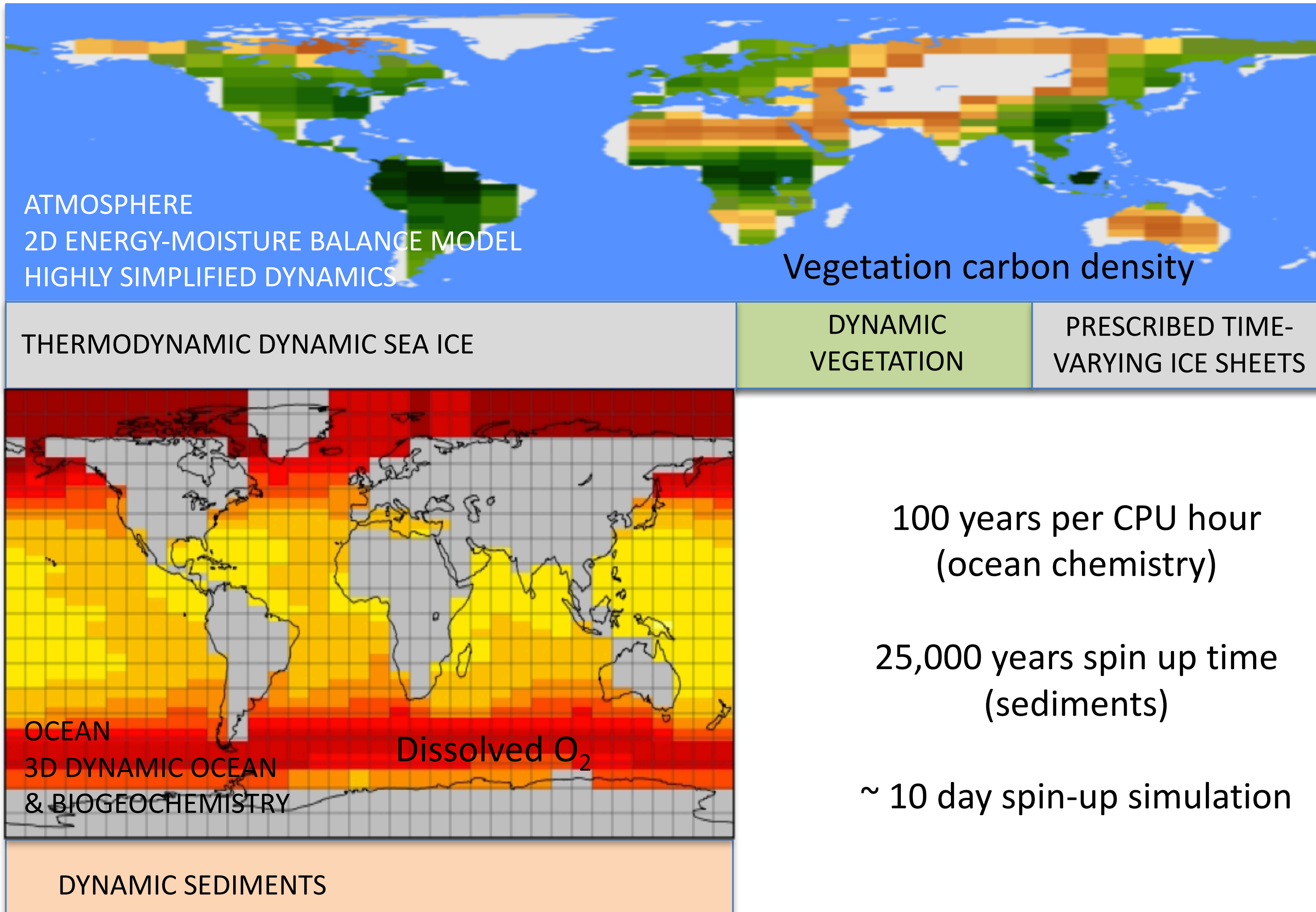
Emulator applications in Earth system modelling

Phil Holden and Neil Edwards
Open University

With thanks to
Rich Wilkinson, Paul Garthwaite and Jonty Rougier

OU MODELS 1) GENIE CARBON CYCLE MODEL



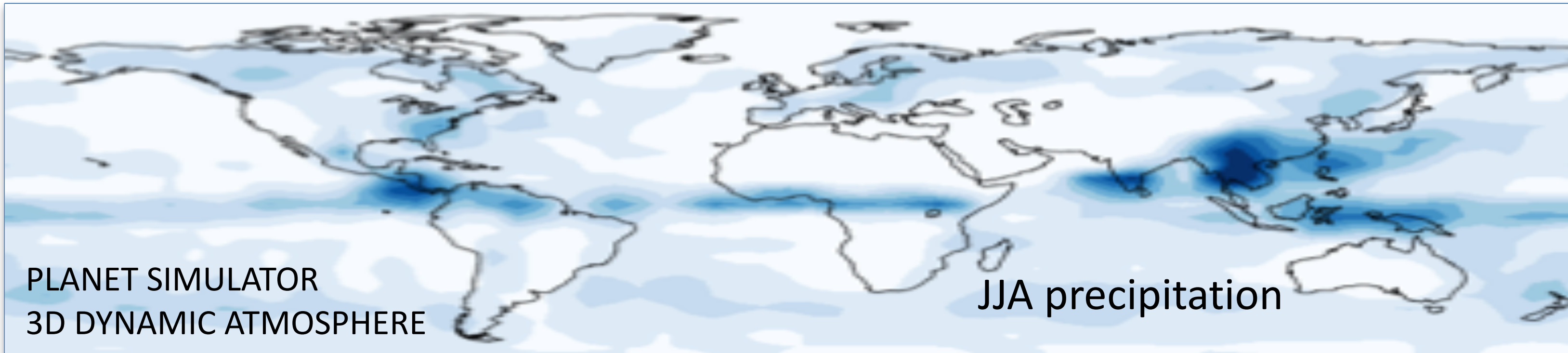
100 years per CPU hour
(ocean chemistry)

25,000 years spin up time
(sediments)

~ 10 day spin-up simulation

Holden et al 2013 “A model-based constraint on CO_2 fertilisation” Biogeosciences

OU MODELS 2) PLASIM-ENTS CLIMATE MODEL



SLAB SEA ICE (NO DYNAMICS)

DYNAMIC VEGETATION

FIXED ICE SHEETS

SLAB OCEAN (HIGHLY SIMPLIFIED DYNAMICS)

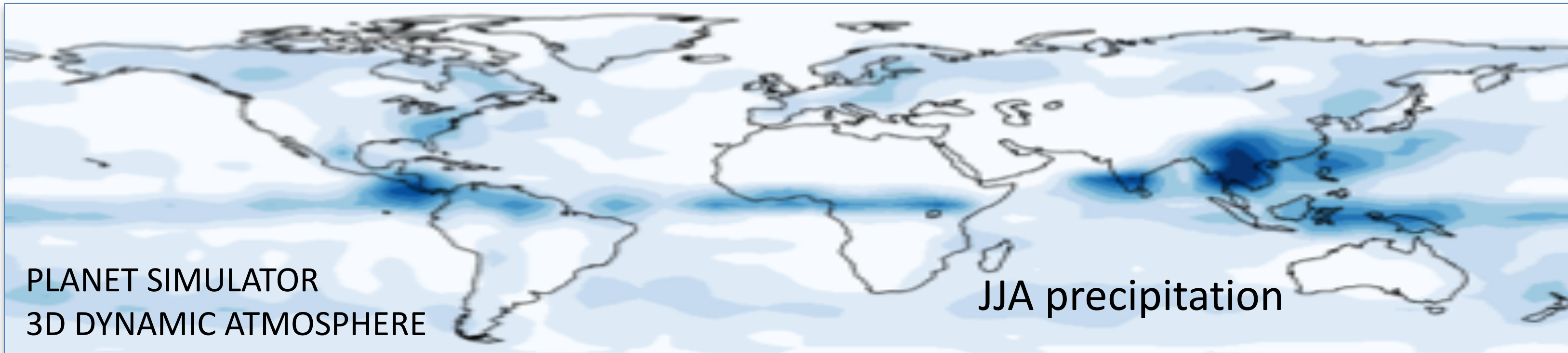
2 years per CPU hour (atmosphere)

200 years spin up time (vegetation)

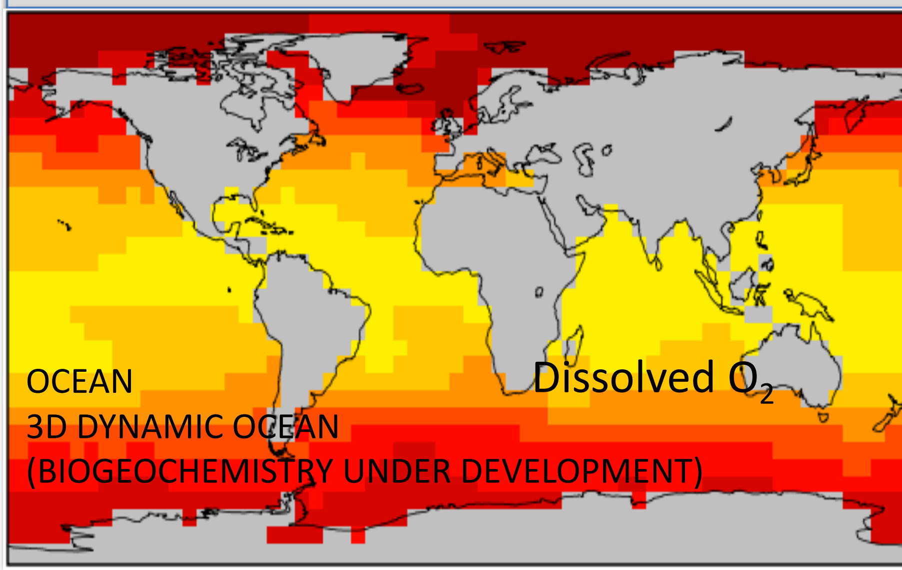
~ 2 day spin-up simulation

Holden et al 2014 “PLASIM-ENTSem v1.0: a spatio-temporal emulator of future climate change for impacts assessment” Geoscientific Model Development

OU MODELS 3) PLASIM-GENIE CLIMATE-(CARBON CYCLE) MODEL



THERMODYNAMIC DYNAMIC SEA ICE	DYNAMIC VEGETATION	FIXED ICE SHEETS



2 years per CPU hour (atmosphere)

2,000 years spin up time (ocean)

~ 20 day spin-up simulation

Holden et al 2016 “PLASIM-GENIE v1.0: a new intermediate complexity AOGCM” Geosci. Mod. Dev.

Why emulation?

A single simulation with an intermediate complexity Earth system model typically take days of computing

("IPCC-complexity" models months of *super*computing)

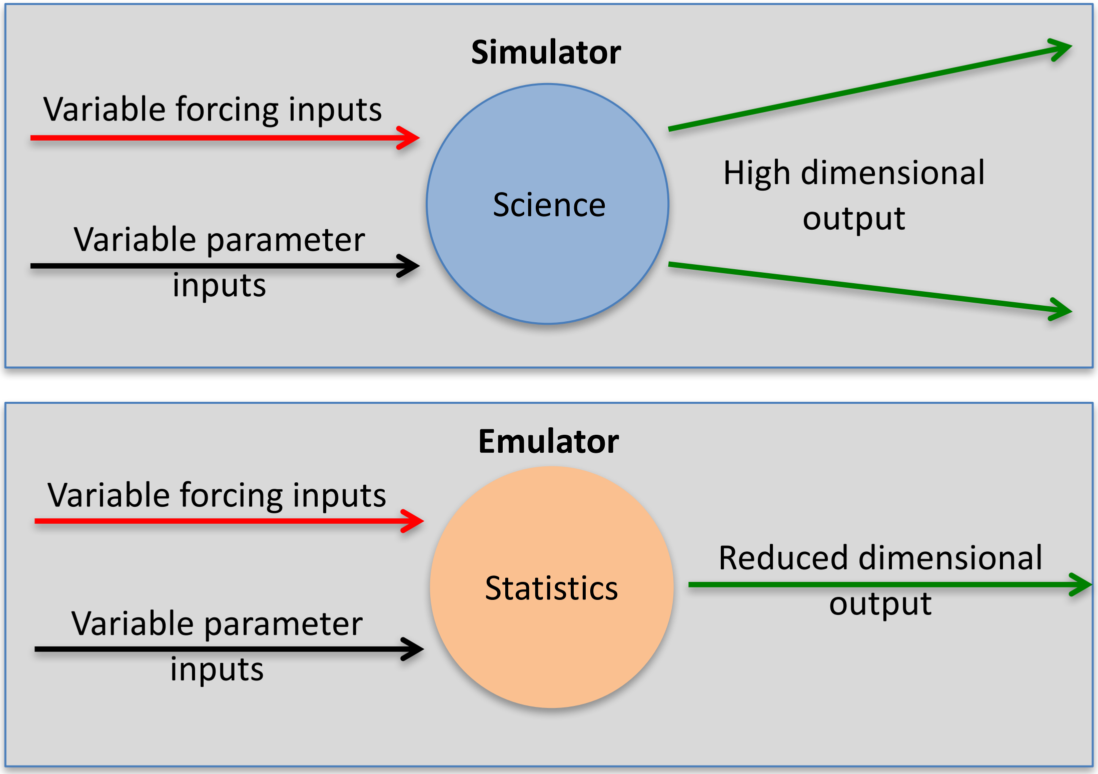
A range of applications are very difficult (often intractable)

Open University emulation work falls in two main categories

1) Exploring relationships between high-dimensional input space and (high-dimensional) output space, for calibration and process understanding

2) Interdisciplinary work, coupling climate models to e.g. economics, impacts, biogeographic models

What is emulation?



Emulator is statistically trained on the output of an ensemble of simulations

Limitations:

Each variable separately emulated

Emulator error

Cannot extrapolate beyond the "training ensemble"

Emulation (1) Scalar inputs -> scalar outputs

Scalar emulators

$$\varsigma\left(\theta\right) = a + \sum_{i=1}^{n} b_i \theta_i + \sum_{i=1}^{n} \sum_{j>i}^{n} c_{ij} \theta_i \theta_j + \sum_{i=1}^{n} d_i \theta_i^2$$

Total effects

$$V_{Tk} = b_k^2 Var\left(\theta_k\right) + d_k^2 Var\left(\theta_k^2\right) + \sum_{i=1, i \neq k}^{n} c_{ik}^2 Var\left(\theta_i\right) Var\left(\theta_k\right)$$

Note Gaussian Process a widely-used alternative (we do use them too)

better emulation (reduced code error) with uncertainty estimate

though note: simulator uncertainty >> code error

GP more demanding of CPU, less transparent interpretation

Emulation (2) Scalar inputs -> high dimensional outputs

Singular vector decomposition and emulation

D = simulation data (G grid points x N simulations)

P = principal components (G grid points x C components)

E = √eigenvalues (C components x C components)

S^T^ = component scores (C components x N simulations)

Holden and Edwards 2010 "Dimensionally reduced emulation of an AOGCM" Geophys. Res. Lett.

$$\boldsymbol{D=PES^T}$$

DECOMPOSITION

$$\begin{pmatrix} d_{11} & . & . & d_{1N} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ d_{G1} & . & . & d_{GN} \end{pmatrix} \approx \begin{pmatrix} p_{11} & . & p_{1C} \\ . & . & . \\ . & . & . \\ . & . & . \\ p_{G1} & . & p_{GC} \end{pmatrix} \times \begin{pmatrix} e_{11} & 0 & 0 \\ 0 & . & 0 \\ 0 & 0 & e_{CC} \end{pmatrix} \times \begin{pmatrix} s_{11} & . & . & s_{1N} \\ . & . & . & . \\ s_{C1} & . & . & s_{CN} \end{pmatrix}$$

$$\boldsymbol{s_1} = (s_{11}, s_{12}, .., s_{1N}) = f_1(\boldsymbol{q}_1, \boldsymbol{q}_2, .., \boldsymbol{q}_N)$$

$$\boldsymbol{s_2} = (s_{21}, s_{22}, .., s_{2N}) = f_2(\boldsymbol{q}_1, \boldsymbol{q}_2, .., \boldsymbol{q}_N)$$

etc

EMULATION

where $\boldsymbol{q}_i$ is the 25-element vector of parameter and forcing inputs for the *i*th simulation

f_j is a quadratic polynomial regression for the *j*th component score

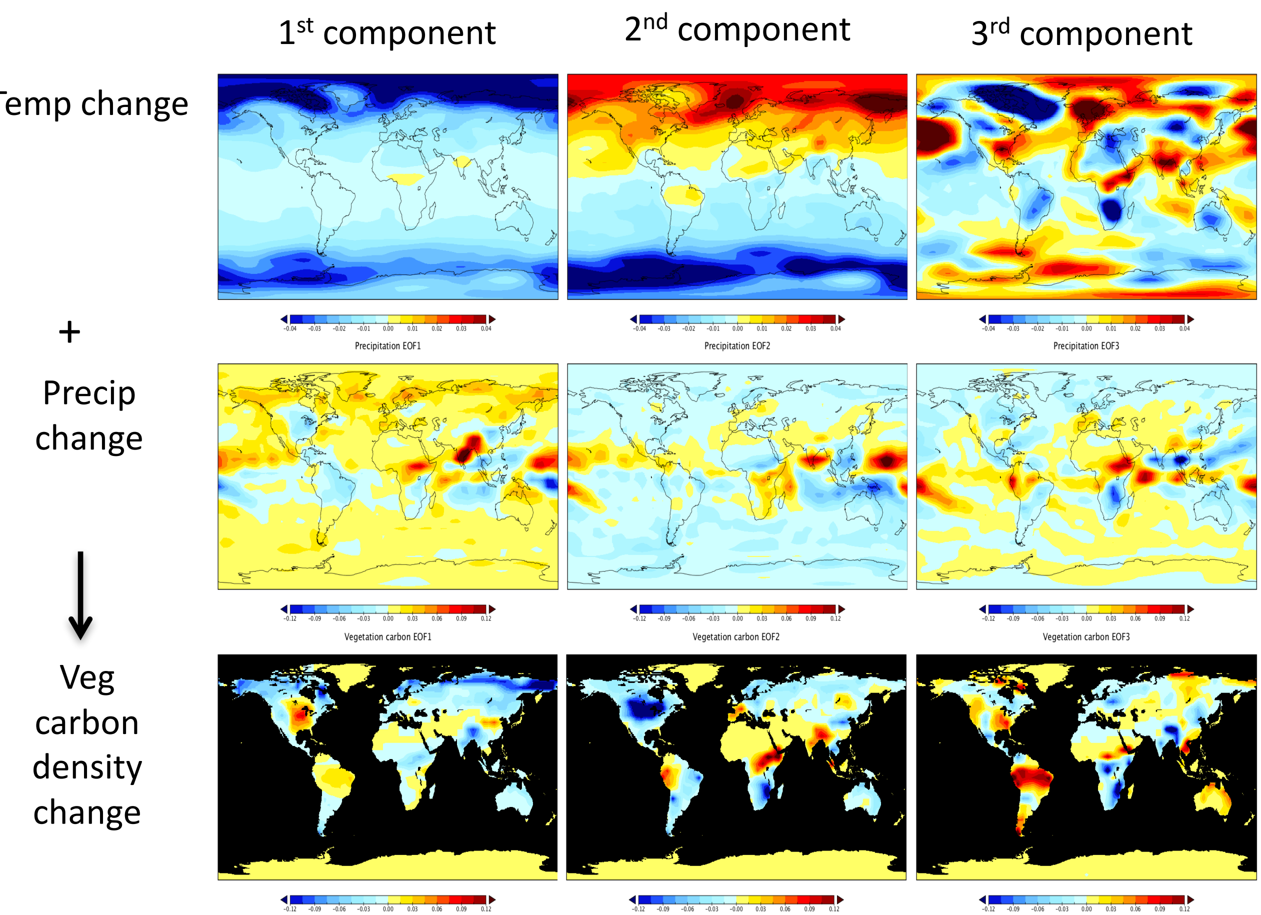
i.e. emulation is reduced to a scalar function of inputs *c.f.* the standard emulation problem

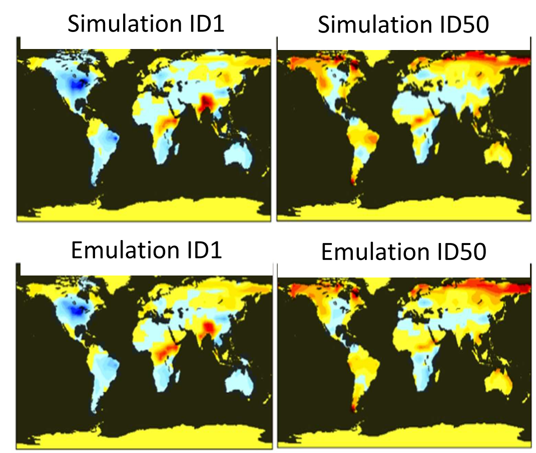
Emulation (3) High dimensional inputs -> high dimensional outputs

Forcing fields (temperature and precipitation) -> Output fields (vegetation carbon density)

SVD applied to both input and outputs -> scalar PC scores

-> standard scalar emulation problem





Model coupling application in progress (Giang Tran)

Holden et al 2015 “Emulation and interpretation of high dimensional climate model outputs” J. App. Stat.

Precalibration (or history matching)

The problem, to build a comprehensive map of output uncertainty from high dimension input space.

We wish to restrict ourselves to using parameter inputs that simulate “plausible” modern climate states

We vary many (~20) parameters, over their entire reasonable ranges

BUT small regions of this high-dimensional input space give reasonable simulations (typically ~1%)

To derive, say, 250 plausible parameter sets by searching randomly with the simulator might require

~ 250 * 100 simulations * 1 week CPU ~ 500 years CPU

-> Use emulators to search for plausible parameter space

Edwards et al 2011 “Precalibrating an intermediate complexity climate model” Climate Dynamics
Holden et al 2010 “A probabilistic calibration of climate sensitivity…” Climate Dynamics

1,000 member GENIE-1 ensemble "D"; Maximin Latin Hypercube with broad, uniform distributions for 26 parameters

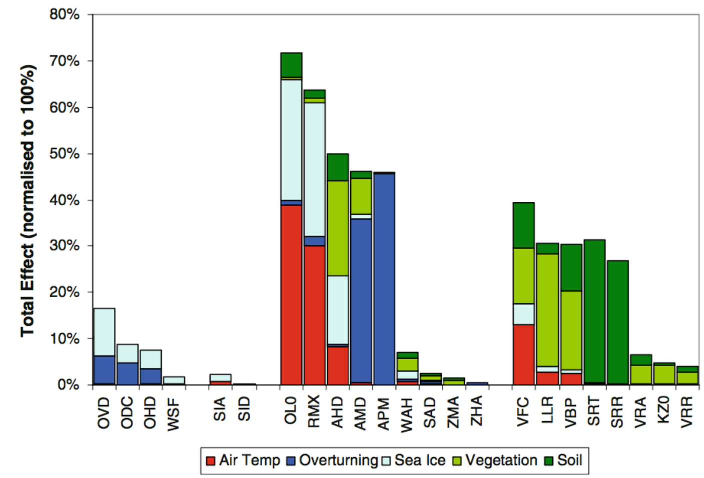
Modern plausibility tests (Eq. 3)

10 plausible ensemble members

Emulate GENIE-1 output

Five plausibility emulators (Atlantic overturning, global SAT, Antarctic sea ice, vegetative & soil carbon

Calculate Total Effect (Eq. 4)



Rejection sampling of emulator output (Eq. 5)

1,000 member GENIE-1 ensemble "P"; emulator-plausible parameterisations

Modern plausibility tests (Eq. 3) & no "runaway" LGM cooling

894 plausible members = **MPC parameter set**

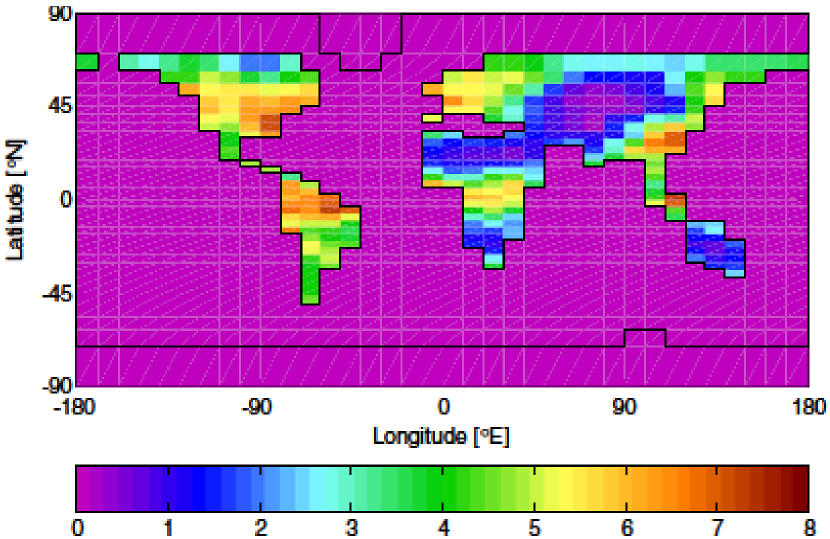
Plausible LGM Antarctic anomaly?

480 plausible members = **LPC parameter set**

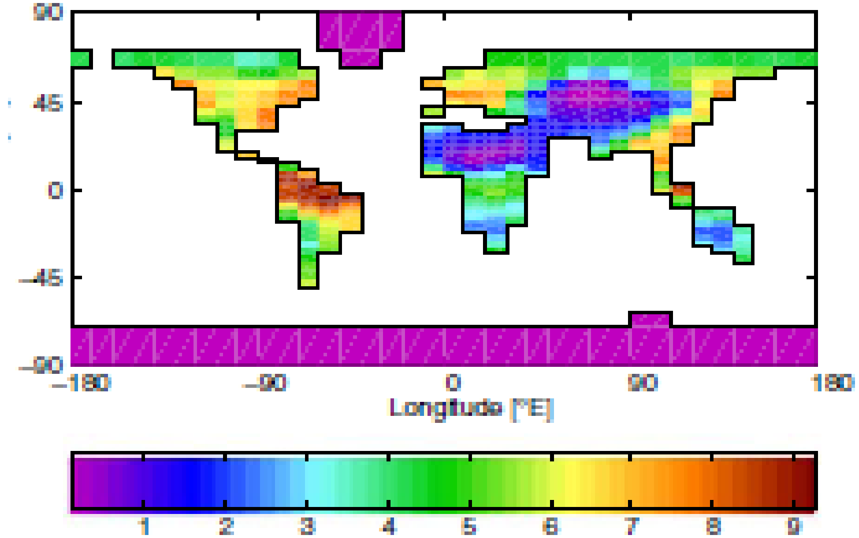
Holden, Edwards, Oliver, Lenton, Wilkinson, 2010 "A probabilistic calibration of climate sensitivity…" Climate Dynamics

Precalibration reproduces the spatial structure of the tuned model

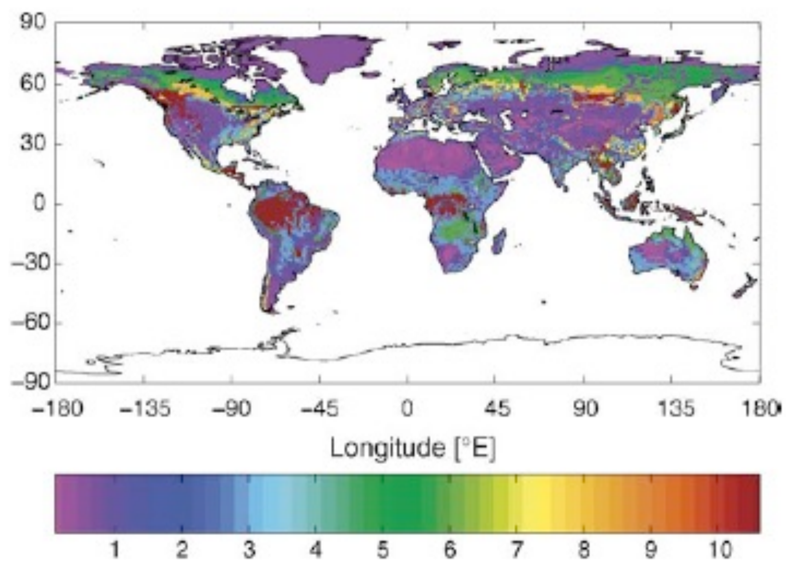
ensemble average



”traceable” parameters (Lenton et al 2006)



observations (Olson et al 1985)



vegetation carbon density $kgCm^{-2}$

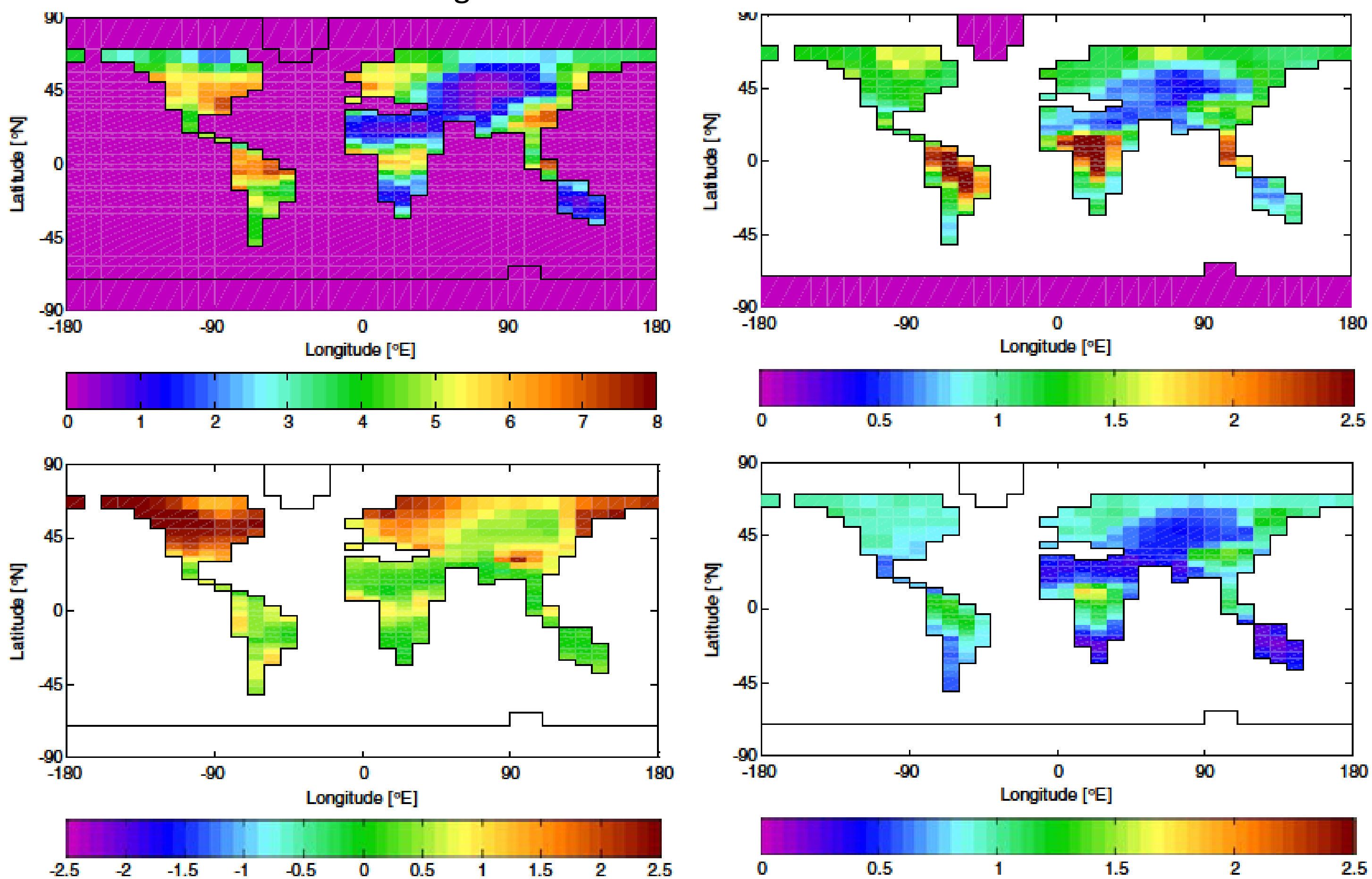
…but provides wide range of feedback strengths

The Open University

Ensemble average | Ensemble standard deviation

Preindustrial

2xCO_2 change



Calibrated model outputs
"A model-based constraint on CO_2 fertilisation"

Holden, Edwards, Gerten and Schaphoff 2013, Biogeosciences

Elevated atmospheric CO_2 stimulates photosynthesis, a major sink for anthropogenic emissions (~25%)

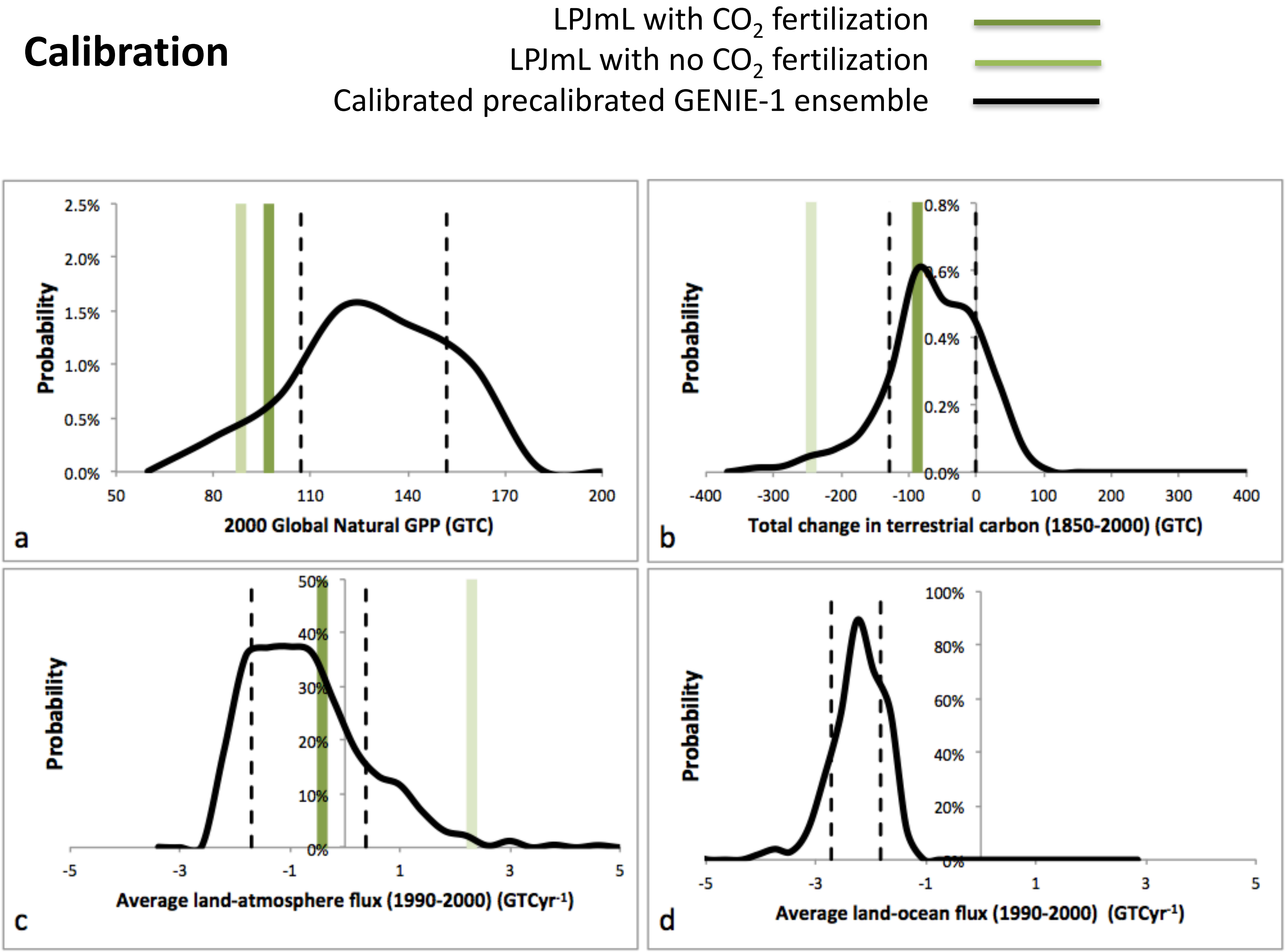
Well demonstrated under controlled conditions, but highly uncertain in nature

e.g. nitrogen limitation or temperature limitation may be dominant controls in some ecosystems

Top down, globally-averaged quantification – what global response reproduces present day CO_2 when forced with historical emissions?

Application for a pre-calibrated ensemble

Calibration



Interpreting model outputs
"Controls on the spatial distribution of oceanic $\delta^{13}C_{DIC}$"

Holden, Edwards, Müller, Oliver, Death and Ridgwell, 2013, Biogeosciences

Plants and fossil fuels are strongly depleted in ^{13}C due to preferential uptake of light carbon (^{12}C) by photosynthesis

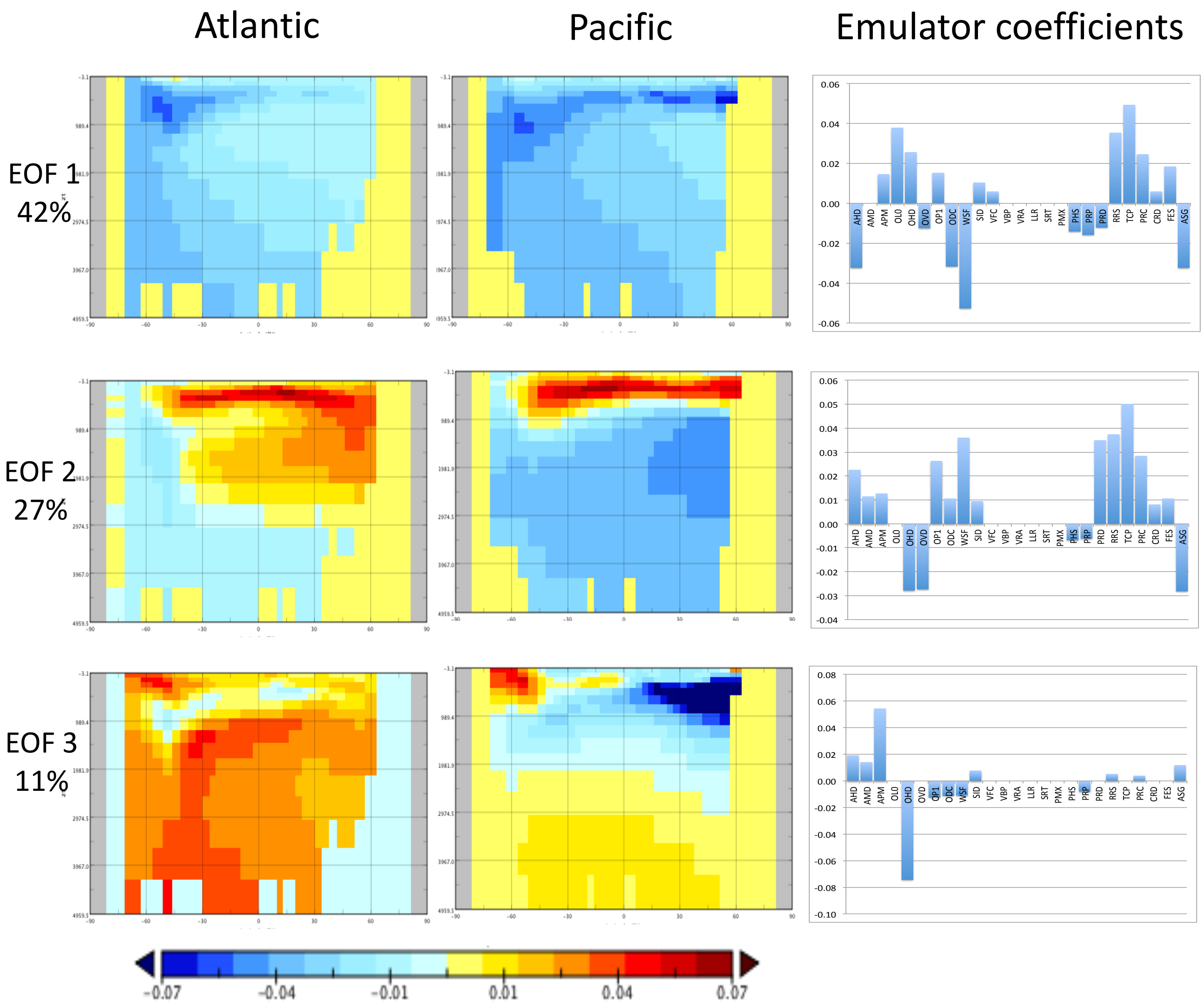
Ocean is a major sink for anthropogenic emissions of CO_2. The imprint of is ^{13}C used to help constrain ocean uptake.

Oceanic ^{13}C distribution is driven by complex interplay between

- air-sea gas exchange
- temperature dependent solubility
- marine productivity
- water column remineralisation of organic matter
- ocean circulation
- ocean mixing (wind driven and density driven)

Can a model help us understand the drivers and uncertainties of the ^{13}C imprint?

EOFs of preindustrial (natural) ^{13}C distribution in the ocean



Global average d13C

WSF➔ surface mixing
AHD➔ eq-pole temp grad
ASG➔ air-sea gas exch
RRS/TCP➔ POC export
OL0➔ SST

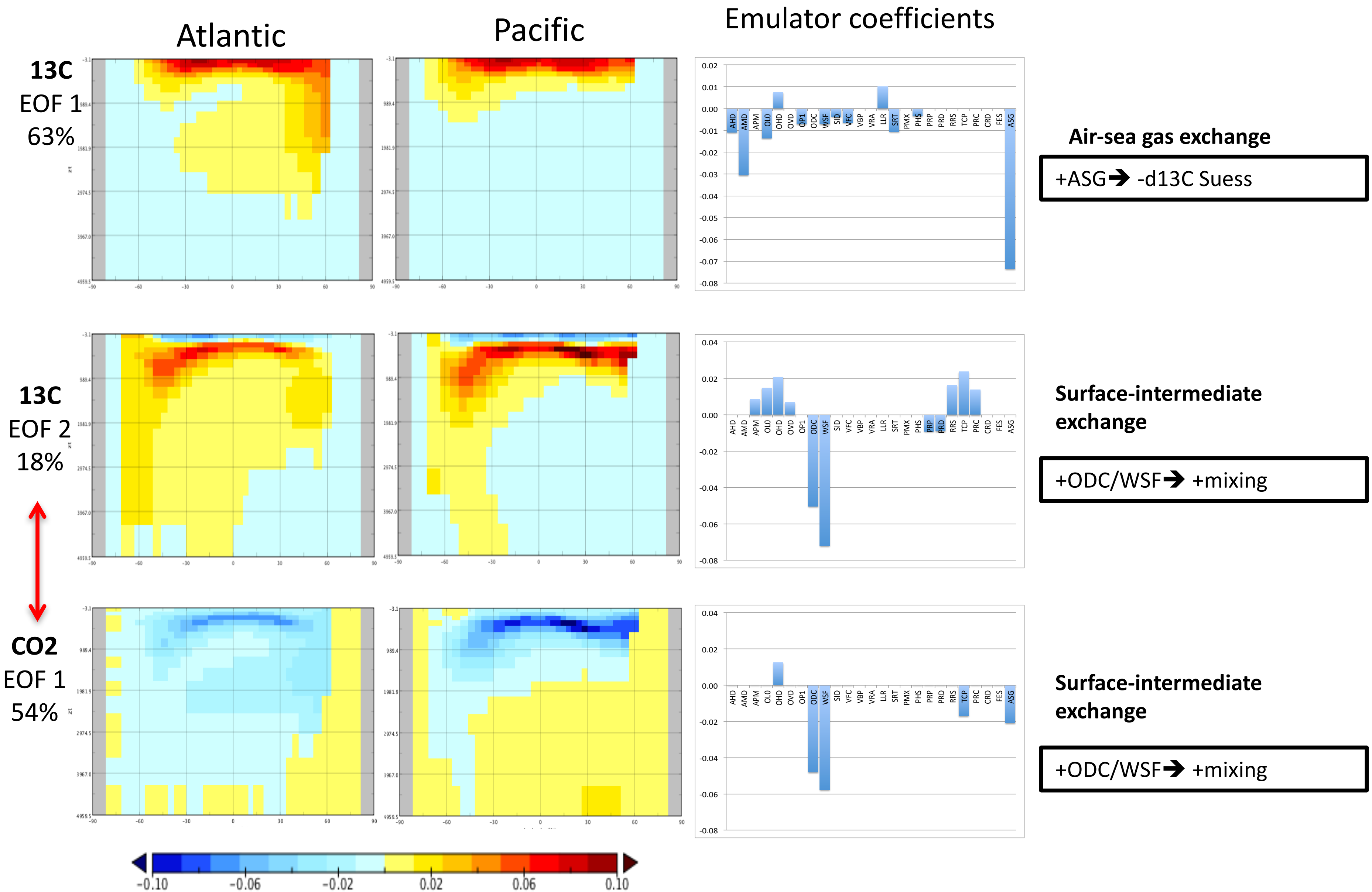
Surface-deep exchange

PRD/RRS/TCP➔
marine productivity

Competing AABW/NADW

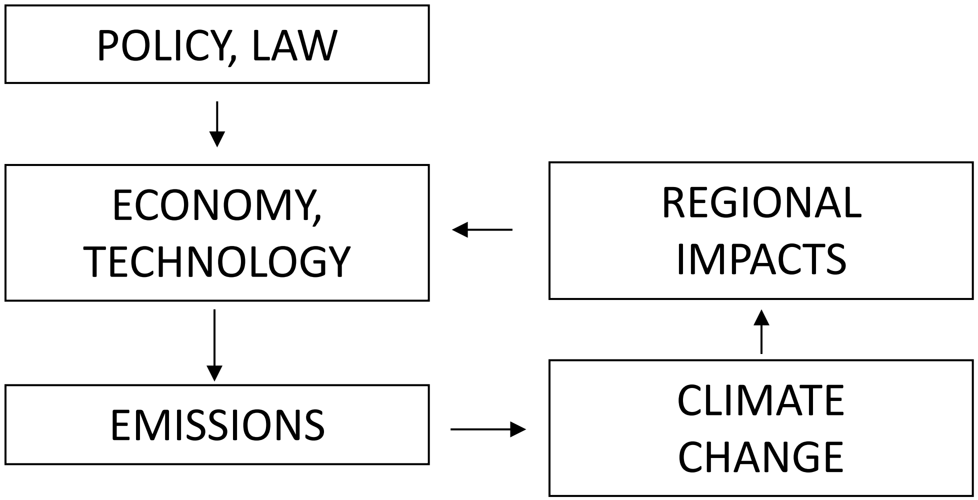
APM➔ NADW
OHD➔ AABW

EOFs of Suess effect (fossil fuel burning) ^{13}C and CO_2 ocean imprints



Emulating spatial fields for coupling applications

1) Integrated Assessment Modelling



Climate simulations need to be very fast

-> only possible with highly simplified models

Climate needs to be spatially resolved (regionally variable impacts)

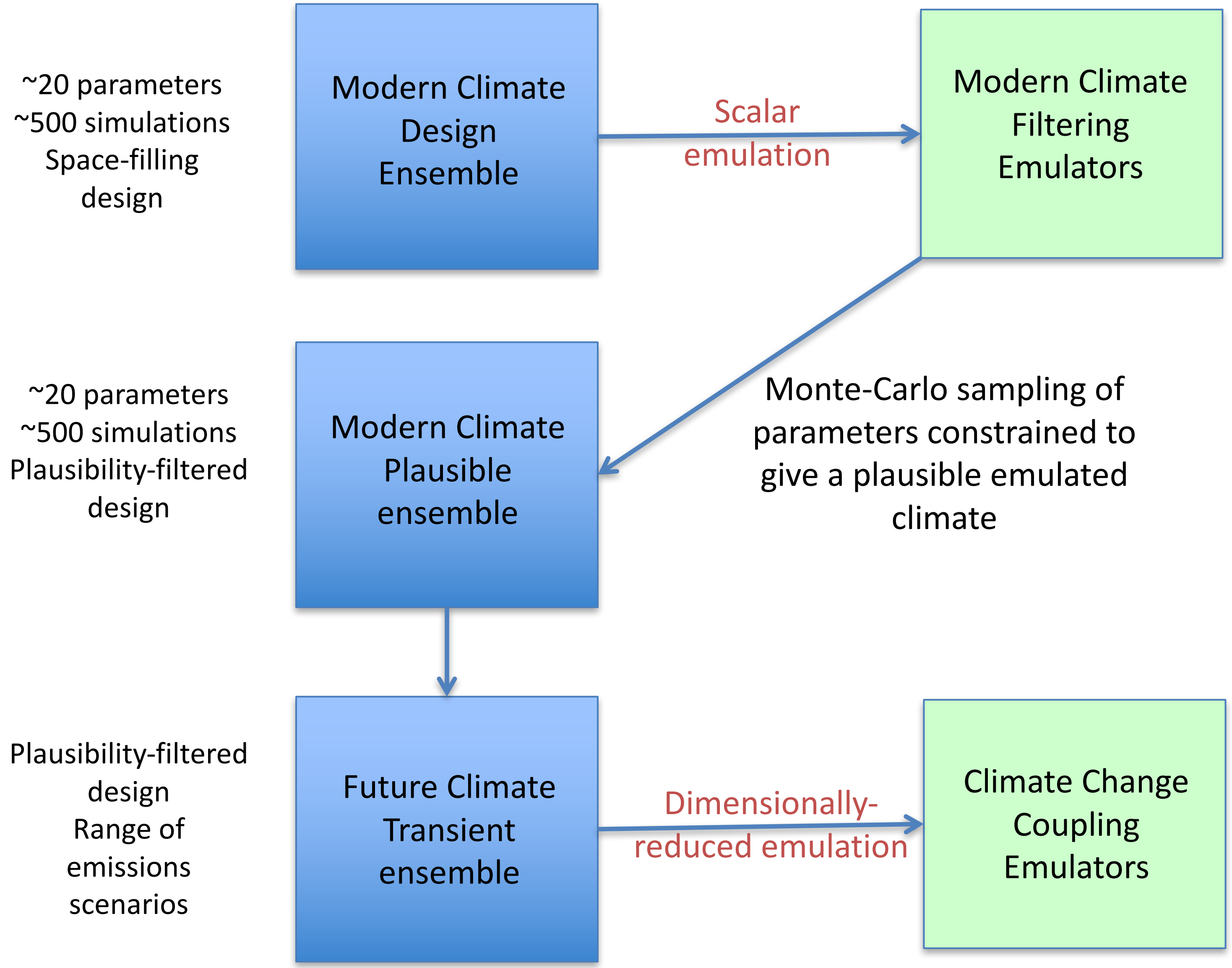
-> simple climate models are poorly suited

For robust decision making uncertainty should be quantified

-> single simulations are inadequate

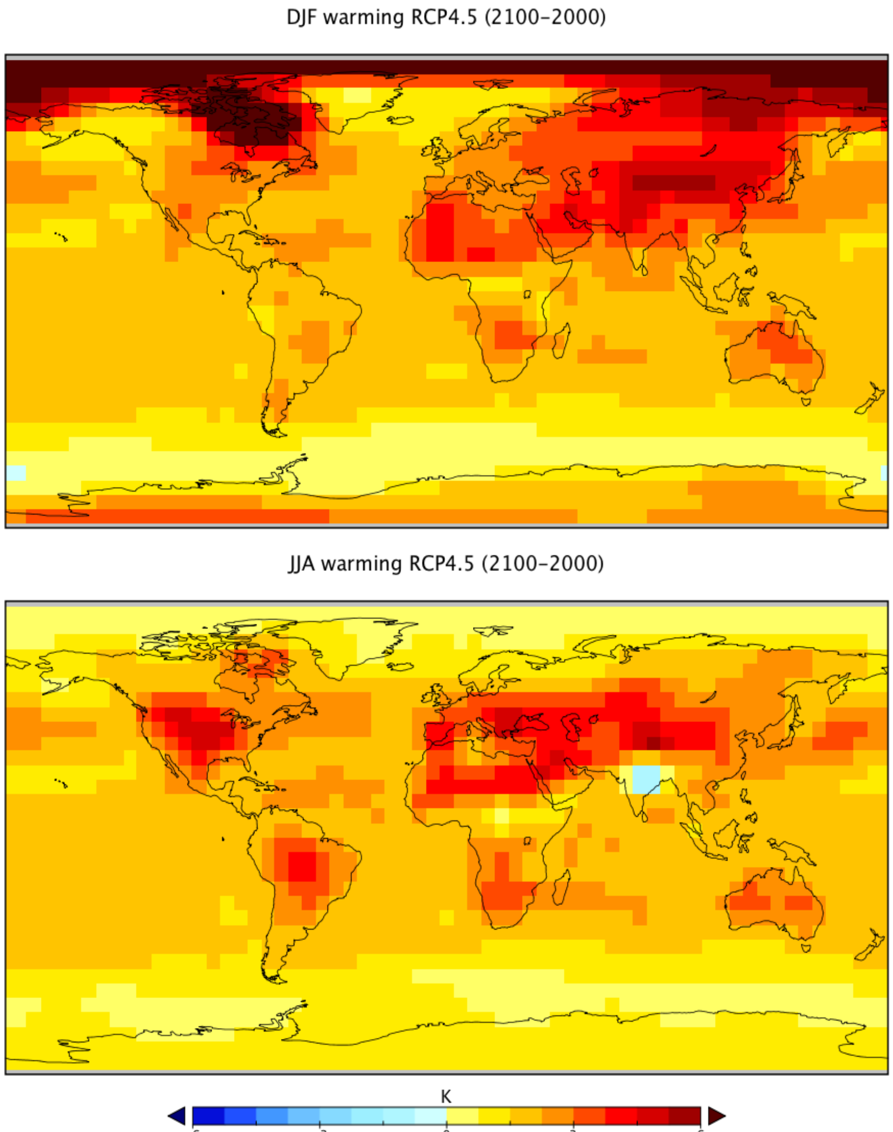
-> parameter space should be sampled

Developing a coupling emulator

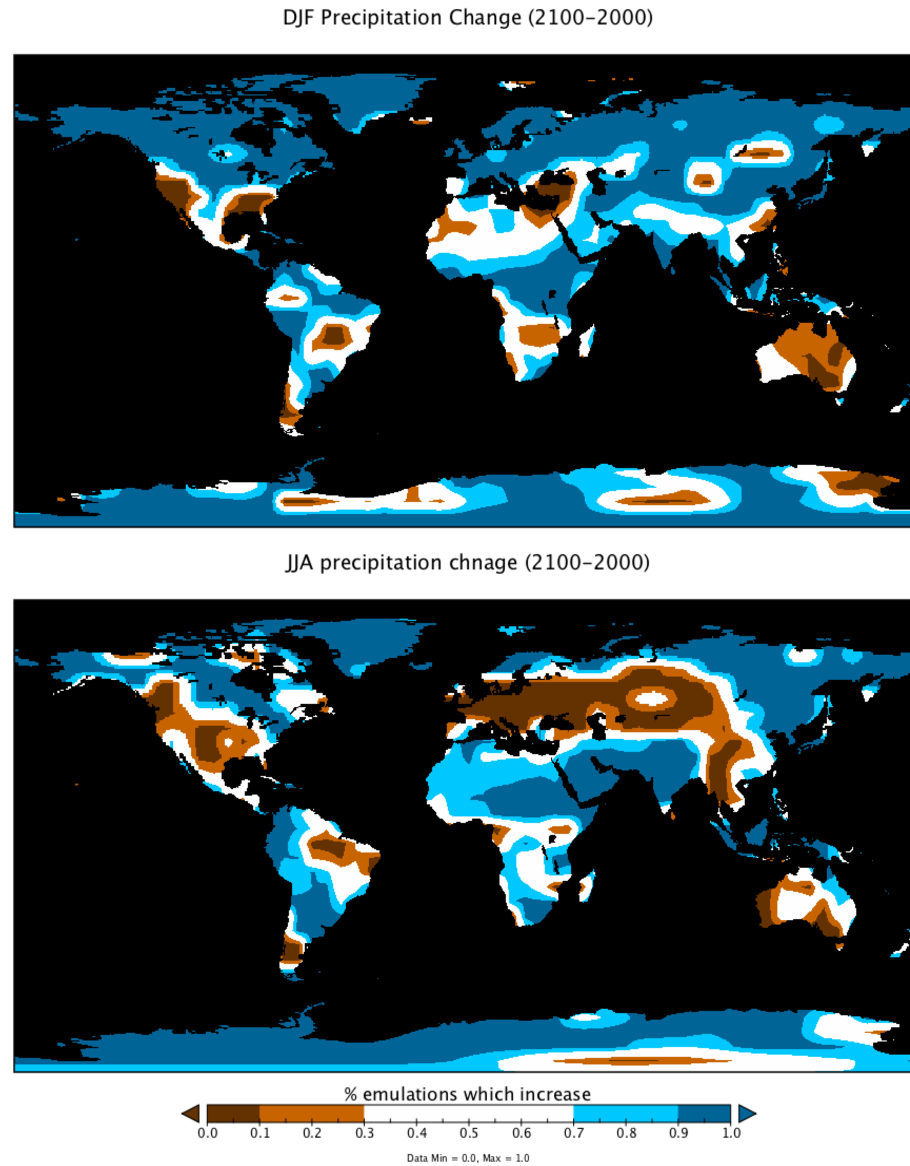


Holden et al 2014 “PLASIM-ENTSem v1.0: a spatio-temporal emulator of future climate change for impacts assessment” Geoscientific Model Development

Emulated mean field (SAT)



Emulated uncertainty field (precipitation)



Spatially resolved + uncertainty. Can deal with spatially variable forcing e.g aerosols

“Worldwide impacts of climate change on energy for heating and cooling”

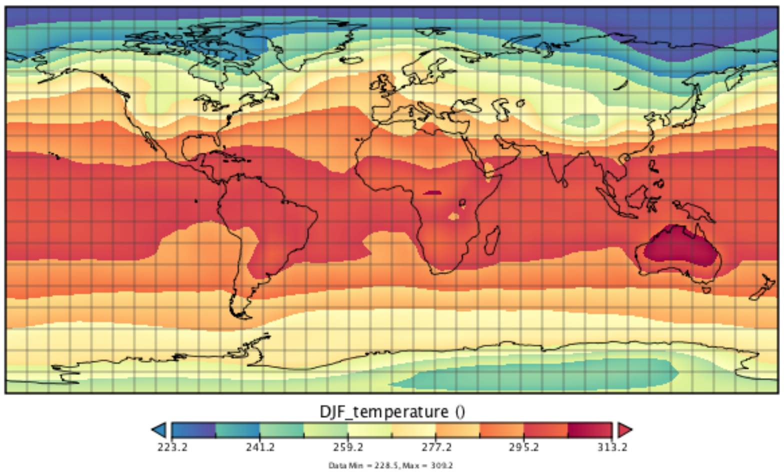
Labriet et al 2013, Mitigation and Adaptation Strategies for Global Change

The energy sector is not only a major contributor to greenhouse gases, it is also vulnerable to climate change and will have to adapt to future climate conditions.

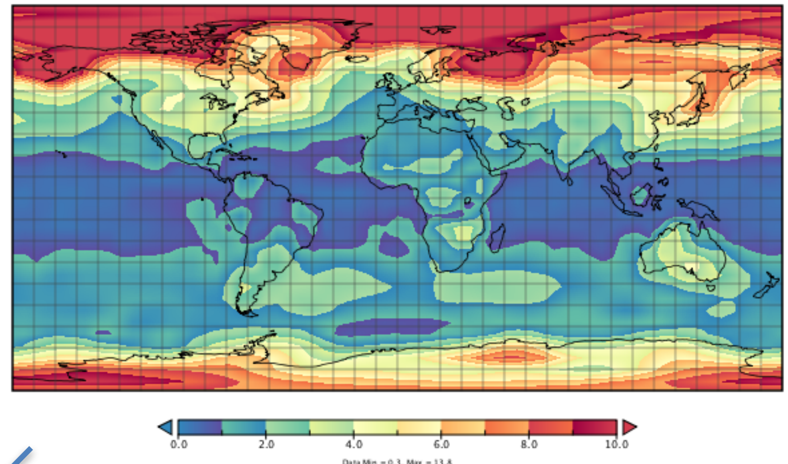
-> Integrated study, coupling technological, economics and climate models

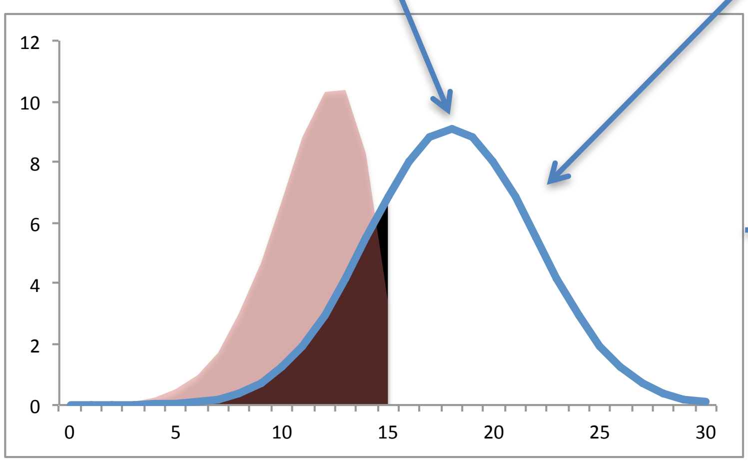
Degree Days – post-process mean and SD fields

Emulated mean temperature



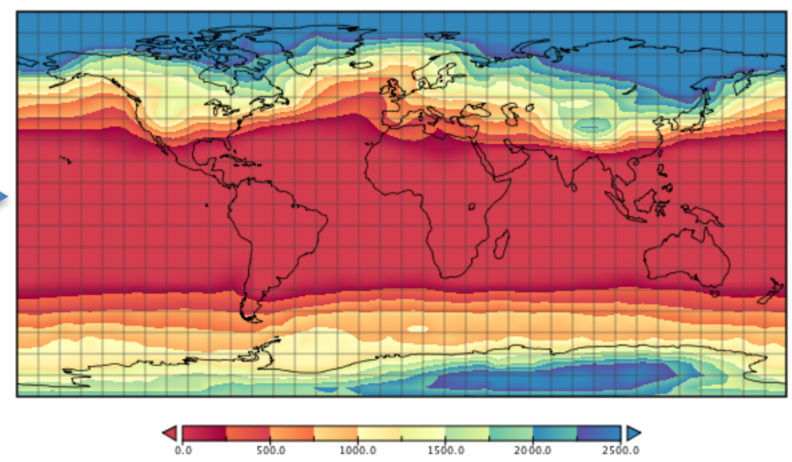
Emulated St. Dev. temperature





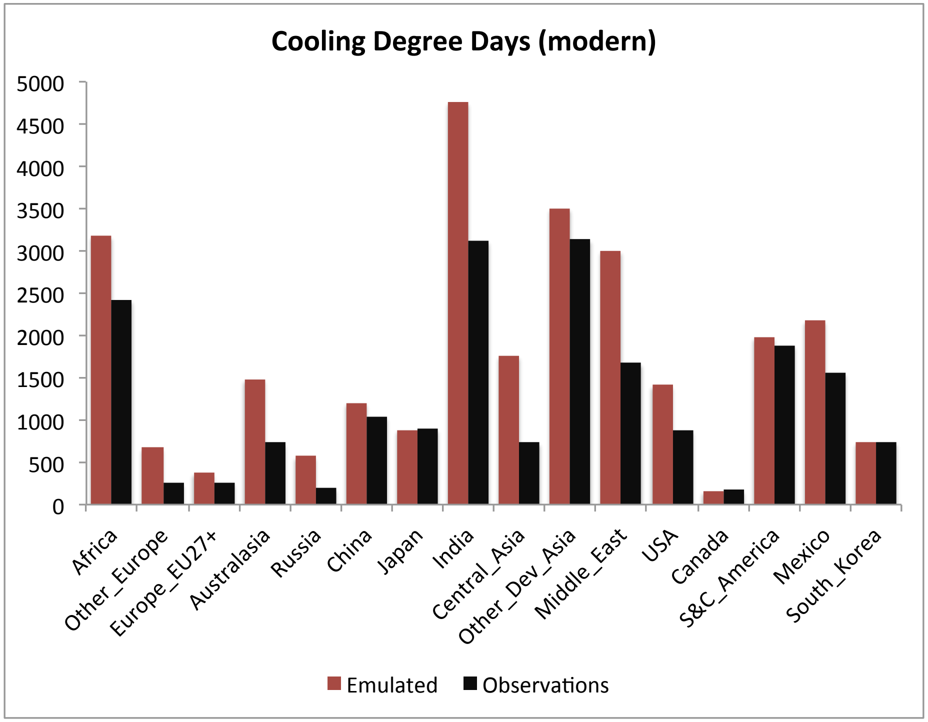
Grid-point Heating DD calculation
(Regionally defined Tref)

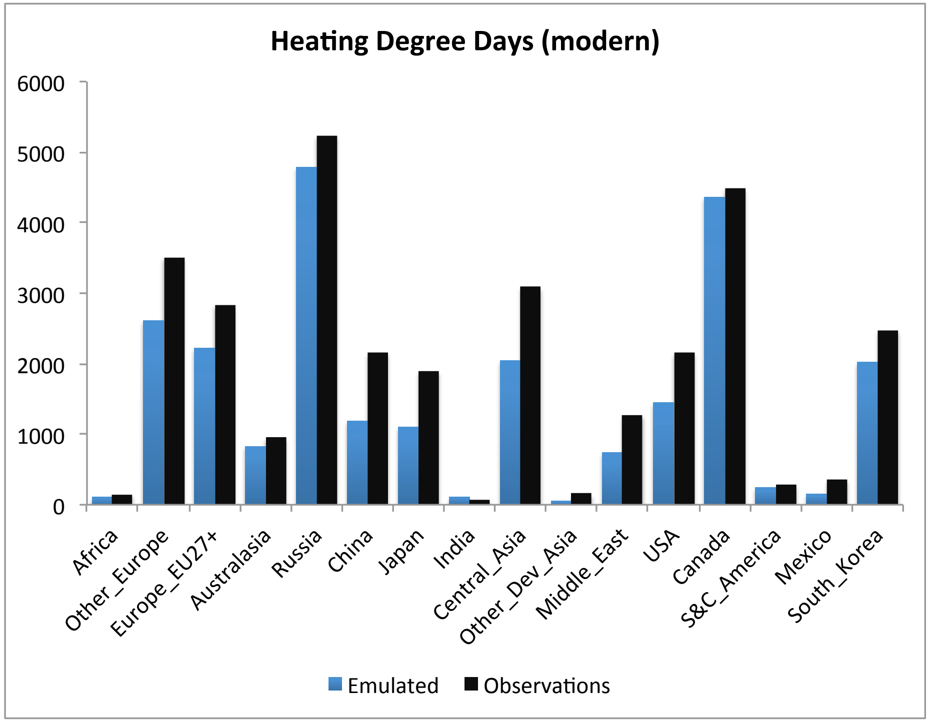
Post-processed DJF Heating DDs



Validation of simulated present-day regional DDs

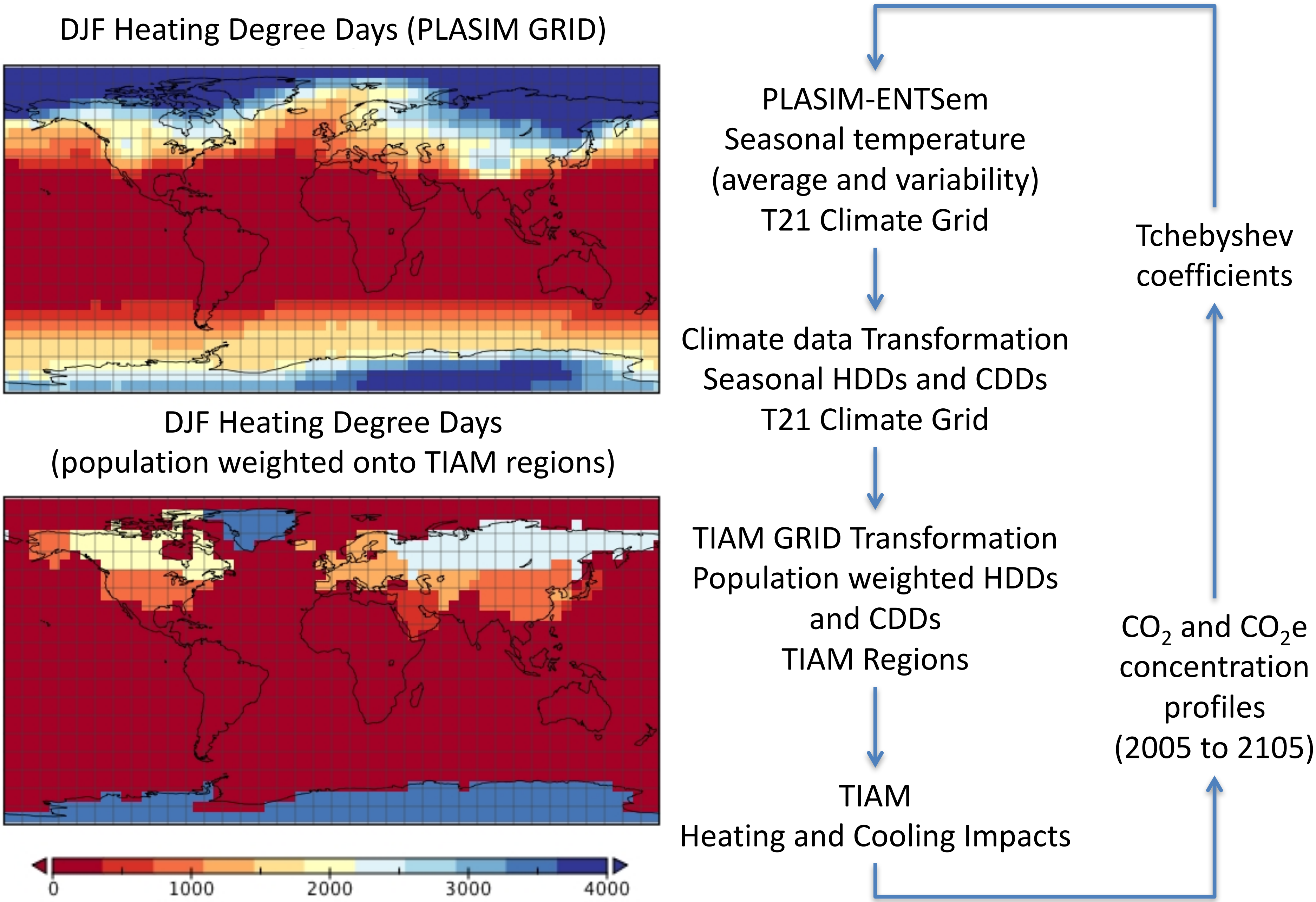
18°C global reference temperature





Regional differences well captured.
Emulator warm bias (though note observational data historical)

Observations: Baumert and Selman, World Resources Institute, 2003


DJF Heating Degree Days (PLASIM GRID)
DJF Heating Degree Days
(population weighted onto TIAM regions)
0
1000
2000
3000
4000
PLASIM-ENTSem
Seasonal temperature
(average and variability)
T21 Climate Grid
Climate data Transformation
Seasonal HDDs and CDDs
T21 Climate Grid
TIAM GRID Transformation
Population weighted HDDs
and CDDs
TIAM Regions
TIAM
Heating and Cooling Impacts
Tchebyshev
coefficients
CO_2 and CO_2e
concentration
profiles
(2005 to 2105)

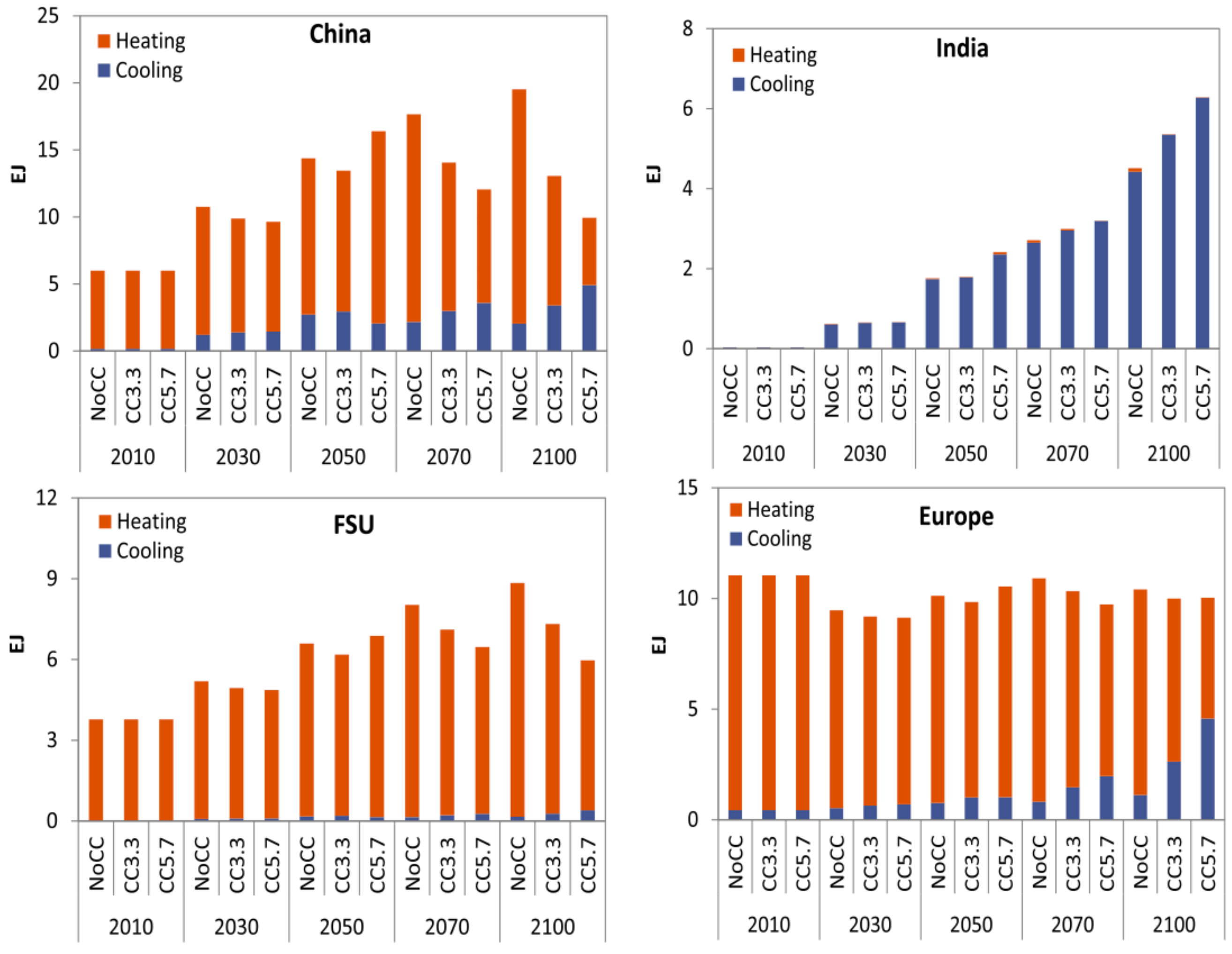
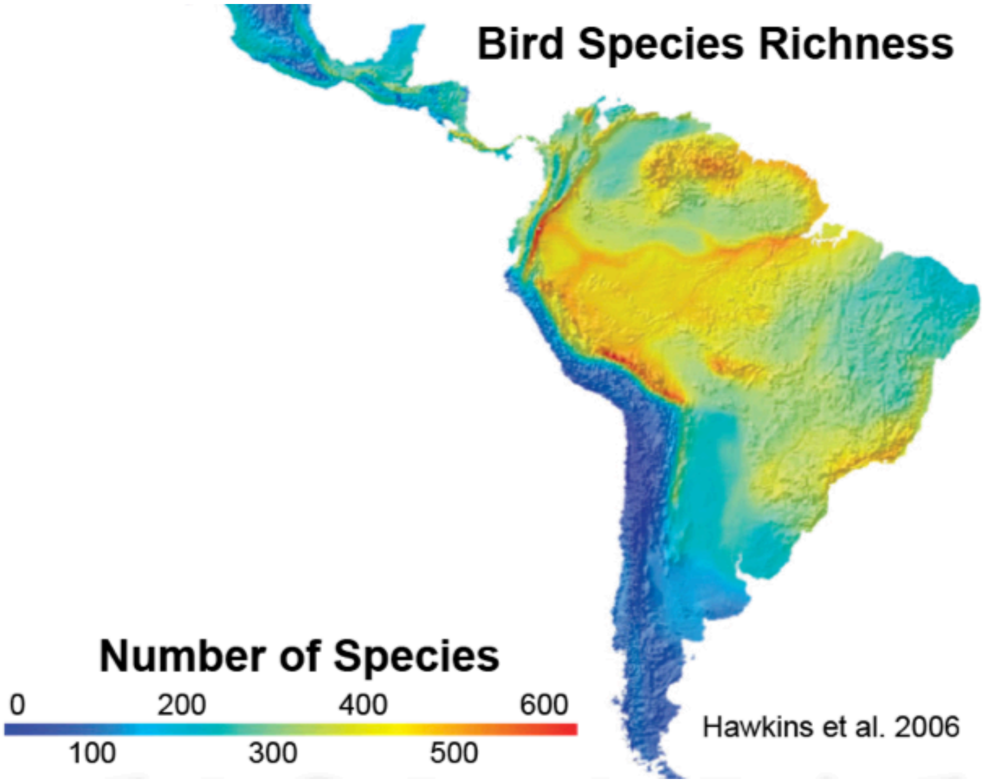


Fig. 9 Total final energy consumed for heating and cooling with and without climate change impacts in China, India, FSU and Europe for no climate change (No CC), 3.3 °C (CC 3.3) and 5.7 °C (CC 5.7) scenarios

Global energy requirements approximately neutral
(heating and cooling approximately cancel)
But major regional differences and changes to energy sectors
(electricity/fossil fuel)

Emulating spatial fields for coupling applications
2) Spatial and temporal dynamics of biodiversity

Rangel, Colwell, Holden, Edwards, Gosling and Rahbek
work in progress



- Biodiversity is structured in highly complex spatial and temporal patterns
- Many mechanisms have been proposed to explain biodiversity patterns
- A coupled modelling approach

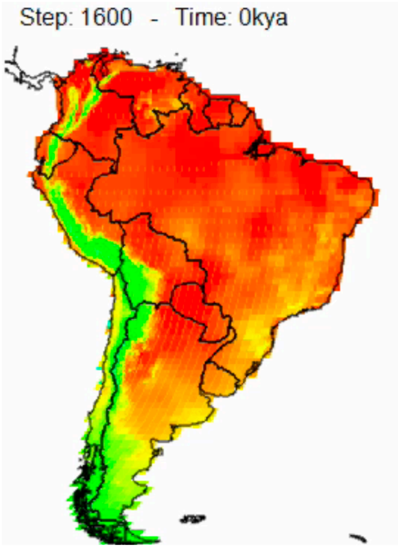
Mechanisms

- Range shifts, contractions and expansions
- Evolutionary adaptation
- Long-distance dispersal to disjunct habitats
- Interspecific competition
- Allopatric speciation (isolated populations evolve differently)
- Extinction

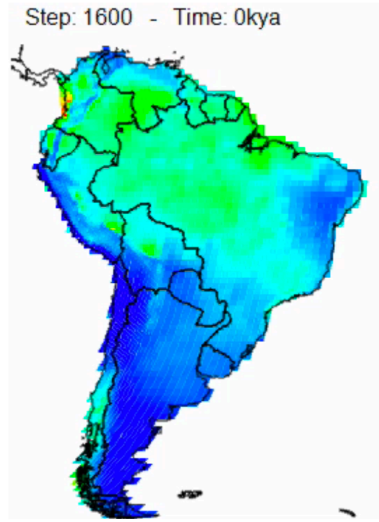
Assumptions

- Species have tolerances to climate that affect their geographical distributions over space and time.
- Climatic tolerances can evolve by natural selection in dynamic environments.
- et al

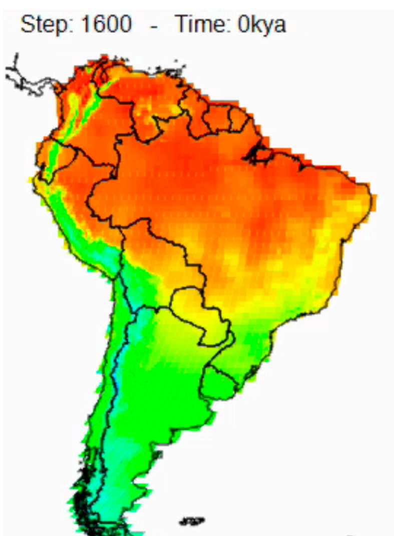
Warmest



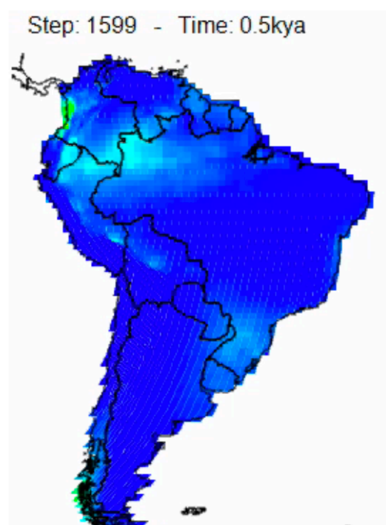
Wettest



CLIMATE



Coolest



Driest

Time integrated species richness