Steps towards a next-generation land surface model

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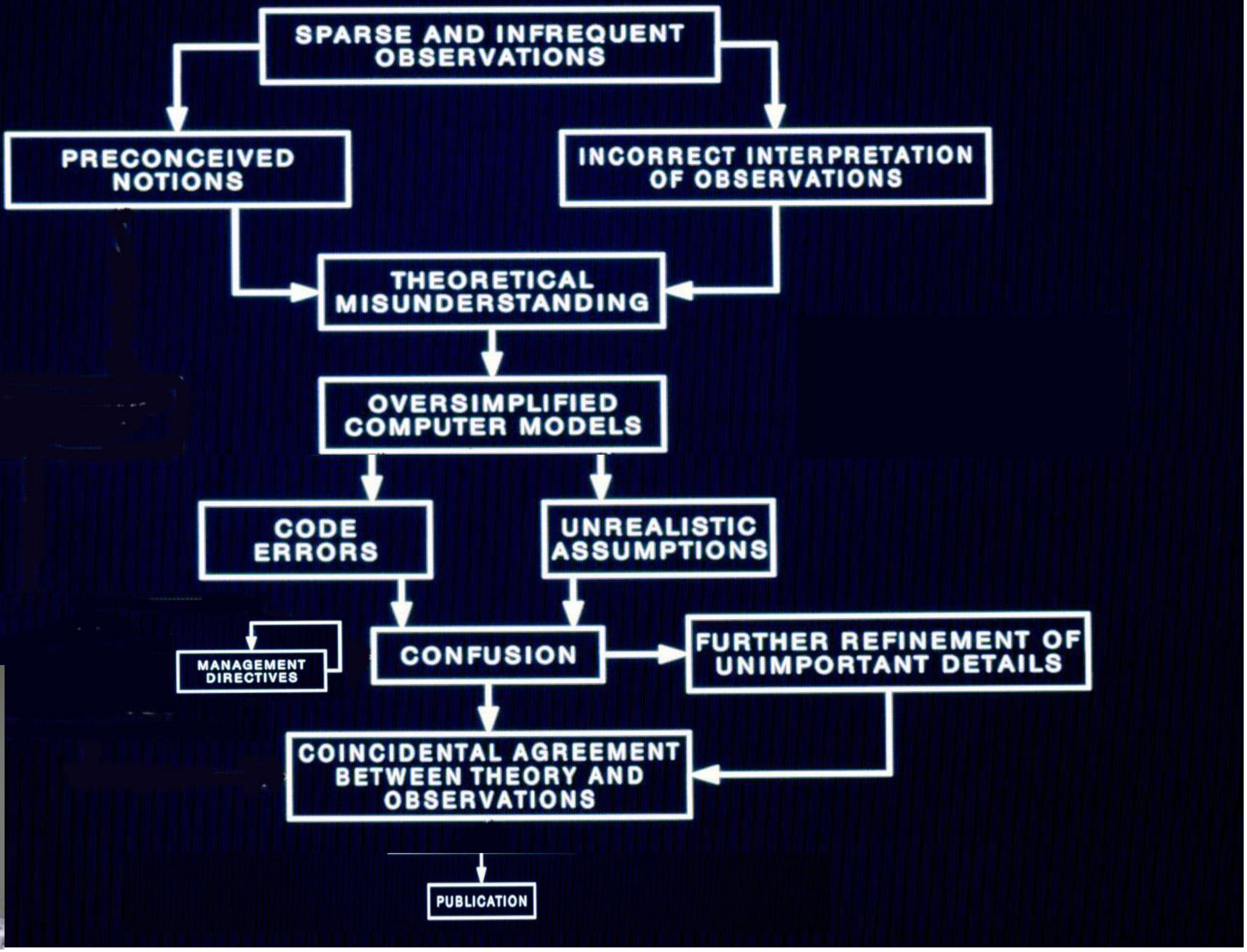
Giulia Mengoli (*ICL* and *Euro-Mediterranean Center on Climate Change)*
Rebecca Thursa Thomas (*ICL*)
Han Wang *(Tsinghua University)*

Solomon, AM (1988)

FLOWCHART: COMPUTER MODEL DEVELOPMENT



SPARSE AND INFREQUENT OBSERVATIONS

PRECONCEIVED NOTIONS

INCORRECT INTERPRETATION OF OBSERVATIONS

THEORETICAL MISUNDERSTANDING

OVERSIMPLIFIED COMPUTER MODELS

CODE ERRORS

UNREALISTIC ASSUMPTIONS

MANAGEMENT DIRECTIVES

CONFUSION

FURTHER REFINEMENT OF UNIMPORTANT DETAILS

COINCIDENTAL AGREEMENT BETWEEN THEORY AND OBSERVATIONS

PUBLICATION

A change of strategy

- **Most** elements of current LSMs rest on shaky scientific foundations.
- Result: key outcomes, e.g. temperature and CO_2 responses of GPP, **differ** among models.
- New foundations **are being constructed** for ‘next-generation’ models.

  Immediate challenges:

  - separation of different ecophysiological time scales
  - ‘closing the loop’ between GPP and fAPAR
  - compatibility with existing infrastructure (next-generation JULES?)

What next-generation models will look like

- Continuously varying traits will replace PFTs
- Acclimation and adaptation of traits will be central – trait values will be predicted, not prescribed
- Explicit theoretical basis for predictions (optimality hypotheses)
- Beyond benchmarking – **greatly expanded use of data** (including atmospheric measurements, trait data, remote sensing products...) **during model development**

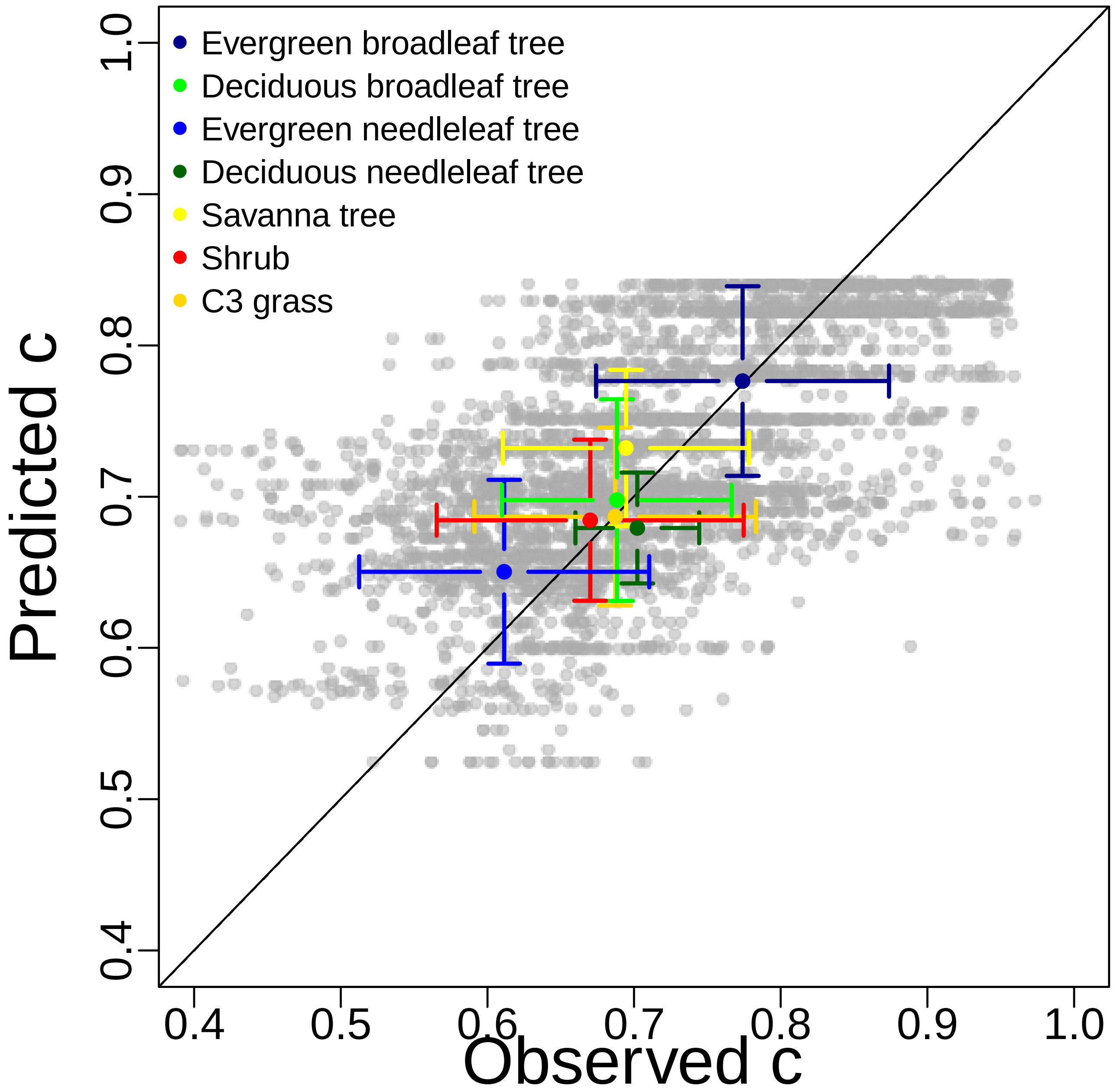
Successful prediction of traits and rates (at leaf to canopy scales)

- c_i:c_a ratio (Wang *et al.* 2017 *Nature Plants*)
- Altitude effects on photosynthesis (Wang *et al.* 2017 *New Phytologist*)
- GPP (Wang *et al.* 2017 *Nature Plants*)
- Leaf N (Dong *et al.* 2017 *Biogeosciences*)
- V_{cmax} (Togashi *et* al. 2018 Biogeosciences; NG Smith *et al.*, *Ecology Letters* in revision)
- J_{max}:V_{cmax} ratio (Wang *et al.* 2017 *Nature Plants*)
- R_{dark} (H Wang *et al.,* submitted to *Ecology Letters*)
- LMA and leaf lifespan (H Wang *et al.,* in prep.)
- Leaf-to-air ΔT (A Kamolphat *et al.,* in prep.)
- Recent GPP trends (Cai *et al.*, in prep.)

Global leaf $\delta^{13}C$ data => logit (χ)

	predicted	fitted
temperature (K)	0.054	0.052 ± 0.006
ln vpd	–0.5	–0.55 ± 0.06
elevation (km)	–0.08	–0.11 ± 0.03

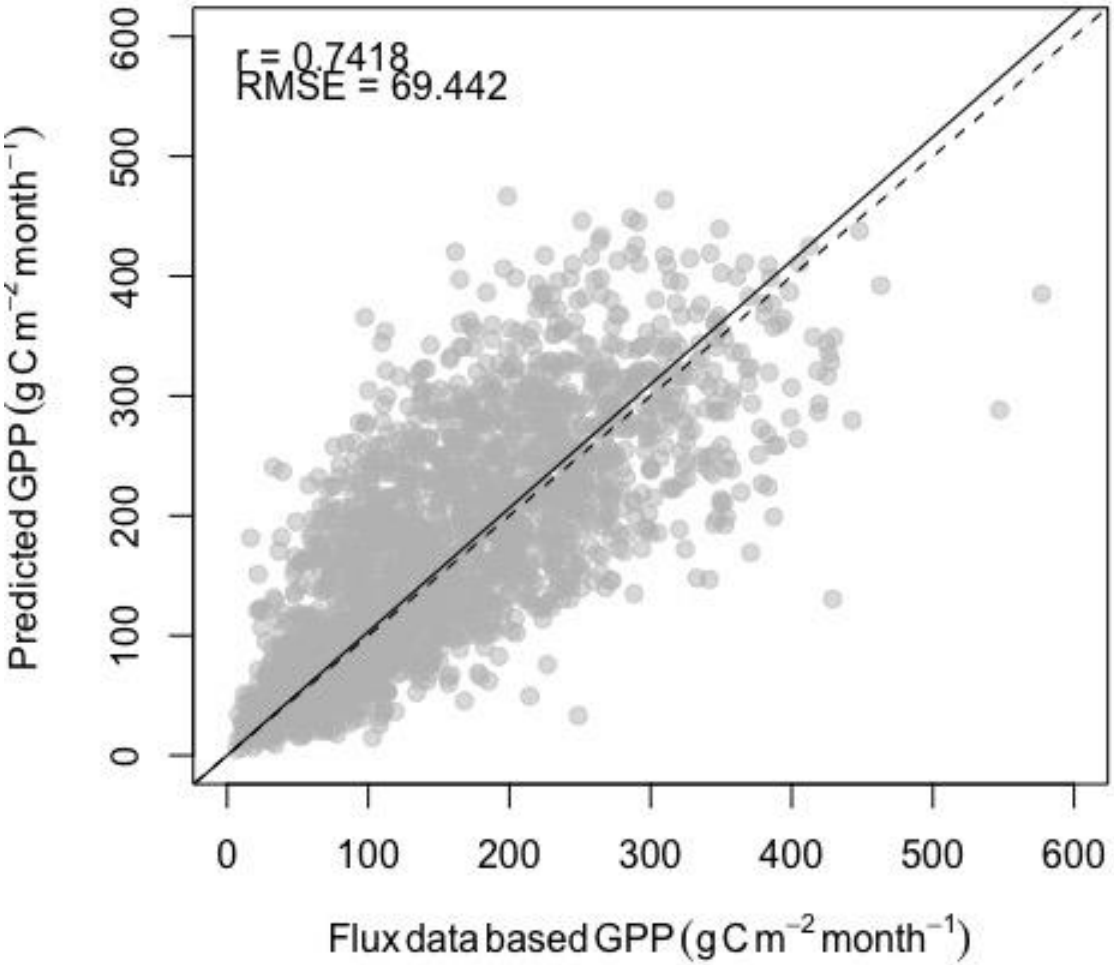
Wang *et al.* 2017 *Nature Plants*



Wang *et al.* 2017 *Nature Plants*

Effect of 2000 m altitude shift compared to data by Körner & Diemer (1987) *Functional Ecology*

Variable	Observed (mean ± SE)	Predicted	Prediction formula
$\chi_h - \chi_l$	-0.1 ± 0.02	-0.098	$\frac{\partial \chi}{\partial z} = -\frac{0.114}{2}\left(\frac{RH}{1-RH} + \frac{P_o}{P_o + K_o}\right)\chi(1-\chi)$
$(PPFD_h - PPFD_l)/PPFD_l$	0.054^a	0.054	$\frac{1}{PPFD}\frac{\partial PPFD}{\partial z} = 0.027$
$(V_{cmaxh} - V_{cmaxl})/V_{cmaxl}$	0.41 ± 0.13	0.28	$\frac{1}{V_{cmax}} \cdot \frac{\partial V_{cmax}}{\partial z} = 0.027 + \left(\frac{1}{\chi + \kappa} - \frac{1}{\chi + 2\gamma^*}\right)\frac{\partial \chi}{\partial z} + \frac{0.114\kappa}{\chi + \kappa}$
$(A_h - A_l)/A_l$	ns	-0.004	$\frac{1}{A} \cdot \frac{\partial A}{\partial z} = 0.027 + \left(\frac{1}{\chi - \gamma^*} - \frac{1}{\chi + 2\gamma^*}\right)\frac{\partial \chi}{\partial z}$



Monthly GPP
(from eddy covariance flux towers)

$$A_J = j_0 I_{abs} m \sqrt{1 - \left(\frac{c^*}{m}\right)^{\frac{2}{3}}}$$

$$m = \frac{c_a - G^*}{c_a + 2G^* + 3G^* \sqrt{\frac{1.6 D h^*}{b\left(K + G^*\right)}}}$$

φ_0 = 0.085
from literature

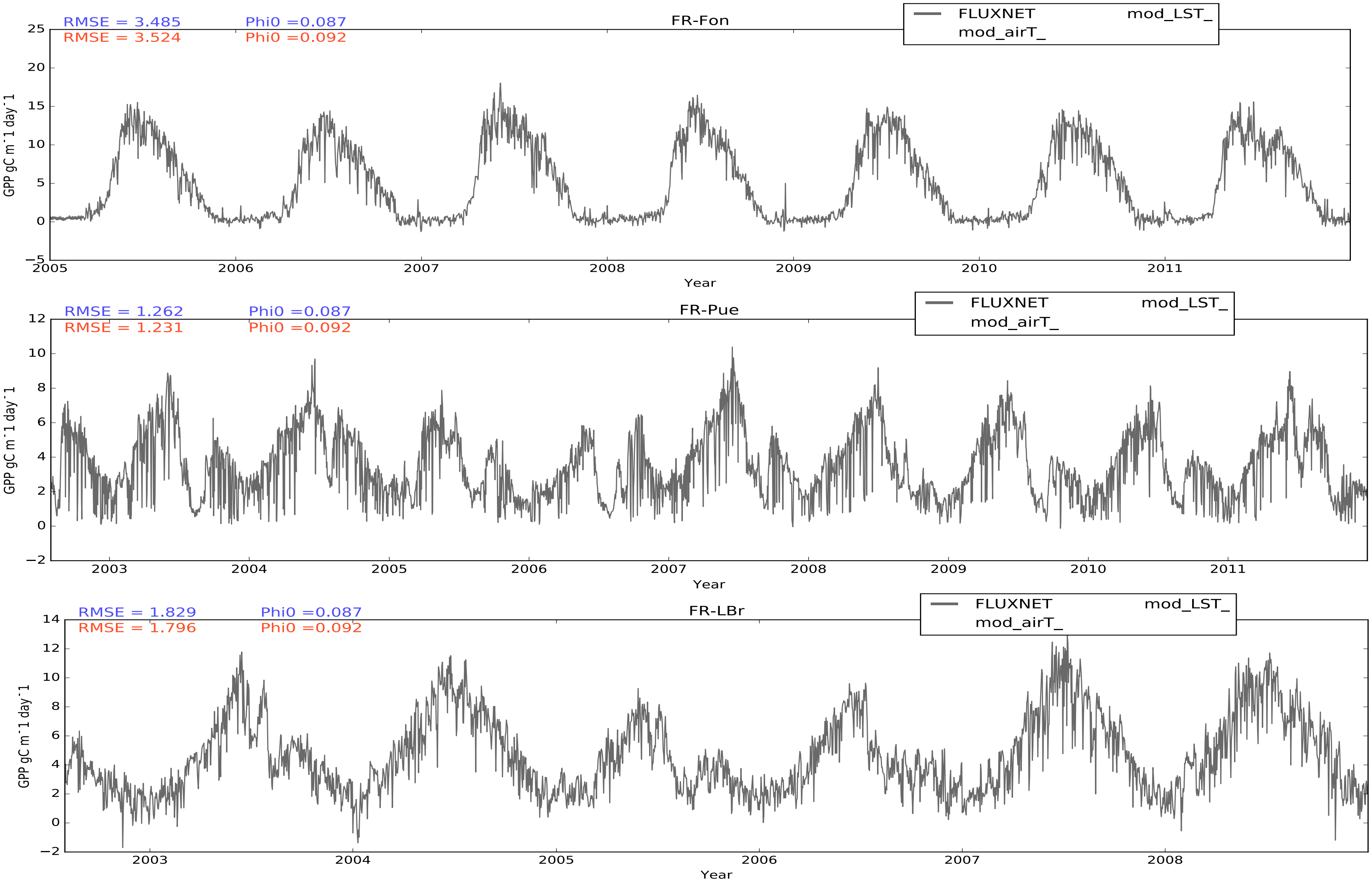
c^* = 0.41
from experiments

β = 146
from $\delta^{13}C$ data

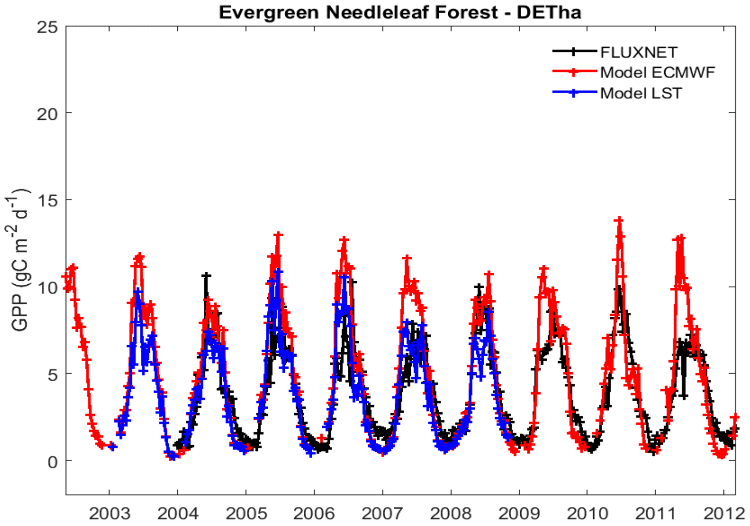
Wang *et al.* 2017
Nature Plants

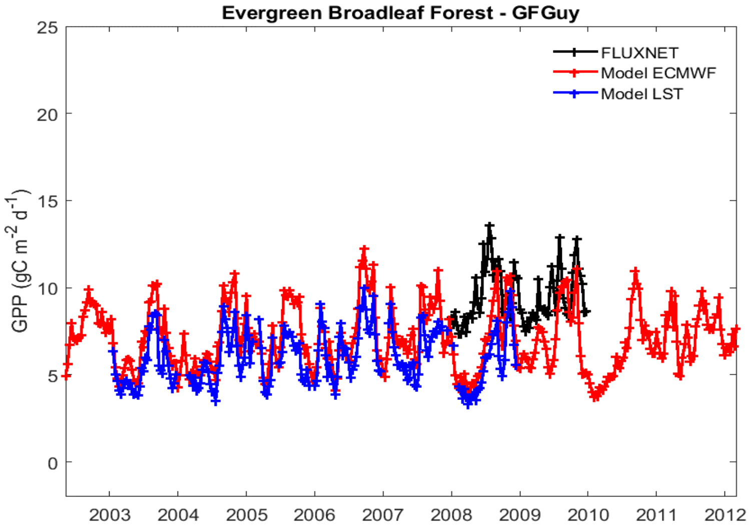
Green vegetation cover = MODIS EVI
Temperature, vpd, sunshine hours = CRU CL2.0
CO_2 = NOAA GlobalView

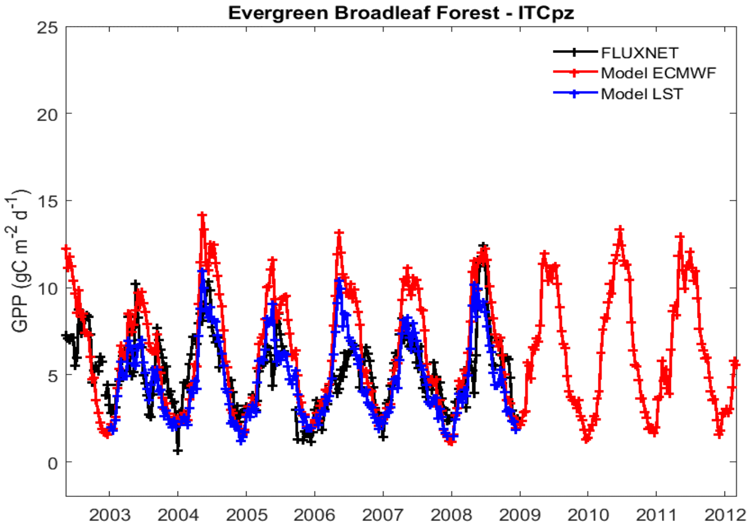
Comparison with seasonal cycles of GPP

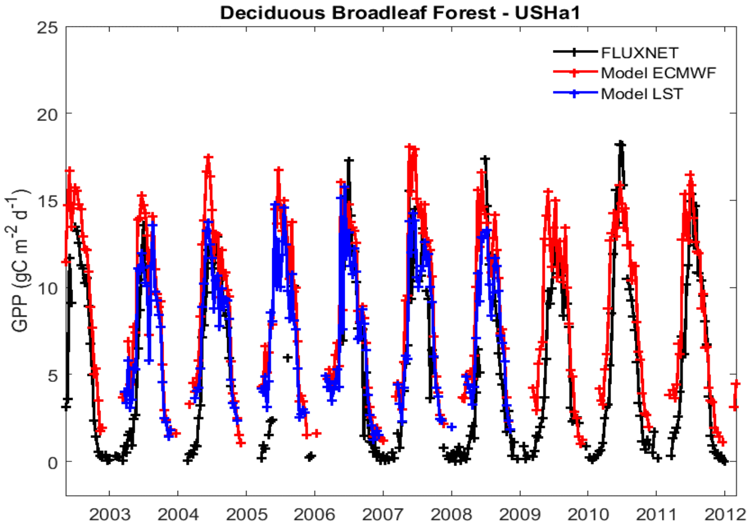


Terra-P validation sites: flux data (black), model (red, blue)


Evergreen Needleleaf Forest - DETha


Evergreen Broadleaf Forest - GFGuy


Evergreen Broadleaf Forest - ITCpz


Deciduous Broadleaf Forest - USHa1

M Balzarolo *et al.* (in revision)

Comparison with experimental CO_2 effects

Comparison with Ainsworth & Long’s (2005) meta-analysis of FACE experiments (≈ 200 ppm CO_2 enhancement):

	meta-analysis	**model**
Light use efficiency	12.2 ± 9 %	15.2 %
Water use efficiency	54.3 ± 17 %	55 %
Stomatal conductance	–20.0 ± 3 %	–15.0 %

Other satellite-based models, e.g. the widely used MODIS GPP, do not show any of these responses.

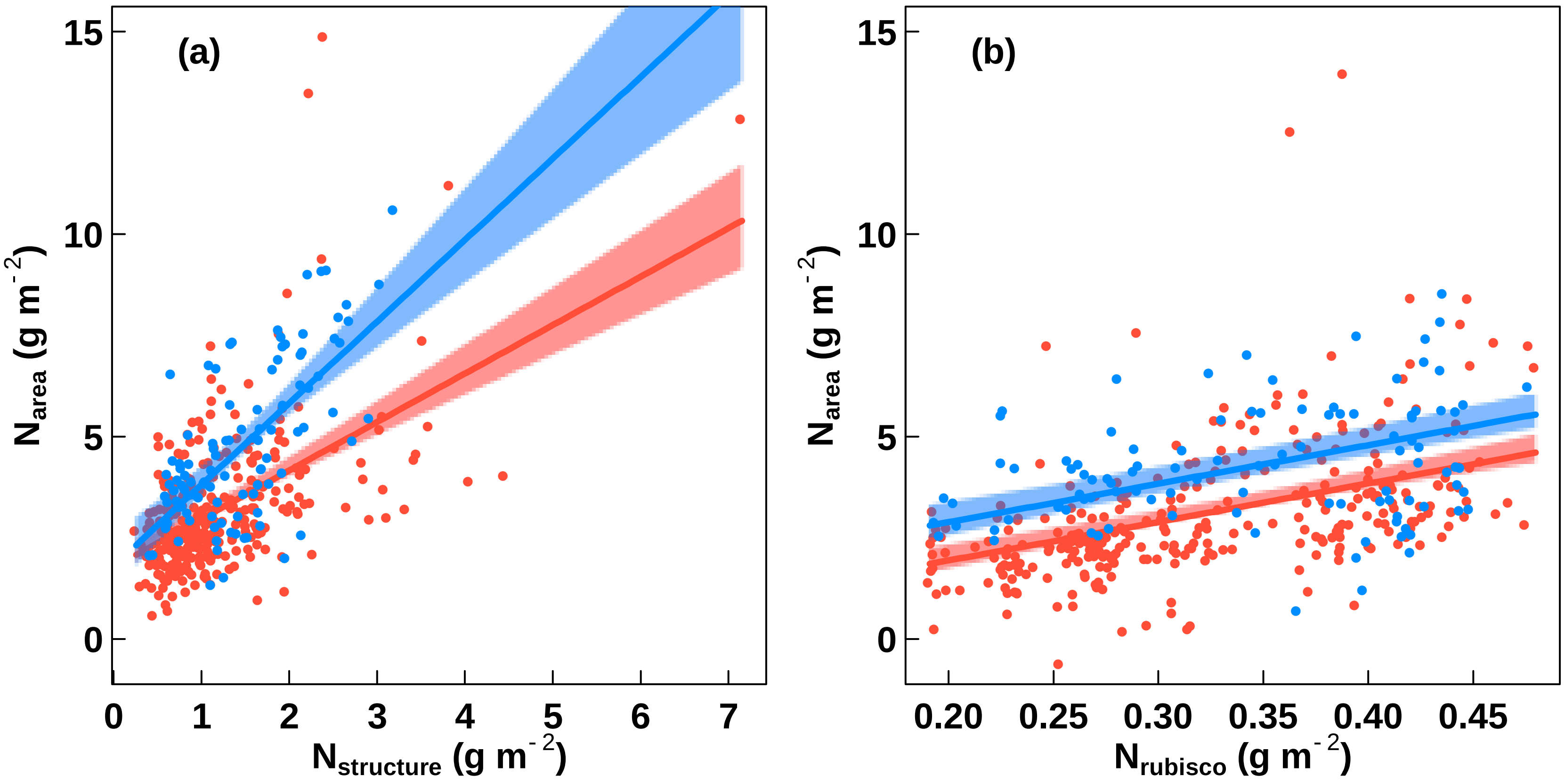
Wang *et al.* 2017 *Nature Plants*

Leaf N (ln N_{area}) across Australia

	predicted	fitted
χ (from δ^{13}C)	–0.62	–0.61 ± 0.25
ln PAR	1	0.87 ± 0.10
mean annual T	–0.048	–0.047 ± 0.007

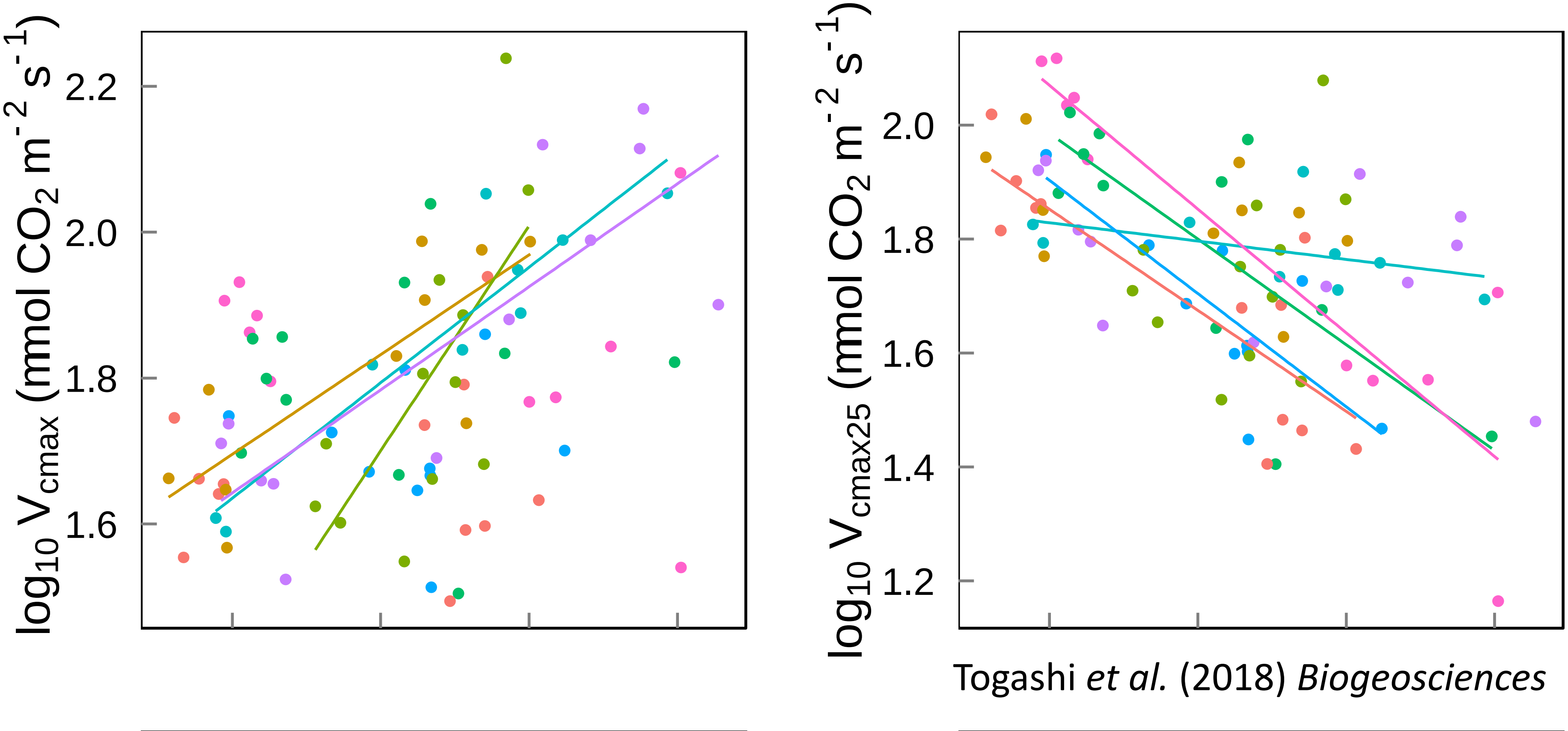
Dong *et al.* (2017) *Biogeosciences*

N_{area} from LMA (left) and predicted V_{cmax} (right)



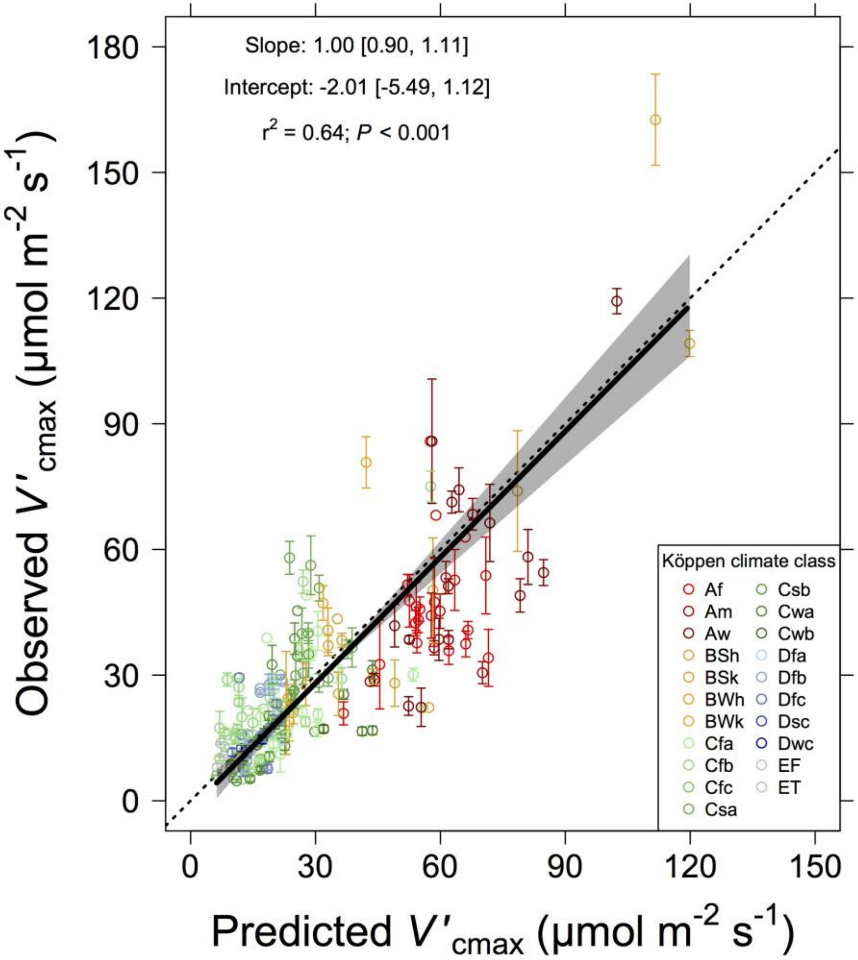
Dong *et al.* (2017) *Biogeosciences*

Seasonal acclimation of V_{cmax}
(repeat measurements on the same plants: Great Western Woodlands, Australia)



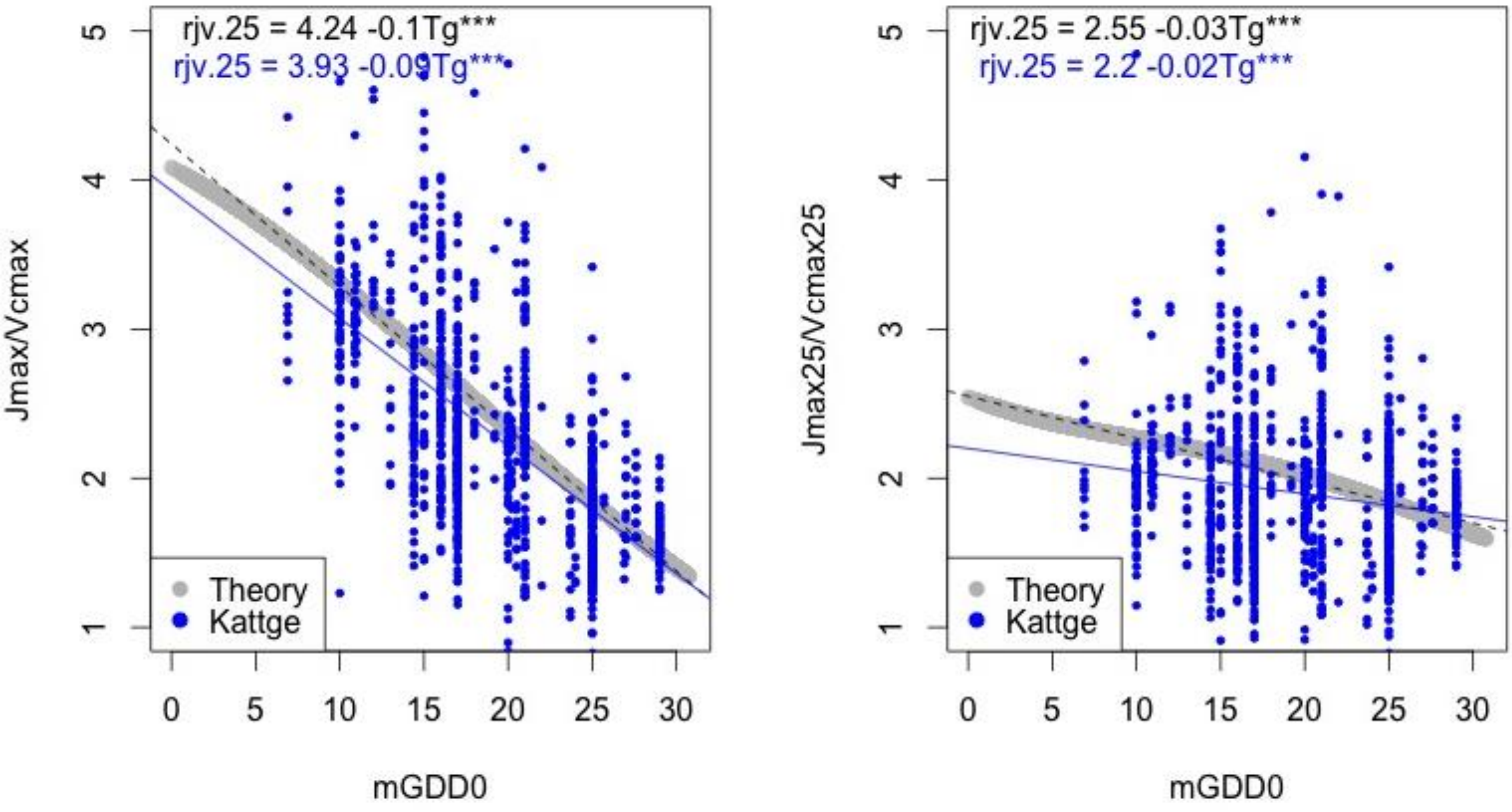
Togashi *et al.* (2018) *Biogeosciences*

V_{cmax} around the world



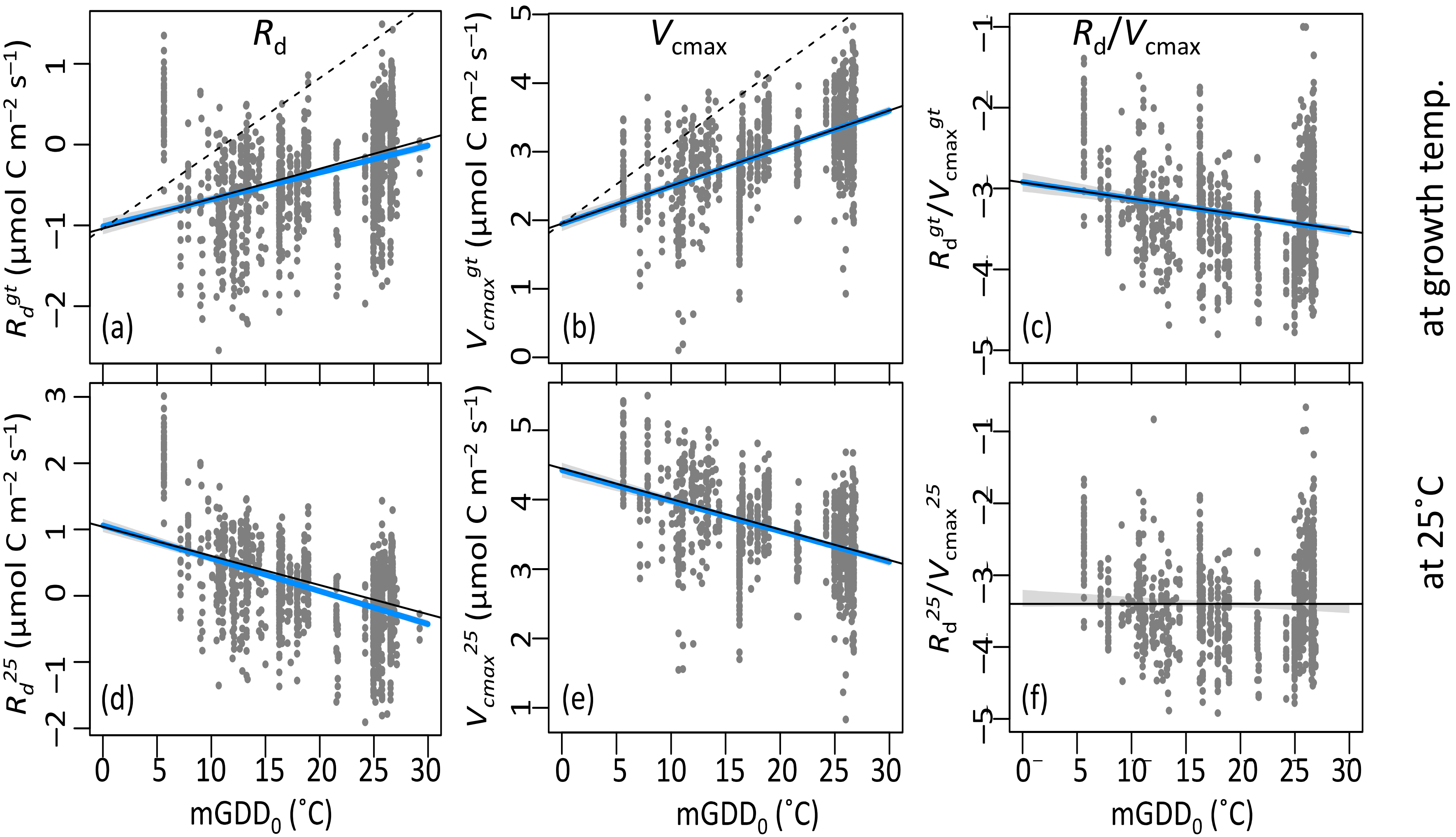
NG Smith *et al.*
in revision

J_{max}:V_{cmax} ratios (experimental data)

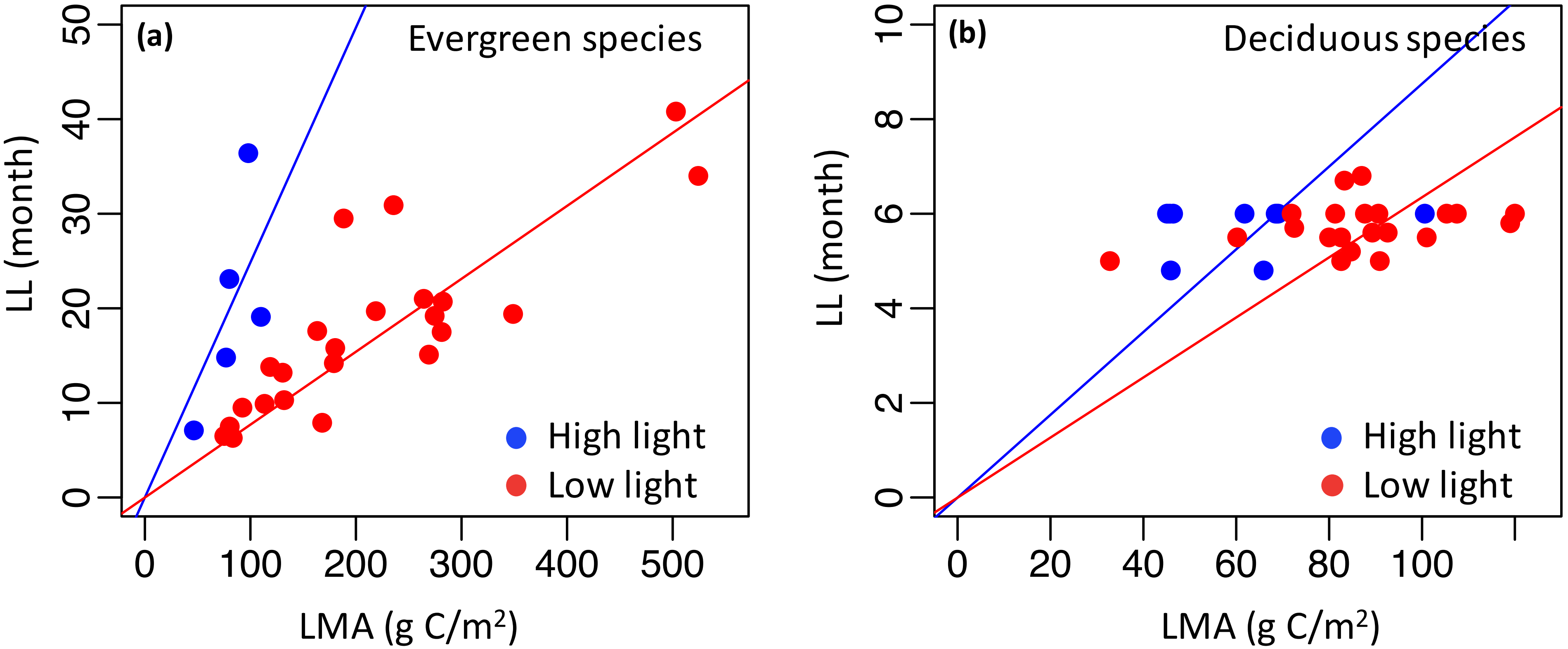


H Wang *et al.* (unpublished results)

R_{dark}, V_{cmax} and their ratio (not an enzyme kinetic response)

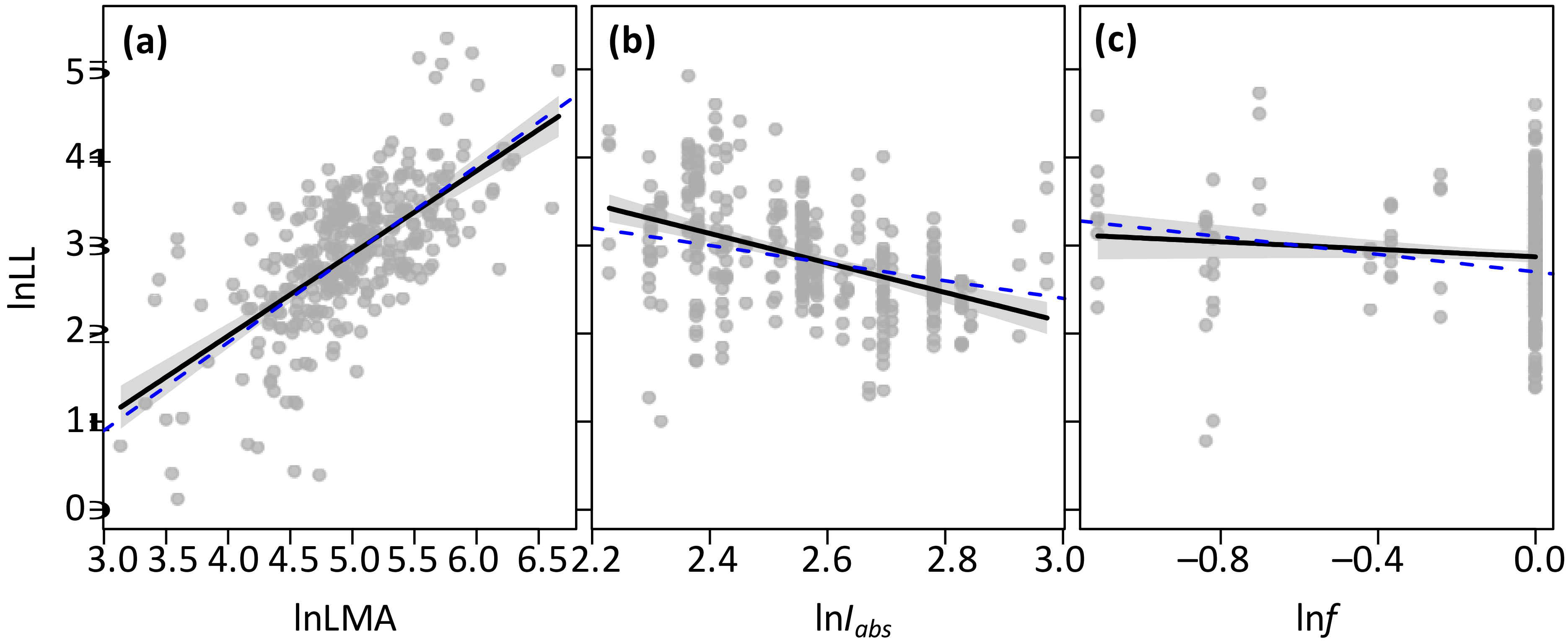


Leaf lifespan (LL) and LMA: examples from GlopNet sites



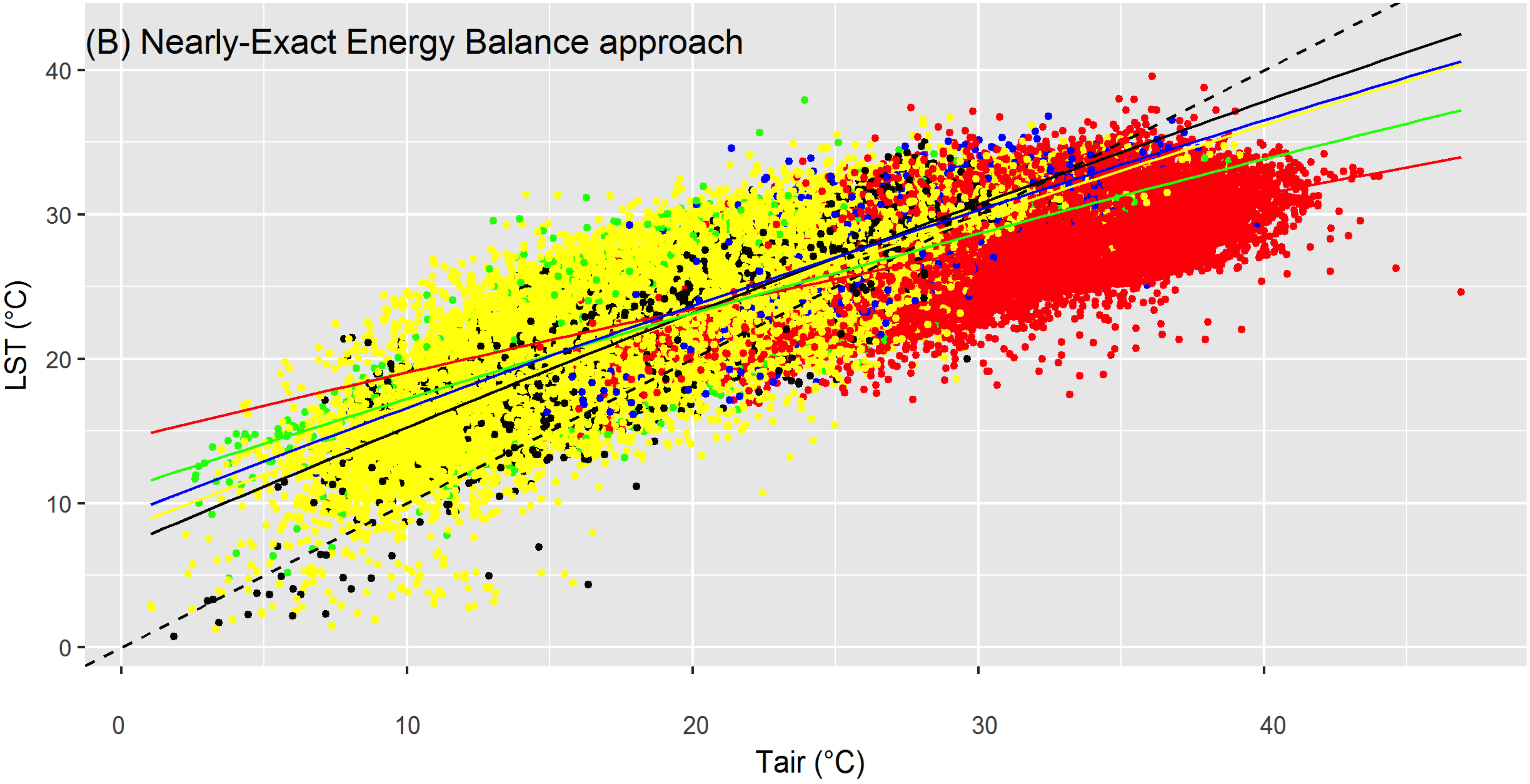
Predicted responses from combined Kikuzawa-Xu-Wang model
Wang *et al.* in prep.

Leaf lifespan (LL) from LMA, mean canopy light (I_{abs}), growing-season length (f) in evergreens



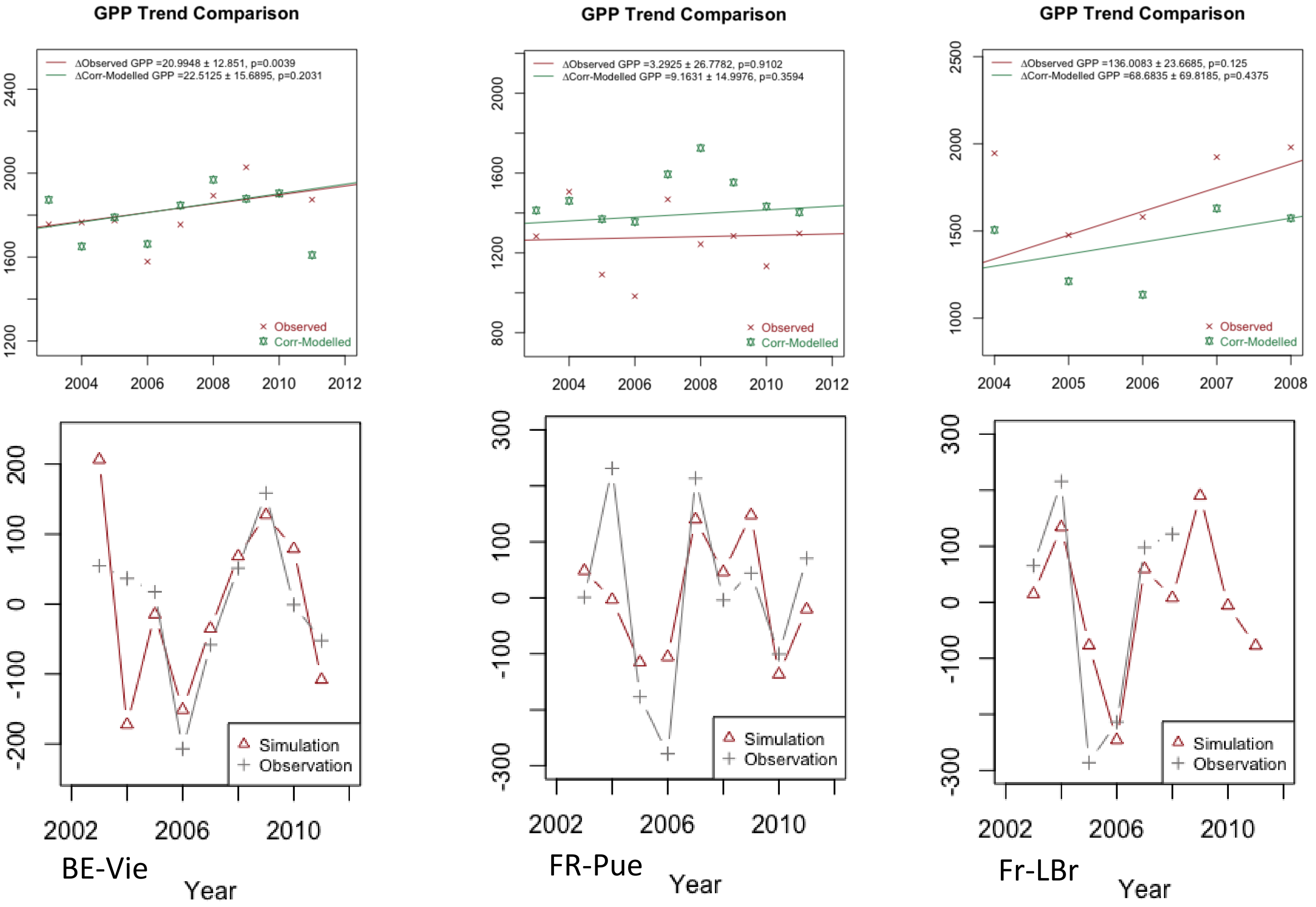
Predicted responses from combined Kikuzawa-Xu-Wang model
Wang *et al.* in prep.

Canopy versus air temperature (‘biophysical homoeostasis’)



A Kamolphat *et al.* in prep. (collaboration with CEH: Gallego-Elvira, Mercado, Oliver, Taylor)

Data-model comparison of recent GPP changes

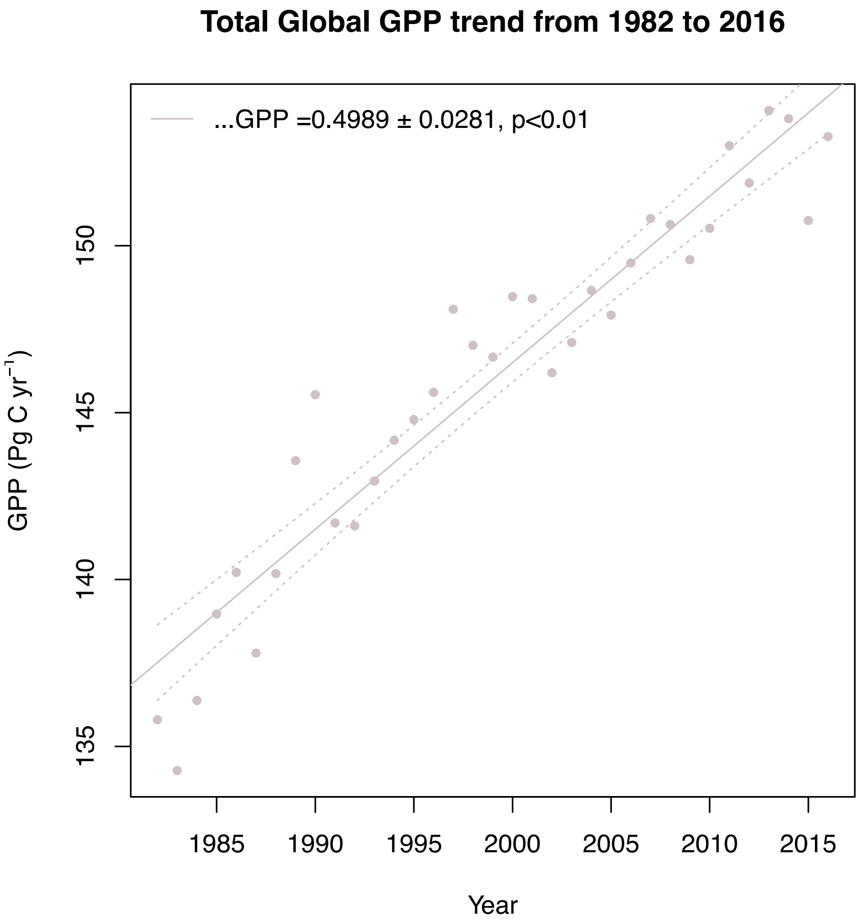


TREND

VARIATION

W. Cai *et al.* (in prep.)

Modelled global GPP trend, 1982–2016



Total Global GPP trend from 1982 to 2016

W. Cai *et al.* (in prep.)

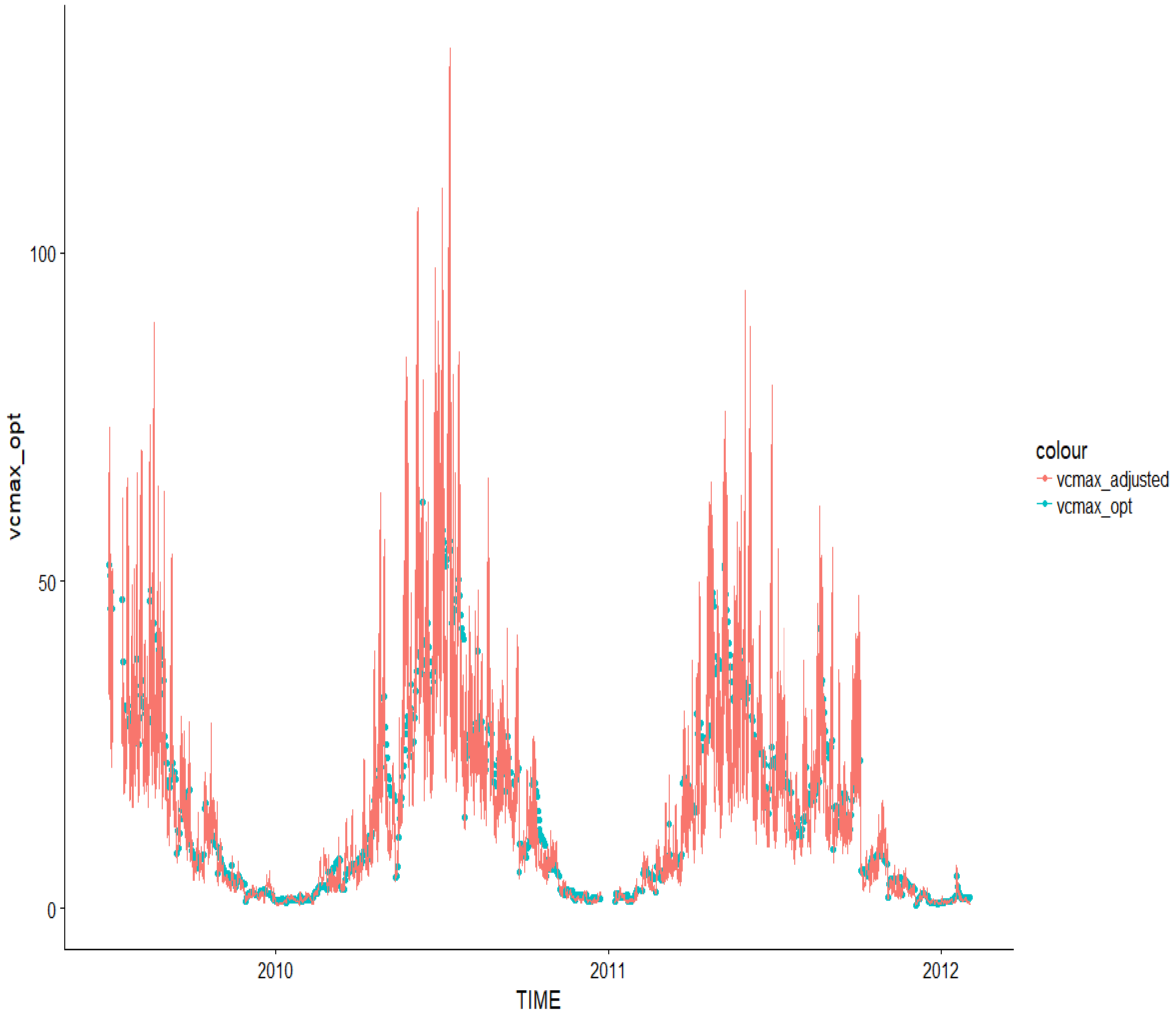
4.5 ± 0.6%/yr from COS
(Campbell *et al.* 2017 *Nature*)

6.3 ± 0.5%/yr from model
(W. Cai *et al.* in prep.)

Separation of time scales

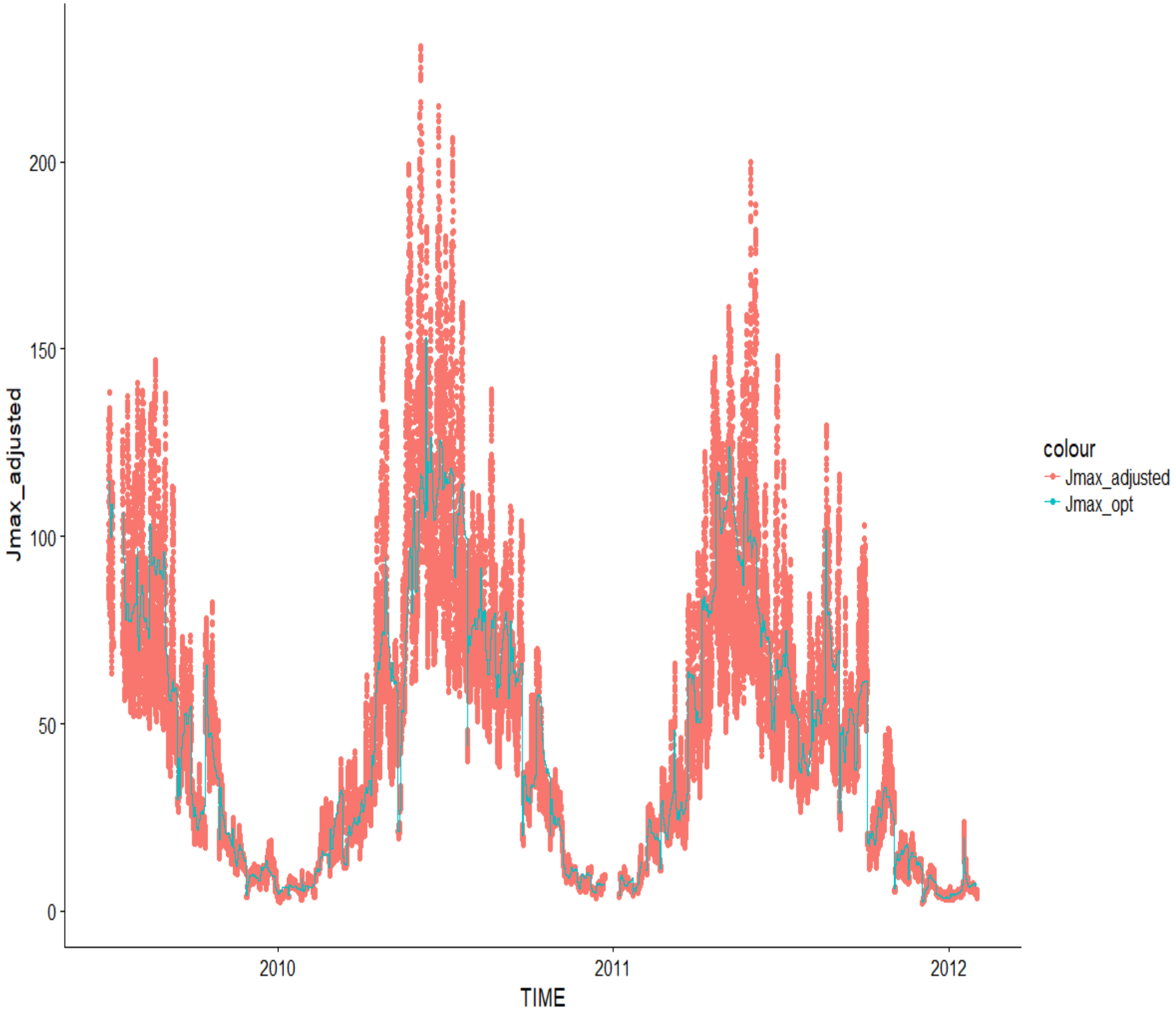
- V_{cmax}[gt] and J_{max}[gt] vary according to a 15-day running mean, optimized to average conditions (acclimation)
- Instantaneous V_{cmax} and J_{max} follow enzyme kinetics
- χ varies instantaneously, optimized to current conditions (stomatal regulation)
- Assimilation follows the Farquhar model, $A = \mathrm{min}(A_{\mathrm{C}}, A_{\mathrm{J}})$
- Case study at BE-Vie

Time-varying V_{cmax}



G Mengoli
in prep.

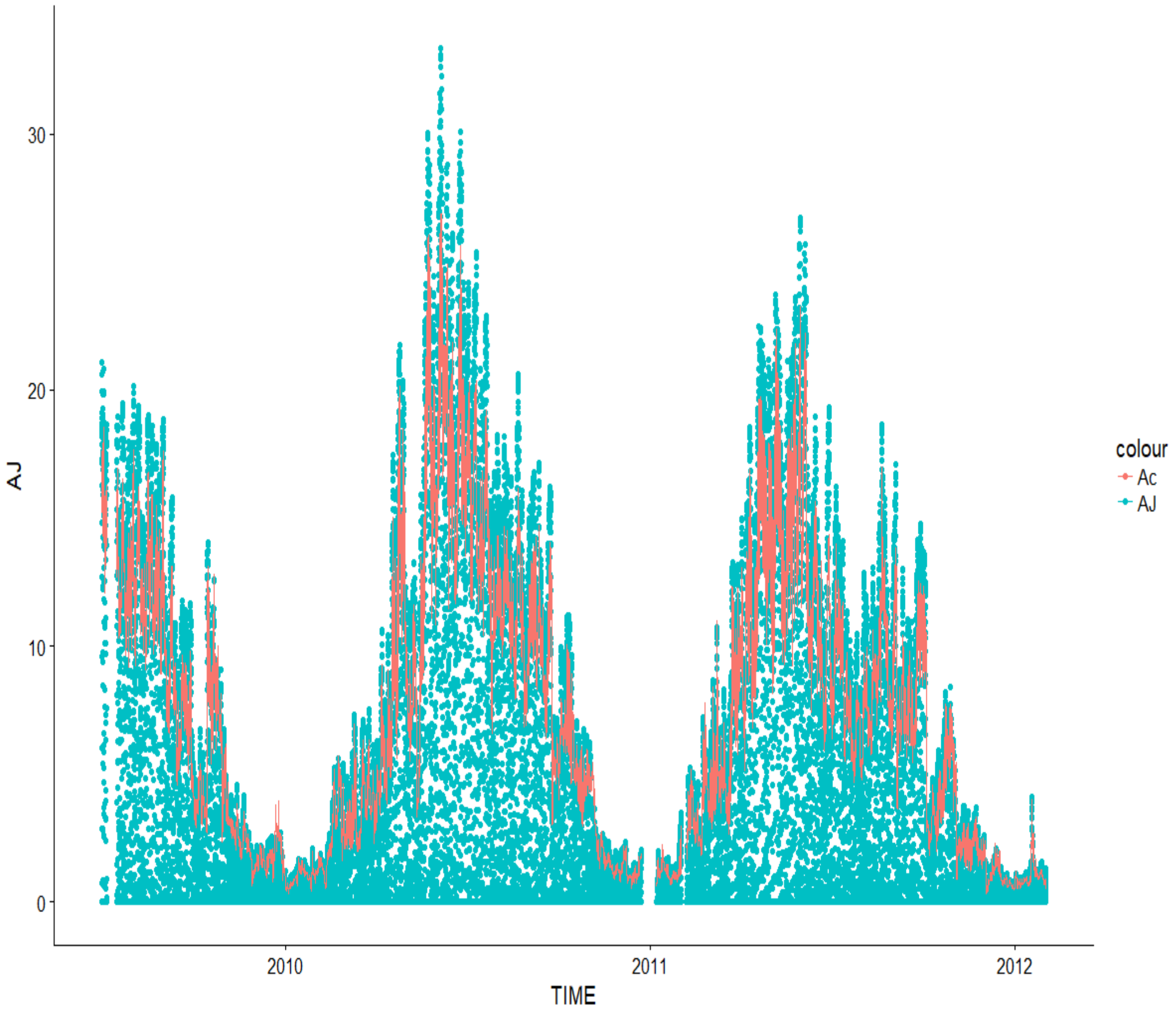
Time-varying J_{max}



G Mengoli
in prep.

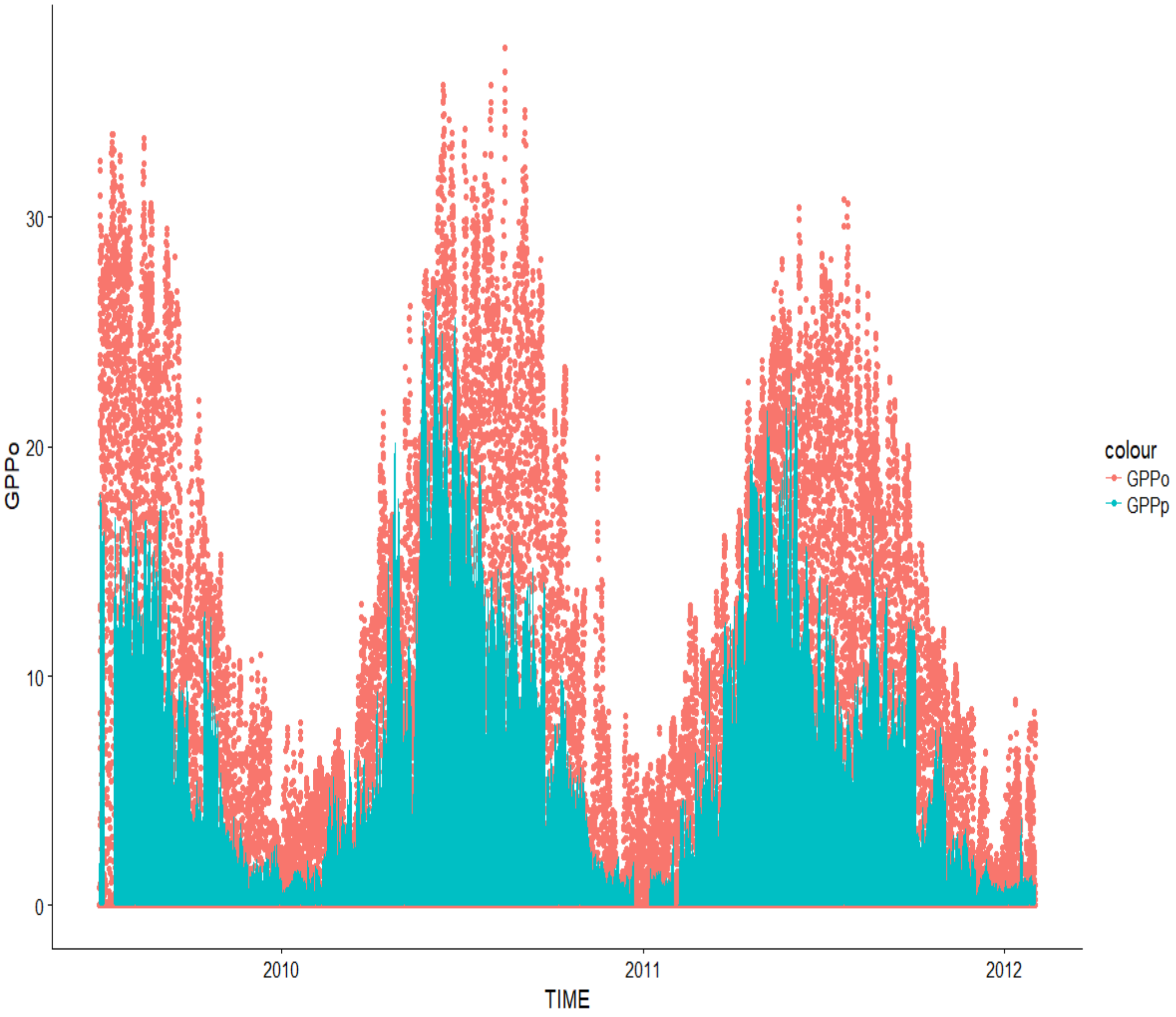
Time varying A_c & A_J

phi0 = 0.093



G Mengoli
in prep.

Time varying GPP_p & GPP_o



G Mengoli
in prep.

Concluding remarks

- I have focused on some of the most **fundamental** processes affecting land-atmosphere carbon and water exchanges.
- Most of what I have shown is **not in any** of the JULES ‘lego bricks’.
- Traits that vary (adaptively) in time and space are **held constant** in JULES.
- Cool leaves (ΔT < 0) in daytime: **never simulated anywhere** by JULES.
- These issues are **not** confined to JULES. They are probably common to all current LSMs!
- What are we going to do about it?