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Supplement of

Improving the dynamics of Northern Hemisphere high-latitude vegetation in the ORCHIDEE ecosystem model

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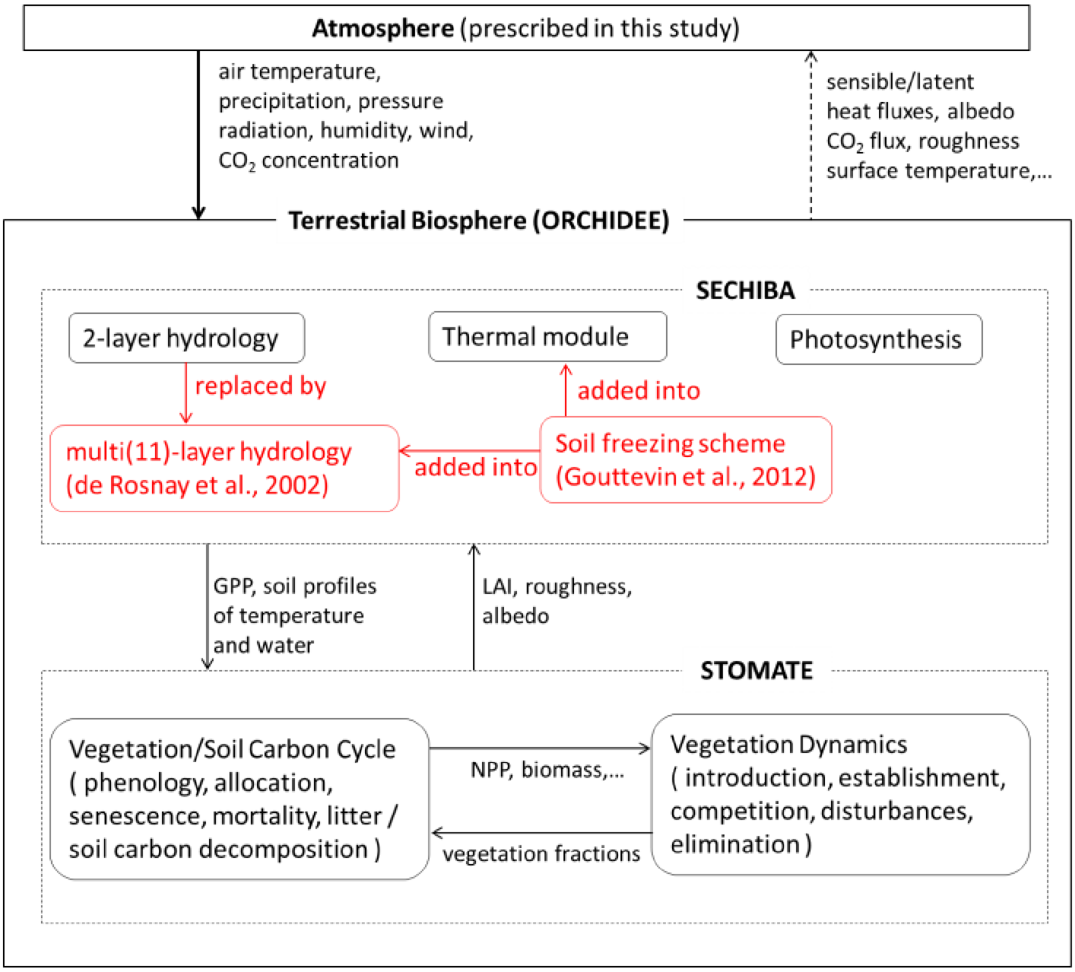

Figure S1. Basic structure of ORCHIDEE (rev1322). The improved or new processes compared with Krinner et al. (2005) are marked red.

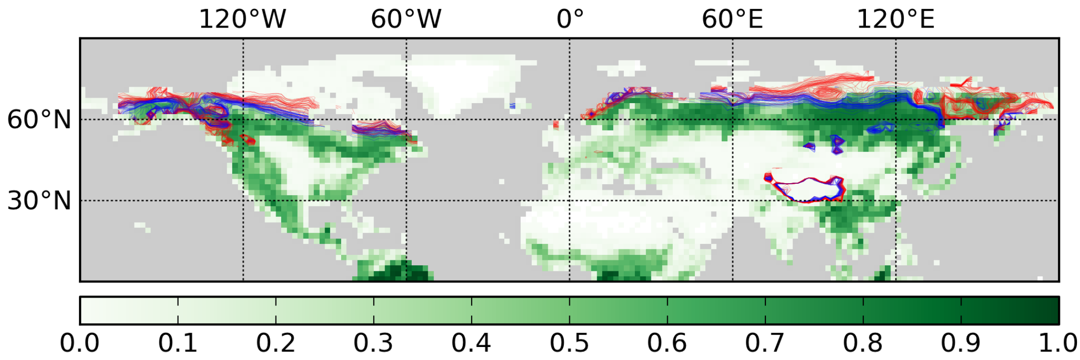

Figure S2. T_{ws} (blue) and T_{GS} (red) isotherms of 7°C for the 50 years from 1951 to 2000, representing northern treeline constraints in Krinner et al. (2005) and new parameterizations (ORC-HL-NVD) respectively, on the map of tree fractions calculated from ESA land-cover map.

Justification for the use of beta diversity (β) and dissimilarity index (*D*)

1. The advantage of β against RMSE

Beta diversity (β) was firstly proposed as a metric to estimate the variation in species composition among different sites (Legendre et al., 2005; Legendre et al., 2013). Poulter et al. (2011) use the β metric to assess the reclassification similarity of different PFT maps derived from remotely-sensed land-cover datasets. The β metric was calculated as the root of the sum of square error over all PFTs (Eq. 7 and 8). It is larger than or equal to zero, and can be $\sqrt{2}$ at maximum, in the limit case a grid cell has 100% of one single PFT in one dataset and has 100% of another PFT in the other dataset.

The β metric is similar to root mean square error (RMSE) which is widely used in many fields. But if we use RMSE with the following equation, the value will be dependent on the number of PFTs in the model or dataset. Unlike the β metric which has a fixed range ($[0, \sqrt{2}]$), RMSE will have smaller maximum value as the total number of PFTs increase, making it incomparable between different models.

$$RMSE_{c,M\_Oi} = \sqrt[2]{\frac{\sum_{k=1}^{n}(V_{k,c,M} - V_{k,c,Oi})^2}{n}}$$

where $V_{k,c,M}$ is fractional abundance for PFT *k* and for grid cell *c*, simulated by model; $V_{k,c,O}$ is fractional abundance for PFT *k* and for grid cell *c*, from observational dataset *i*; and *n* is the number of PFTs.

Another way to calculate RMSE is to use the following equation:

$$RMSE_{k,c,M\_O} = \sqrt[2]{\frac{\sum_{i=1}^{S}(V_{k,c,M} - V_{k,c,Oi})^2}{S}}$$

where *S* is the number of datasets.

This method also has a shortcoming: it gives one value for each PFT, and taking the mean RMSE over all PFTs is not appropriate because the redundant PFTs in a grid cell may lead to too optimistic results, blurring the information about the major PFTs in this grid cell.

Considering the shortcomings of RMSE and use of the β metric in assessment of dissimilarity in PFT maps (Poulter et al., 2011; Ottlé et al., 2013), we think it better to adopt β rather than RMSE to evaluate the model results in vegetation distribution.

2. Justification of dissimilarity index (*D*) for PFT groups

For PFT groups, we used dissimilarity index (*D*) instead of β, although β could be calculated for each group using Eq. 7 and 8, saying that there are only two PFTs in the equation. This is because that, take needleleaf deciduous trees (PFT9) as an example: they are mainly distributed in eastern Siberia; outside this region, models and observational datasets have ~0 of needleleaf deciduous and ~1 of non-needleleaf deciduous; thus, the Northern Hemisphere average of $\beta_{\text{needleleaf-deciduous}}$ will be very small due to "high agreement" outside Siberia. Unlike *D*, in β calculation, we cannot simply exclude the grid cells where the corresponding group does not exist, since β, by definition, takes into account the case when both maps give "absence" of the corresponding group in the grid cell. Therefore, we chose *D* for PFT groups rather than β.

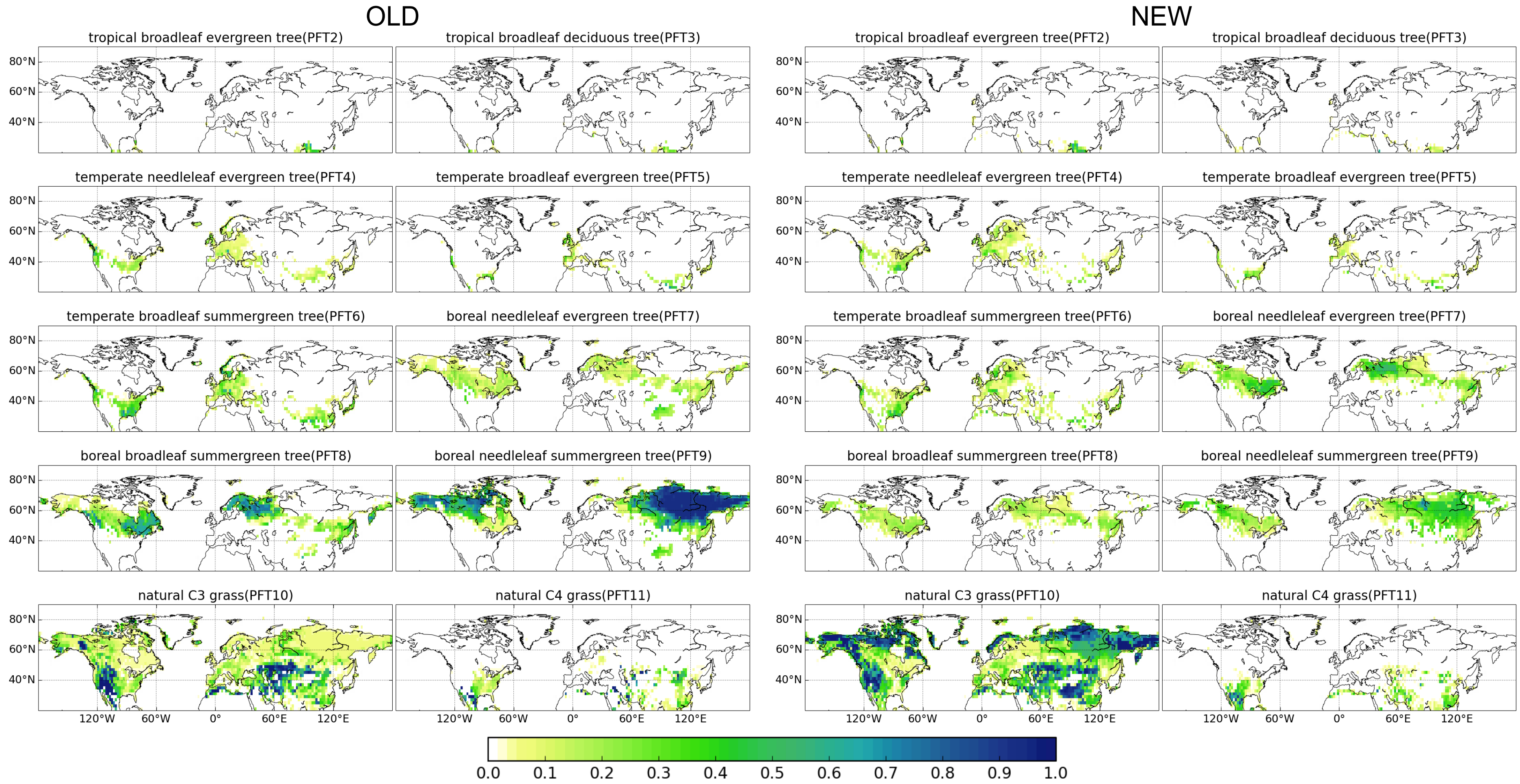

Figure S3. Fractional cover of 10 natural PFTs for OLD and NEW.

Resolution dependency of the β and S_V metrics

In order to test the resolution dependency of the β and S_V metrics, we conducted two additional runs similar to OLD and NEW except for a 1°×1° resolution. The figure below displays β and S_V values for 1°×1° runs, showing similar spatial patterns as 2°×2° runs.

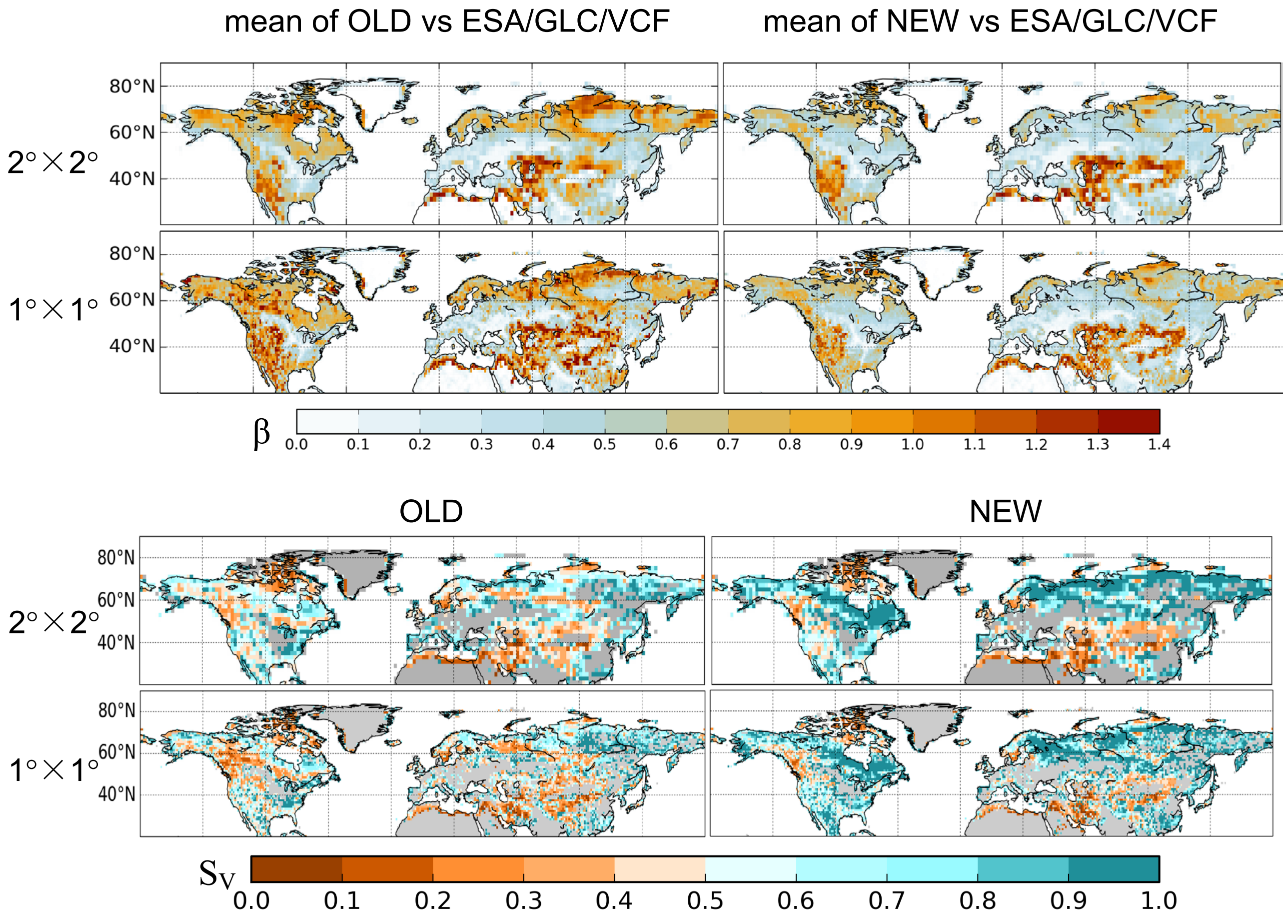

Figure S4. β and skill score (S_V) metrics for different resolutions. The 2°×2° subplot is the same as Fig. 5 (bottom panel) and Fig. 6 in the main text.

Table S1. Mean β metric over Northern Hemisphere (20-90°N) between models and observational datasets, and mean S_V over different countries/regions.

β	2°×2°				1°×1°			
	OLD	NEW	ESA	GLC	OLD	NEW	ESA	GLC
ESA	0.58	0.56			0.70	0.62		
GLC	0.56	0.48	0.25		0.68	0.54	0.29	
VCF	0.65	0.47	0.37	0.35	0.77	0.52	0.43	0.41

$\boldsymbol{S}_{\mathrm{V}}$		Asian Russia	European Russia	Canada	USA	Europe	China	Northern Hemisphere (20°N-90°N)
2°×2°	OLD	0.68	0.63	0.53	0.66	0.62	0.57	0.60
	NEW	0.89	0.89	0.70	0.69	0.65	0.61	0.72
1°×1°	OLD	0.69	0.57	0.52	0.63	0.58	0.53	0.59
	NEW	0.87	0.91	0.71	0.73	0.67	0.66	0.74

As listed in Table S1, in the coarser 2°×2° runs, due to smoothing effect, the β values for both model vs. data and data vs. data are decreased by 9~18% compared with 1°×1° runs. For S_{V} however, there is little difference between the two resolutions (relative differences are mostly within 5%), since the smoothing effect on both numerator and denominator partly offset each other. It indicates that the resolution at which the model runs has minor influence on the S_{V} metrics.

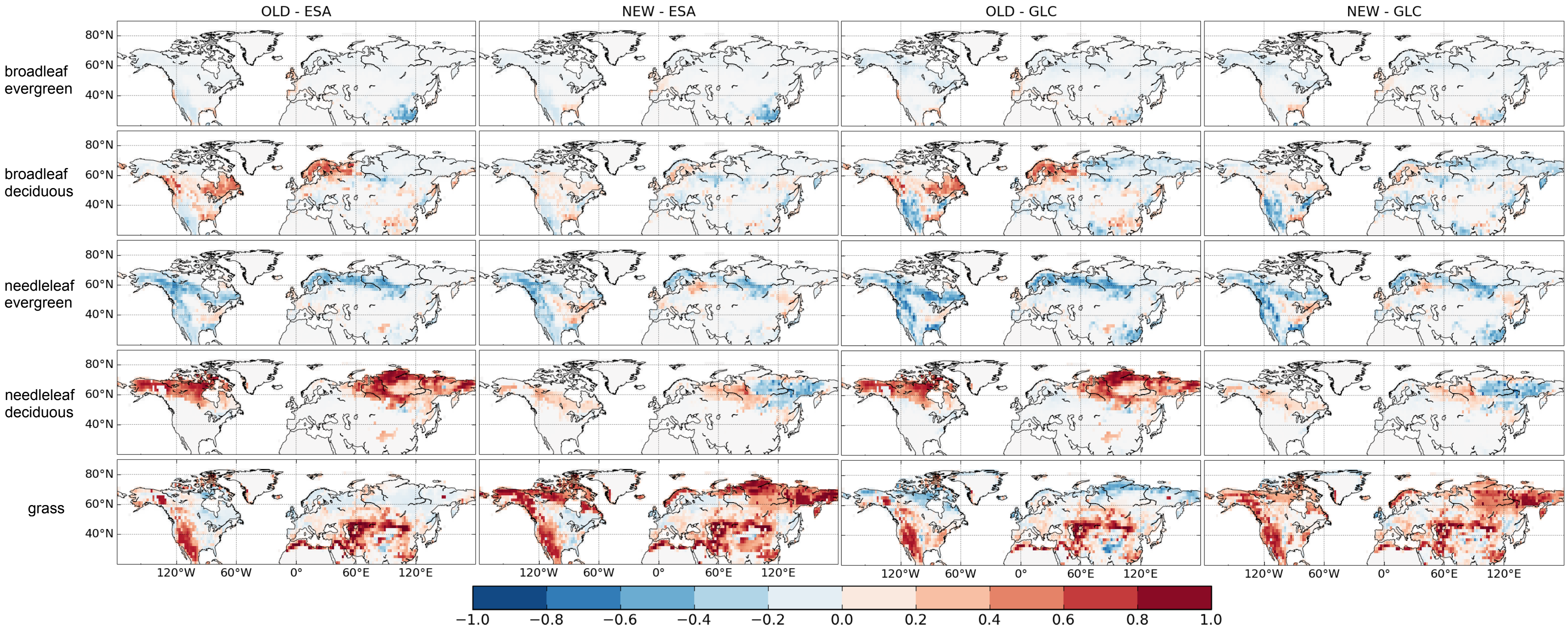

Figure S5. Difference of fractional cover between model (OLD and NEW) and observation-derived PFT maps (ESA and GLC) for PFT groups including grass and four tree subtypes.

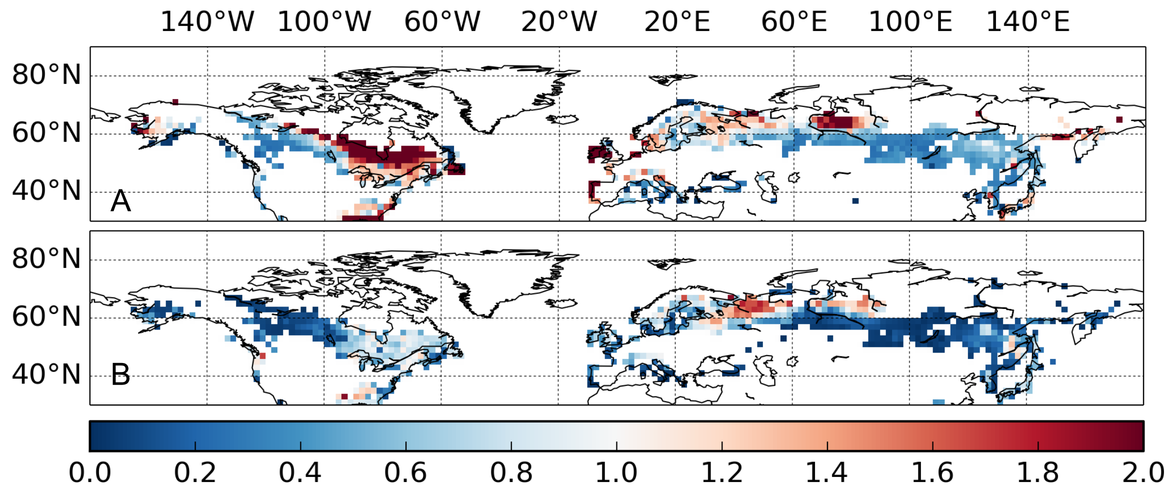

Figure S6. (A) Ratio of forest biomass from NEW to Thurner et al. (B) Ratio of forest NPP (average during 2001–2010) from NEW to MODIS NPP. Since MODIS NPP does not separate NPP by tree, grass and crop, the grid cells with > 40% of grass and crop (according to NEW result) are masked out to reduce the disparity between 'forest' NPP and 'total' NPP.