Global Terrestrial Carbon Flux (TCF) model simulations from 2000 to 2010
Version 1.0

Contact Information:
Yonghong Yi and John S. Kimball
Numerical Terradynamic Simulation Group (NTSG)
The University of Montana
Missoula MT, 59812
Email: yonghong.yi@ntsg.umt.edu; johnk@ntsg.umt.edu
URL: http://ntsg.umt.edu
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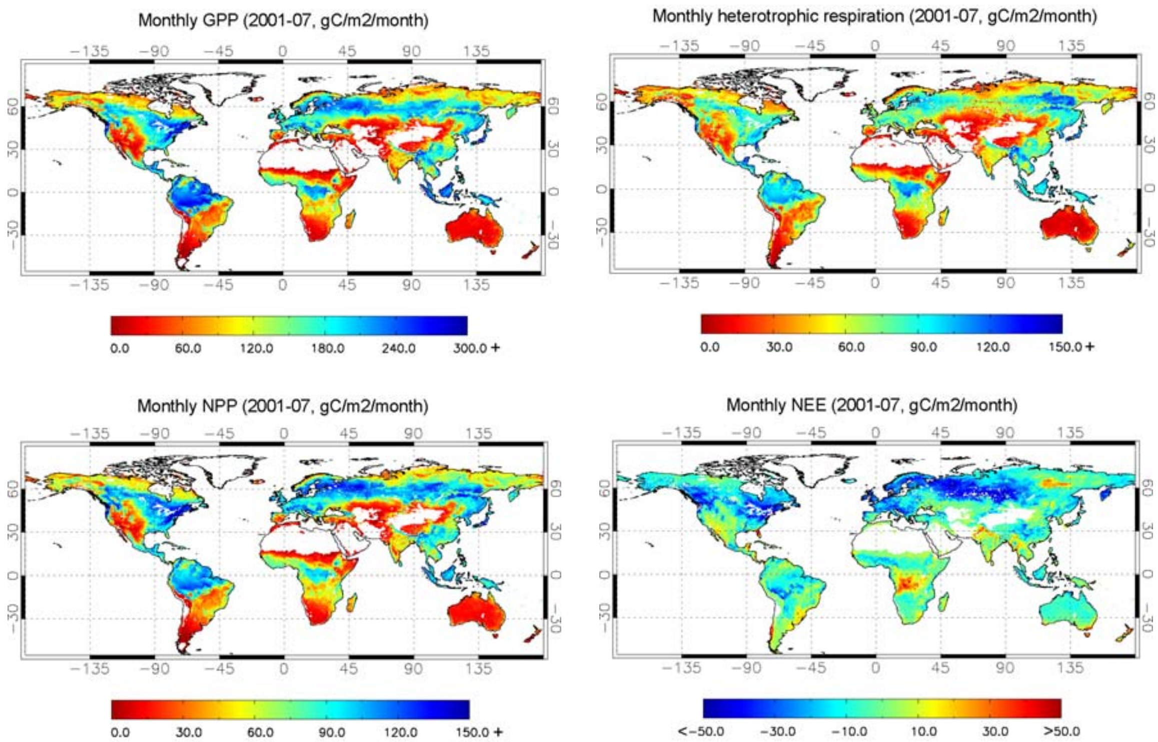
Data Description:

This data directory includes estimated cumulative monthly gross primary production (GPP), net primary production (NPP), heterotrophic respiration (Rh), and net ecosystem CO2 exchange (NEE) fluxes at 0.5° spatial resolution from 2000 to 2010; all carbon flux units are in gC/m2/month. The monthly carbon flux estimates are derived from daily simulations using a Terrestrial Carbon Flux (TCF) model (Kimball et al. 2009). The TCF model is being used to develop an operational Level 4 carbon (L4_C) product for the NASA Soil Moisture Active Passive (SMAP) mission. Details of the TCF/L4_C algorithms and implementation under SMAP are provided in the L4_C Algorithm Theoretical Basis Document (ATBD; Kimball et al. 2011). A brief description of the data in this directory is provided below. These data should be considered preliminary and used with caution, as the TCF/L4_C algorithms are still under development and haven't been adequately validated over a global domain.

The data are in a .csv ascii format provided by the NASA Carbon Monitoring System carbon flux group at the Jet Propulsion Laboratory, California Institute of Technology (Kevin Bowman PI, Joshua Fisher Co-I). The data are in a Geographic lat/lon global projection specified as 720 column x 291 row files. Masked areas that are outside of the modeling domain are specified with a -999 "no data" flag. Individual files are represented for GPP, NPP, Rh and NEE on a monthly basis for Years 2000 to 2010. Each file is approximately 2.5 MB in size, while the entire data directory is approximately 1.29 GB in size. Example images for each model parameter are presented in **Figure 1**.

GPP is produced using a light use efficiency (LUE) model, similar to MOD17 algorithm, based on MERRA reanalysis daily surface meteorology inputs (including air temperature, VPD, and solar radiation), and MODIS NDVI (MOD13A2) inputs. The MODIS 1km resolution FPAR (MOD15A2) and NDVI data were first aggregated to 0.5° spatial resolution including ALL vegetated pixels and using biome-specific empirical relationships between FPAR and NDVI based on the dominant land cover type at 0.5° resolution; the empirical NDVI-FPAR relationships were derived for each biome type using regression analysis of best quality (QC) MODIS (C.5) NDVI-FPAR data. It should be noted that the land cover heterogeneity may introduce great uncertainty during the upscaling process. The MODIS GPP (MOD17A2) product was used to calibrate the GPP algorithm Biome Property Look-Up Table (BPLUT) at 0.5° resolution. Vegetation NPP is estimated as a fixed proportion of annual GPP for individual land cover (BPLUT) classes based on the assumption of conservatism in vegetation carbon use efficiency.

Figure 1. Example images for each monthly TCF parameter.



The TCF model was spun up using MERRA surface soil temperature (≤10cm) and soil moisture (≤2cm), and the internal LUE algorithm based GPP/NPP products to derive Rh and NEE. The TCF algorithms assume dynamic steady-state conditions between NPP and estimated surface (≤10 cm depth) soil organic carbon (SOC) stocks, which were derived by spinning up the algorithms by cycling the 11 year MERRA daily surface meteorology and MODIS GPP records. The TCF algorithms use a hybrid soil moisture response and Arrhenius type exponential soil temperature response curve to estimate moisture and temperature constraints to Rh. The global optimum temperature for Rh was set as 25 °C. These parameters were not based on site calibration, but mainly derived from comparisons with independent global SOC inventory data. The model was run at 0.5° resolution and only the dominant land cover type within each coarse grid cell was considered.

The BPLUT parameters for the global TCF simulations are listed below in Appendix 1. The land cover classification used for these simulations follows the MOD12Q1 (UMD type 2 land cover classification) definitions; specifically, ENF: evergreen needle-leaf forest, EBF: evergreen broadleaf forest; DNF: deciduous needle-leaf forest; DBF: deciduous broadleaf forest; MXF: mixed forest; CSB: closed shrubland; OSB: open shrubland; WSA: woody savanna; SVA: savanna; GRS: grassland; CRP: cropland.

Algorithm Uncertainties and Assumptions

A detailed model error budget analysis and validation of the TCF algorithms is provided elsewhere (Kimball et al. 2009; 2011). To date, the TCF algorithms have largely been developed, tested and evaluated over northern (>45°N) land areas. Global validation of these simulations is still preliminary so the data should be used with caution. A large source of uncertainty in the algorithms comes from the input MERRA surface meteorology; a detailed global validation of the MERRA inputs to the TCF algorithms is provided elsewhere (Yi et al. 2011). These results show a large warm/dry bias over the tropics and other uncertainties, which are imparted to the TCF simulations. Initial algorithm testing using AMSR-E derived soil moisture and temperature inputs across a latitudinal gradient of grassland, boreal forest and tundra tower sites over a 3-year period indicate that the model performance has a mean accuracy range similar to tower CO_2 flux measurement based estimates and relatively detailed site level model simulations of these processes (i.e. NEE RMSE ≤ 30 g C m^{-2} yr^{-1} or 1.6 g C m^{-2} d^{-1}). Larger uncertainties are expected for other climate regimes and biome types.

The TCF model incorporates a number of simplifying assumptions consistent with global satellite remote sensing based algorithms, and may not sufficiently characterize all the major processes regulating CO_2 exchange. The various model constraints, limitations and assumptions are documented more detail elsewhere (Kimball et al. 2000; 2011). The TCF framework assumes that spatial and temporal variability in the relative magnitude and sign of land-atmosphere CO_2 exchange are largely driven by surface soil wetness and temperature variations through direct environmental controls on R_h. The model framework also assumes that surface SOC stocks are in relative equilibrium with these environmental conditions and GPP. This steady-state assumption produces a carbon neutral biosphere (long term cumulative net ecosystem-atmosphere CO_2 exchange (NEE) = 0). Land cover and land use changes (LCLUC) from direct and indirect human development are not directly represented by the model and are expected to exert a large influence on NEE over a global domain, with less impact over sparsely populated northern land areas. The TCF simulations use a static global land cover classification and do not explicitly represent disturbance and LCLUC impacts to

GPP; disturbance and LCLUC impacts to GPP are only partially accounted for through associated changes to photosynthetic canopy cover represented by the NDVI inputs.

The potential productivity contribution and soil insulation effects of understory vegetation and organic ground cover to NEE are not distinguished in the model apart from the general land cover properties specified in the BPLUT. The Nitrogen (N) content of leaf litter and associated impacts to soil heterotrophic respiration (R_h) and NEE are also not distinguished in the model apart from general land cover properties specified in the BPLUT.

The model results are based on simulations using surface (≤5cm depth) soil temperature inputs from the MERRA reanalysis to define the soil heterotrophic respiration (R_h) response to soil temperature. The algorithm is based on the assumption that the bulk of R_h is derived from surface soil layers. This assumption generally holds for most ecosystems, including boreal-arctic biomes, because the bulk of annual litter decomposition is composed of relatively recent (i.e. <5 years old) leaf litter that is more labile than older soil litter layers with higher lignin concentrations. However, in boreal regions, deeper soil layers can contribute up to 40% or more of total R_h, especially later in the growing season as the seasonal warming of deeper layers progresses and lags behind shallower soil layers. The contribution of deeper SOC layers to R_h may also increase over longer (decadal) time periods in boreal-Arctic regions due to the large reservoir of SOC stored in these colder soils and potential warming and destabilization of permafrost and deeper SOC layers under global warming.

Sub-grid scale land cover heterogeneity is a major source of potential TCF algorithm uncertainty, where landscape variability in land cover conditions and NEE may not be adequately represented by the baseline 25-km grid cell resolution (and scaled to 0.5 degree resolution for the current database) of the TCF simulations. Additional algorithm uncertainty is contributed by similar coarse scale (0.5 degree resolution MERRA) daily surface meteorology inputs, which may not adequately represent sub-grid scale terrain variability and associated meteorological effects.

References:

Kimball, J.S., L.A. Jones, K. Zhang, F.A. Heinsch, K.C. McDonald, and W.C. Oechel, 2009. A satellite approach to estimate land-atmosphere CO2 exchange for Boreal and Arctic biomes using MODIS and AMSR-E. *IEEE Transactions on Geoscience and Remote Sensing*, 47(2), 569-587, 10.1109/TGRS.2008.2003248.

Kimball, J.S., R. Reichle, P. O'Neill and K.C. McDonald, 2011. SMAP Algorithm Theoretical Basis Document: L4 Carbon Product. SMAP Project, JPL D-66484, Jet Propulsion Laboratory, Pasadena CA, 65p.

Yi, Y., J.S. Kimball, L.A. Jones, R.H. Reichle and K.C. McDonald, 2011. Evaluation of MERRA land surface estimates in preparation for the Soil Moisture Active Passive Mission. *Journal of Climate* 24(15), 3797-3816.

Appendix 1: The BPLUT parameters for this product.

UMD_VEG	ENF	EBF	DNF	DBF	MXF	CSB	OSB	WSA	SVA	GRS	CRP
FPAR model parameters											
model_code	0	0	0	0	0	1	1	0	0	1	0
scale_coeff	0.83	0.85	0.83	0.85	0.84	0.22	0.16	0.84	0.86	0.18	0.89
offset_coeff	0.084	-0.01	0.084	-0.01	0.037	-0.16	-0.057	-0.018	-0.004	-0.089	-0.052
GPP algorithm parameters											
LUEmax	0.0011	0.0012	0.0011	0.0012	0.0011	0.001	0.00085	0.00111	0.0011	0.00085	0.0011
Tmin_min(°C)	-8	-8	-8	-6	-7	-8	-8	-8	-8	-8	-8
Tmin_max(°C)	8.31	9.09	10.44	9.94	9.5	8.61	8.8	11.39	11.39	12.02	12.02
VPD_min(Pa)	500	1800	500	500	500	500	500	434	300	752	500
VPD_max(Pa)	4000	4000	4160	4160	2732	6000	4455	5000	3913	5500	5071
TCF parameters											
CMfract	0.49	0.71	0.67	0.67	0.59	0.62	0.62	0.72	0.72	0.76	0.78
CUE	0.55	0.45	0.55	0.55	0.5	0.6	0.6	0.5	0.55	0.6	0.55