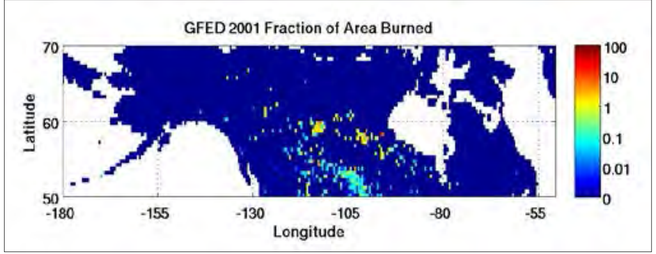

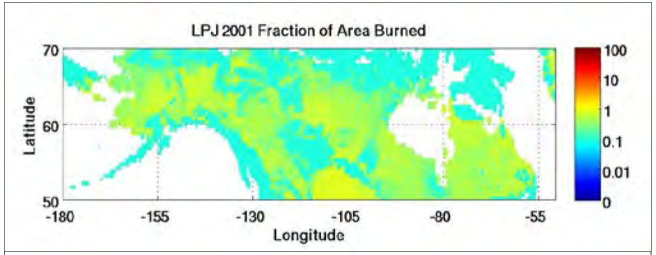

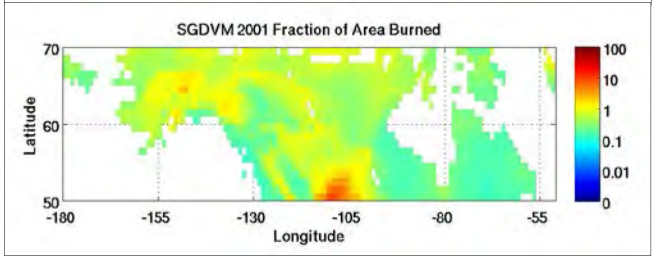

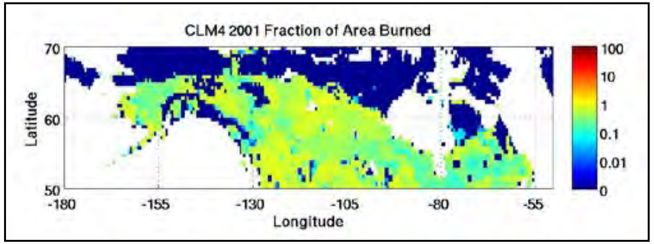

Spatial pattern of burn 2001

Fraction of area burnt per pixel

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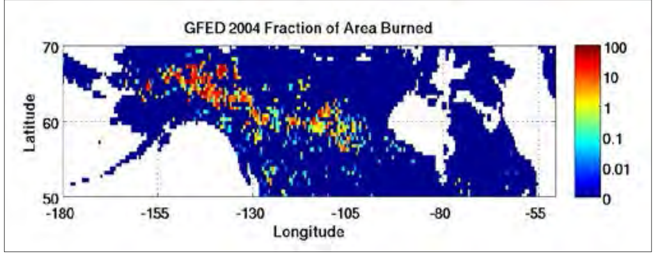

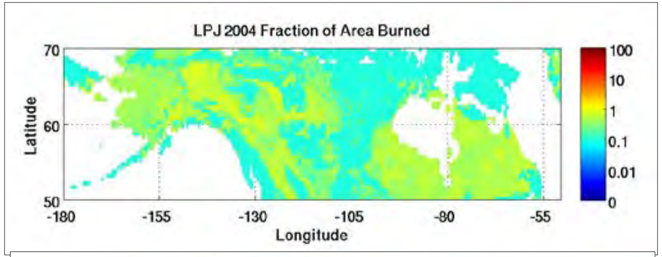

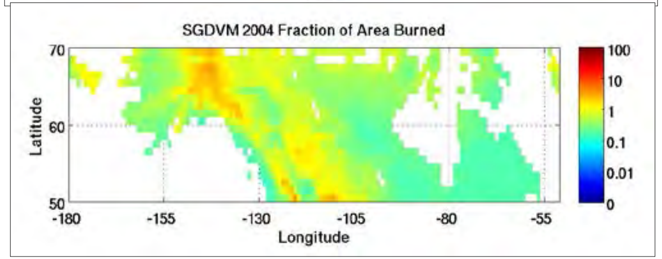

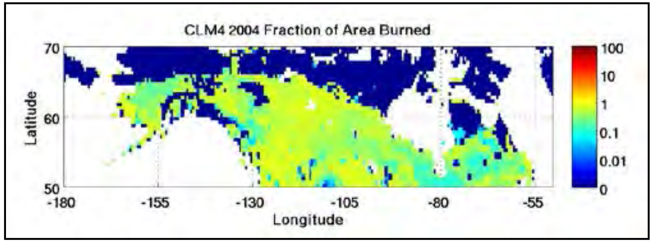

Spatial pattern of burn 2004

Fraction of area burnt per pixel

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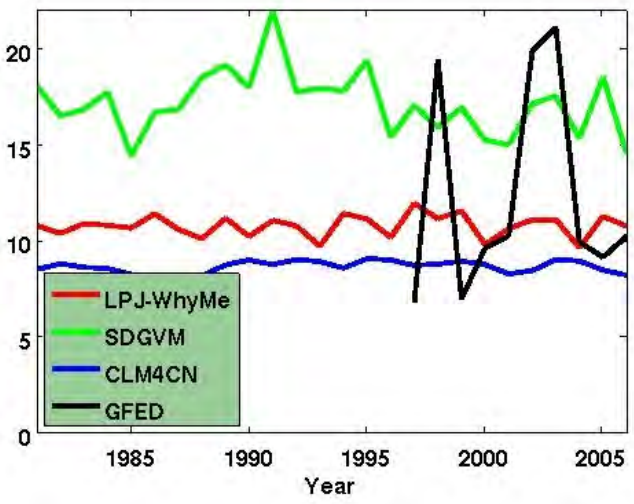
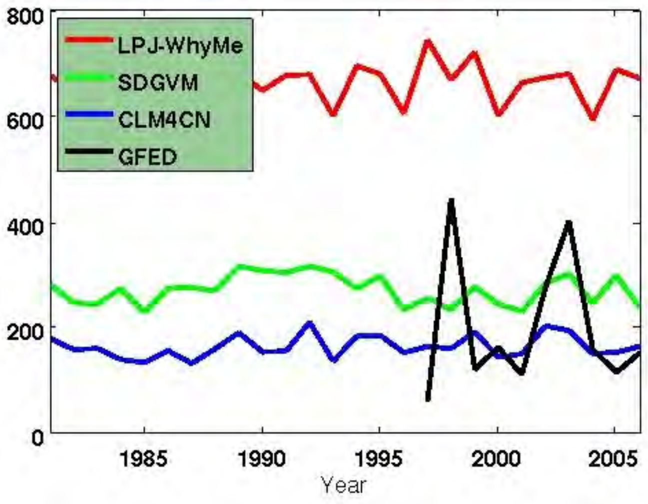
Burnt Area and Emissions

Burnt Area (Mha yr^{-1}), 50º- 75º N



Fire Emissions (TgC yr^{-1}), 50º- 75º N



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CARDAMOM DALEC:
a terrestrial ecosystem carbon cycle analysis

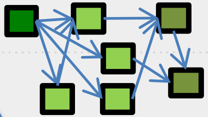
Posterior DALEC Parameter Probability
1° x 1° Pixel Scale Parameter, Flux &

C state likelihood function = observation likelihood & parameter priors
No spin-up
No PFTs
No Steady state

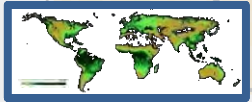
Biometric Data Constraints

Drivers:
ERA-interim 1° x 1° resolution 8-day time-step 2001-2010

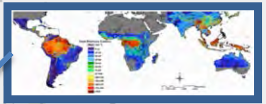
DALEC model



MODIS LAI time series



Pan-Tropical Biomass



Saatchi et al. 2011

HWSD Soil Organic C

Hiederer & Köchy, 2012

$$p(x|c) \propto p(c|x)\, p(x)$$

Parameter probability **p(x|c)** at each pixel derived using a Metropolis-Hastings MCMC algorithm

Dynamic & ecological, data independent constraints.

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Bloom et al., 2013, in prep.

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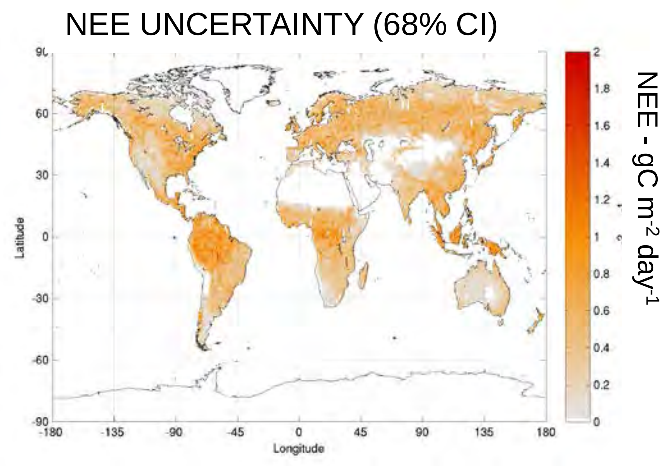
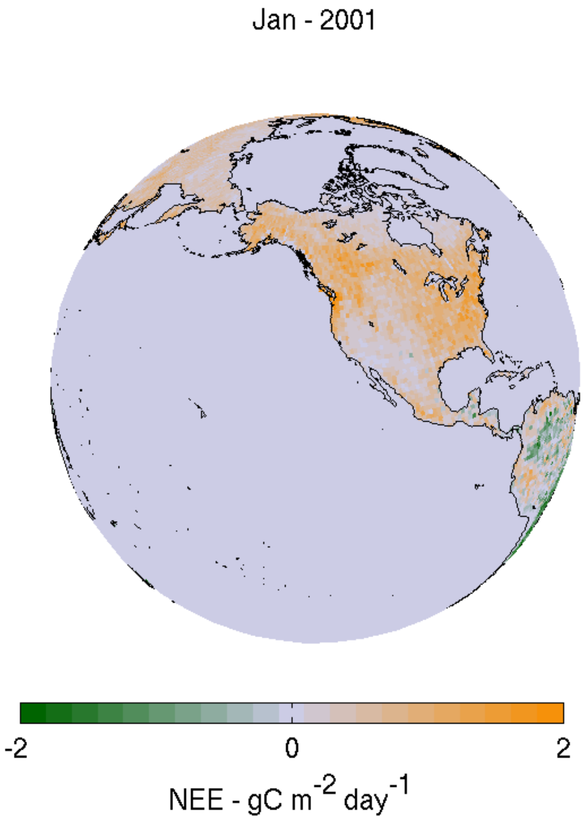
Mean monthly NEE at 1° x 1°

2001-2010: global terrestrial carbon cycle analysis.



Bloom & Williams, in prep.



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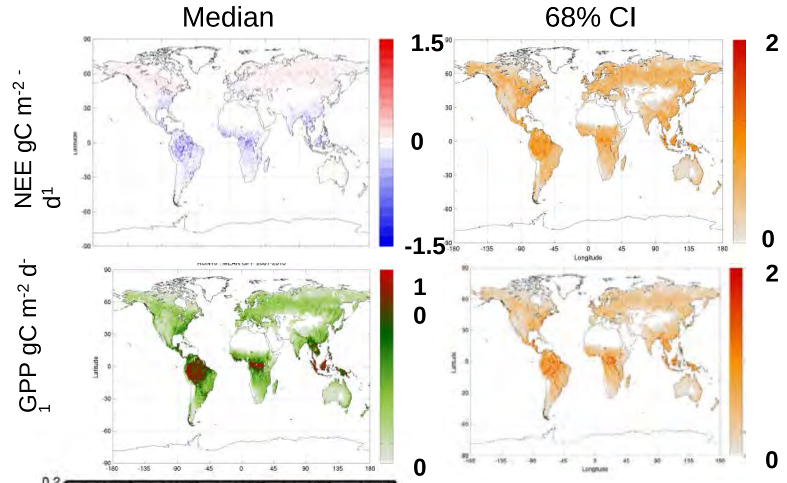
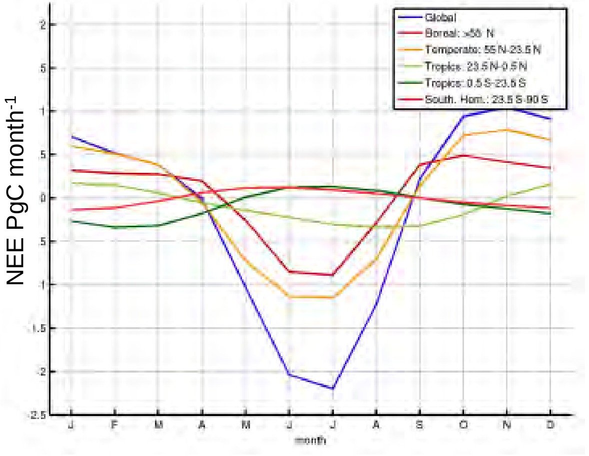
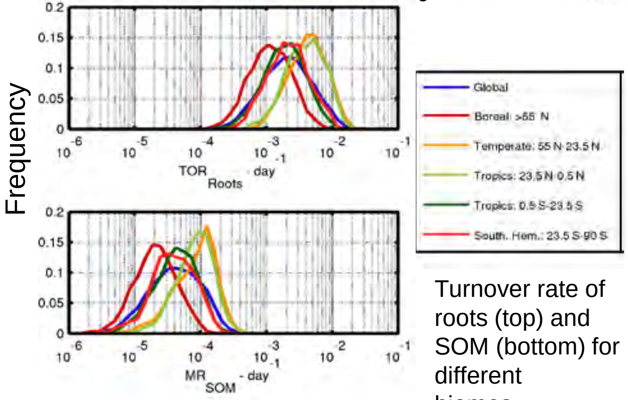
Global patterns, seasonal cycles, residence times





Bloom et al., 2014 in prep



Turnover rate of roots (top) and SOM (bottom) for different biomes

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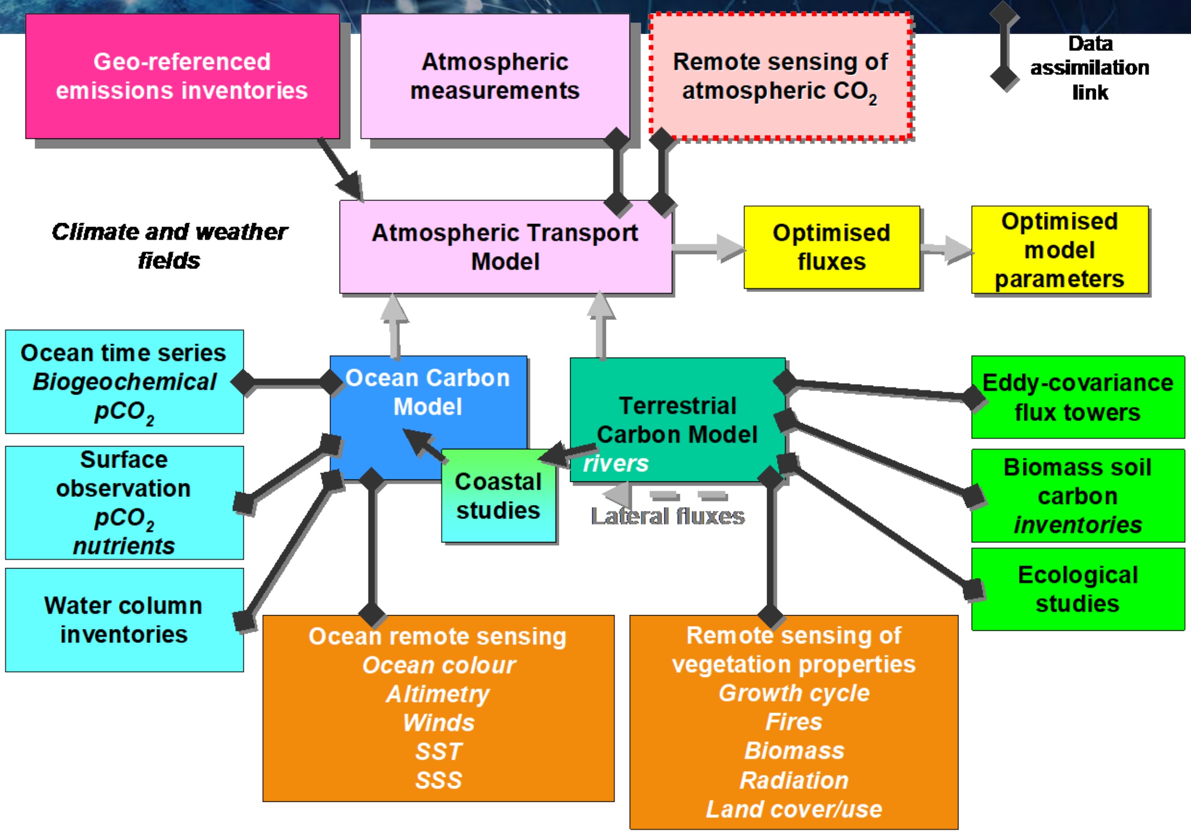
Global Carbon Data Assimilation System



Ciais et al. 2003 IGOS-P Integrated Global Carbon Observing Strategy