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Interactive comment on "Interannual variability in Australia's terrestrial carbon cycle constrained by multiple observation types" *by* Cathy M. Trudinger et al.

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We thank reviewer 1 for their helpful comments, and provide the following responses:

(1) The models (CABLE and CASA-CNP) produce daily carbon and water fluxes, why do the authors used monthly mean flux measurements (P5 L16) as constraints? Also, please make a table for the other biometric data (e.g., leaf NPP, soil carbon and above-ground phytomass and litter etc.) if there are a few data points.

We use monthly mean flux measurements as constraints because the meteorological forcing is not as accurate at the daily timescale. There are too many data points for a

table, instead we include map (Fig. 1 below) showing the location of the biometric and other data that are used for calibration.

(2) Please provide more details on the calculation of the cost function. For example, how "Different types of observations were then weighted relative to each other"?

The weights for each observation group (e.g. ET, GPP etc) were scaled so that each group contributed approximately equally to the cost function calculated with the prior parameters. This is important because the different types of observations can have vastly different magnitudes, and the relative contribution of each group to the cost function should not depend on the units that are used.

(3) The approach of generating ensemble parameter sets is not clear. How does "the null space Monte Carlo method" work? The authors stated that the purpose of using this method is "to quantify uncertainty due to parameter equifinality in model predictions", so my understanding is that this method can generate the posterior parameter distributions. Although the authors have detailed introduction to this method (P6 L27-33), I feel it is still difficult for the readers to understand why the generated parameter sets are suffi- cient to represent the posterior distribution of the parameters. Are there some special features of this method? Otherwise I can't believe only 30 parameter sets are enough to represent possible combination of parameters that are consistent with the observations, given more than 10 parameters are involved in each model. Even if we assume there are only 10 parameters, and each parameter can only be two possible values, there will 2^{10} possible parameter sets. I understand that it may not be feasible to run regional simulations for a huge number of sets of parameters, but the authors need to demonstrate the 30 parameter sets are a good sample of the posterior parameter space.

The null space Monte Carlo method does not calculate posterior parameter distributions. Rather, it is an efficient method to generate multiple parameter sets that are constrained by the calibration observations (Tonkin and Doherty, 2009). By taking into account the calibration and null spaces, it allows for these parameter sets to have the most range in combinations of parameters that are least well constrained by the calibration observations, therefore allowing for a much better representation of parameter equifinality than random combinations of parameters. Clearly, the more parameter sets the better, but we need to balance that with the computational limitations. Figures 7 and S12 show the ensembles of parameter sets (colored symbols), and they have many different values for the parameters that are not well constrained (many more than two values). Our purpose of using this method would perhaps be better described as "to see the effect of uncertainty due to parameter equifinality in model predictions".

Specific points: P1,L15, L16: ecosystem respiration –> heterotrophic respiration

Yes, thank you.

P1,L21: you can give a hint to the readers that the detailed description of BIOS-2 is in section 2.1

Yes

P5, L12, L25: evaporation –> evapotranspiration

Yes, thank you.

P8, L7: R2 is unitless

Yes

Fig 6, Fig S11: change the figure style to 2D. i.e., x axis is parameter, y axis is observation variable (ET, NPP etc), and use colors (light to dark) to represent the in- crease/decrease in variance

Presumably the reason for changing the figure is that some bars were obscured from view. We have changed the figure to 2D, but still use bars rather than colors, and all

bars can be clearly seen now. New figures for observation worth for CABLE (Fig. 2 below) and CASA-CNP (Fig. 3 below) replace the previous Figures 6 and S11.

P9, L12: please give the sources of the six bioclimatic regions

The bioclimatic regions are an aggregation of the agro-climatic classification of Hutchinson et al. (2005) into six classes, as described and used by Haverd et al (2013a, 2013b).

P9, L18: the anomaly from the best case

No, the anomaly is calculated for each ensemble member by subtracting the temporal average for that ensemble member.

References:

Hutchinson, M. F., McIntyre, S., Hobbs, R. J., Stein, J. L., Garnett, S., and Kinloch, J.: Integrating a global agro-climatic classification with bioregional boundaries in Australia, Global Ecology and Biogeography, 14, 197–212, doi:10.1111/j.1466-822X.2005.00154.x, 2005.

Tonkin, M., and J. Doherty, Calibration-constrained Monte Carlo analysis of highly parameterized models using subspace techniques, Water Resour. Res., 45, W00B10, doi:10.1029/2007WR006678, 2009.

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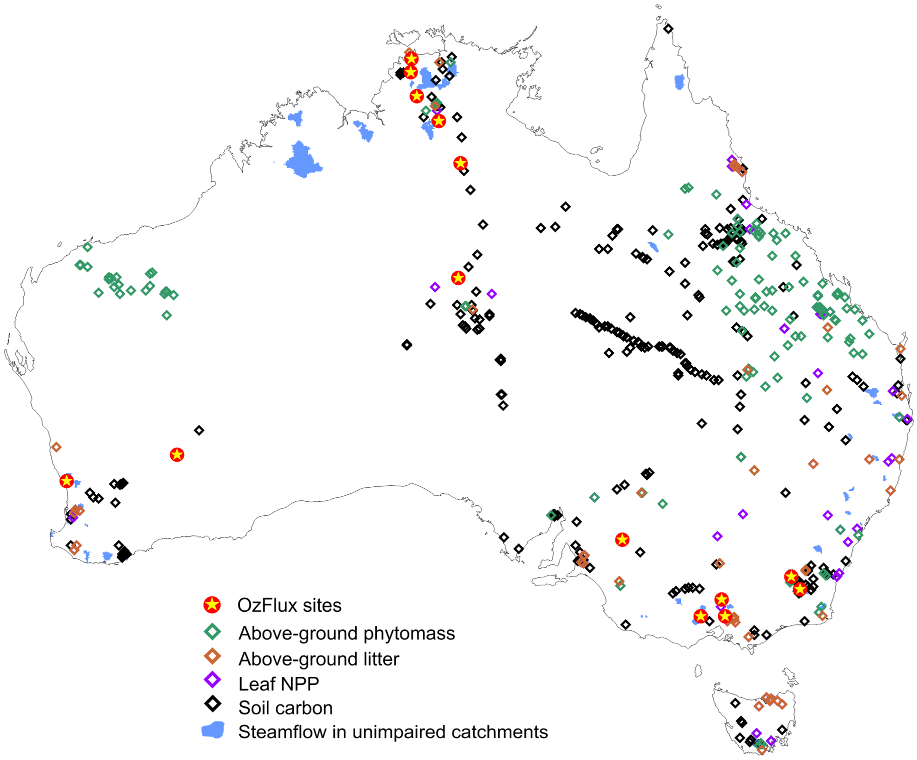

OzFlux sites
Above-ground phytomass
Above-ground litter
Leaf NPP
Soil carbon
Steamflow in unimpaired catchments

Fig. 1.

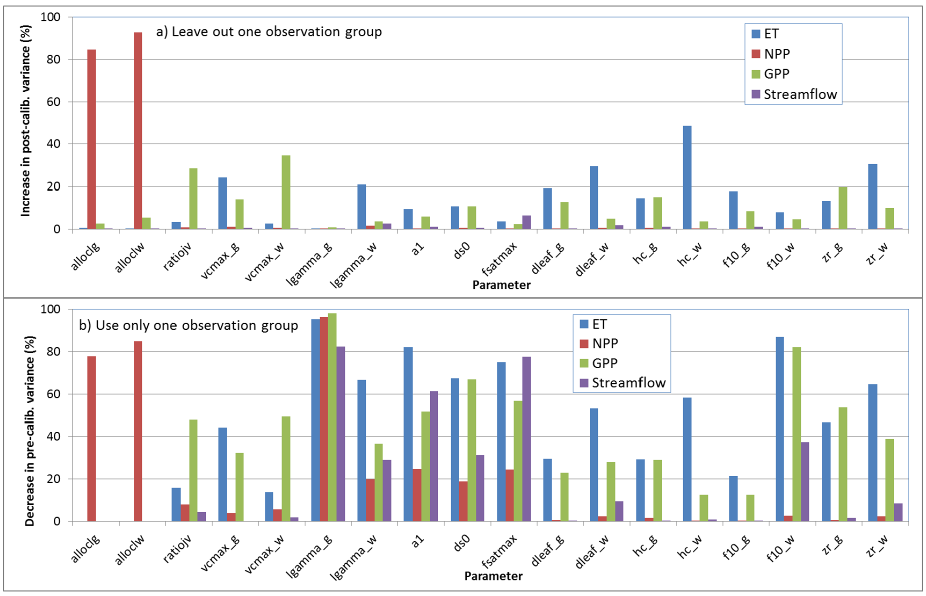
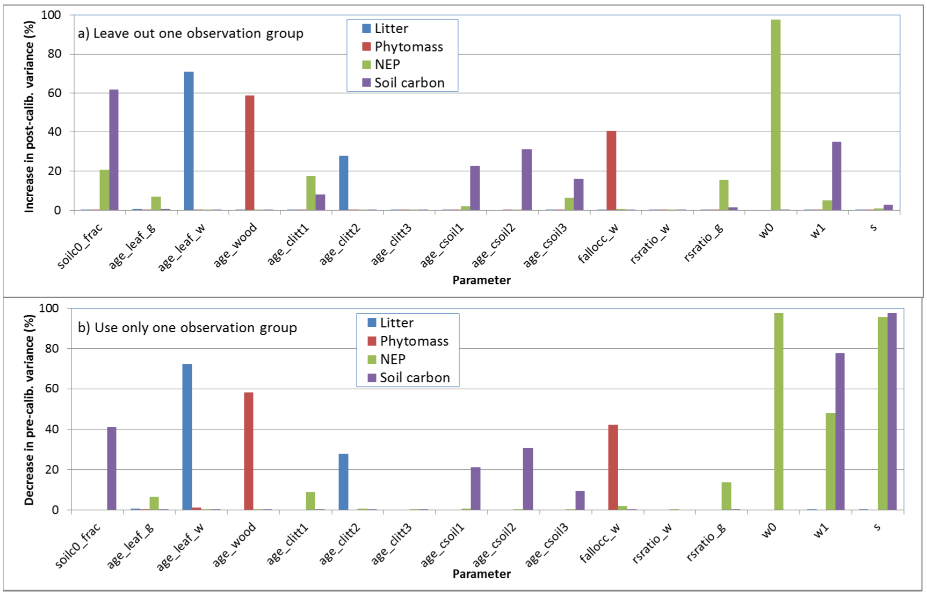

a) Leave out one observation group
Increase in post-calib. variance (%)
100
80
60
40
20
0
ET
NPP
GPP
Streamflow
alloclg
alloclw
ratiojv
vcmax_g
vcmax_w
lgamma_g
lgamma_w
a1
ds0
fsatmax
dleaf_g
dleaf_w
hc_g
hc_w
f10_g
f10_w
zr_g
zr_w
Parameter
b) Use only one observation group
Decrease in pre-calib. variance (%)
100
80
60
40
20
0
ET
NPP
GPP
Streamflow
alloclg
alloclw
ratiojv
vcmax_g
vcmax_w
lgamma_g
lgamma_w
a1
ds0
fsatmax
dleaf_g
dleaf_w
hc_g
hc_w
f10_g
f10_w
zr_g
zr_w
Parameter

Fig. 2.



a) Leave out one observation group
Litter
Phytomass
NEP
Soil carbon
Increase in post-calib. variance (%)
Parameter
b) Use only one observation group
Decrease in pre-calib. variance (%)
soilc0_frac
age_leaf_g
age_leaf_w
age_wood
age_clitt1
age_clitt2
age_clitt3
age_csoil1
age_csoil2
age_csoil3
fallocc_w
rsratio_w
rsratio_g
w0
w1
s

Fig. 3.