Application of Satellite Microwave and Optical-IR Remote Sensing to Characterize Global Soil Moisture Constraints to Soil Respiration

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Abstract

Ecosystem respiration (R_{eco}) is a key component of terrestrial net ecosystem CO_2 exchange (NEE) and difficult to estimate globally. We developed an algorithm for determining daily NEE using synergistic measurements from satellite optical/IR and microwave remote sensing. The algorithm uses soil moisture and temperature information from the AMSR-E microwave radiometer, and gross primary productivity (GPP) inputs from MODIS. AMSR-E soil moisture retrievals are verified using antecedent daily precipitation from the Tropical Rainfall Monitoring Mission (TRMM). We then explore the functional response of R_{eco} to soil moisture by comparing model results to in situ tower based CO_2 flux measurements and soil inventory data using a model-data analysis approach, in preparation for a more detailed Bayesian analysis. The assumed soil moisture response is roughly parabolic, though we find that relative to flux tower observations, the inferred moisture response does not constrain respiration at high soil wetness. This result is likely because the available flux tower network data used in this analysis is not representative of wetter areas. We find that the seasonality of soil respiration and the global distribution of surface (<10cm depth) soil organic carbon (SOC) are reasonably captured by the model. Areas of high disturbance frequency have lower SOC relative to steady-state results. This study represents an important step in monitoring terrestrial NEE from space borne observations and is informing development of future operational carbon products for the NASA Soil Moisture Active Passive (SMAP) Decadal Survey mission. This work was conducted at the University of Montana and Jet Propulsion Laboratory, California Institute of Technology under contract to NASA.

Hypotheses and Objectives

- AMSR-E soil moisture retrievals are sensitive to daily surface (<10cm depth) soil wetting and drying cycles where vegetation biomass water content levels are less than ≈1.5 kg m^{-2}.
- Satellite microwave and optical-IR remote sensing information from MODIS and AMSR-E provide sufficient information on primary climatic drivers and ecological processes for broad-scale mapping and monitoring of NEE and component carbon fluxes (GPP and R_{eco}).
- The functional relationship between satellite indices can be inferred by process model-data analysis with flux tower observations.

Models and Methods

Terrestrial Carbon Flux (TCF) Model

We use a simple Terrestrial Carbon Flux (TCF) process model approach described in [**1**]. The model predicts ecosystem respiration (R_{eco}) , net ecosystem CO_2 exchange (NEE), and surface SOC content using soil temperature and moisture inputs from AMSR-E and GPP (MOD17) from MODIS. The basic model equation is given below:

$$NEE = Tmult * Wmult * \sum_{i=0}^{3} k_i C_i - GPP * (1 - f_{aut}) \quad (1)$$

Surface Wetness Index

Comparisons between in situ soil moisture measurements and coarser scale soil moisture retrievals from satellites are strongly constrained by soil moisture spatial heterogeneity, differing statistical characteristics, and other factors. We therefore use an alternative psuedo-diffusion wetness index described in [**2**] to calculate antecedent wetness indices (SWI) for independent assessment of AMSR-E soil moisture retrievals using in situ and satellite (TRMM) based precipitation information:

$$L \frac{dSWI}{dt} = C(Ws - SWI) \quad (2)$$

The resulting index is then scaled from 0-100 % on a global basis. This approach avoids many of the difficulties associated with direct comparison with site-based soil moisture observations.

Datasets

- **Ameriflux/FLUXNET Tower NEE:** Level 4 data downloaded from ORNL-DAAC. Towers with more than 2 years of data earlier than 2003 and relatively continuous precipitation data were included in the analysis.
- **MODIS GPP:** Obtained from the MODIS MOD17A2 (collection 5) global dataset. Data is provided with 1-km spatial resolution and 8-day composited intervals to reduce cloud contamination. The 1-km product was re-sampled and re-projected to a 25-km Equal Area Scalable Earth (EASE) grid.
- **AMSR-E Temperatures:** Produced at the University of Montana by applying the method of [**3**] to level-3 25-km EASE grid brightness temperatures (Tb). The method uses the 18.7 and 22.3 GHz and H/V polarized Tb to determine factors (vegetation biomass, open water) impacting surface emissivity and atmospheric water vapor absorption. Surface temperature is then estimated using this information in a simple forward radiative transfer model [**3**].
- **AMSR-E SWI and VOD:** Produced at the University of Montana using temperatures, optical depth/roughness, and open water fraction estimates also derived from AMSR-E ([**4**]; see 'AMSR-E Temperatures' above). Data from ascending and descending passes are highly correlated and therefore were combined to improve coverage. Soil wetness was then calculated using Eqn. (2).
- **TRMM Precip:** From the 3B42 0.25° combined gauge corrected TRMM/IR product [**5**]. The 0.25° product was re-sampled and re-projected to a 25-km Equal Area Scalable Earth (EASE) grid. These 3-hourly data were summed to effective daily rates. Soil wetness was then calculated using Eqn. (2).

AMSR-E Soil Moisture Correlates with TRMM Precip.

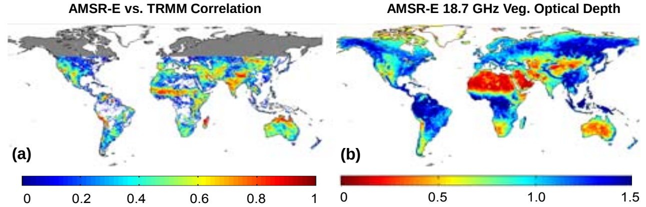


Fig. 1: (a) Pearson correlation between soil wetness calculated using eqn. (2) with AMSR-E soil moisture vs. soil wetness calculated from TRMM using eqn. (2). Areas of non-significant correlation ($p < 0.01$) are colorless and areas where the TRMM data product is not available are grey. **(b)** AMSR-E 18.7 GHz vegetation optical depth is a measure of the opacity (frequency dependent) of the overlying vegetation, which is a required input of the soil moisture algorithm [**4**].

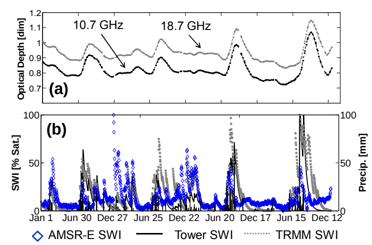


Fig. 2: Example time series of vegetation optical depth at two frequencies **(a)** and soil wetness index **(b)** at a selected tower location (Audubon Research Ranch, Arizona). Precipitation recorded at the tower site is also reported. Period of record is from spans Jan. 1, 2003 to Dec. 31, 2006.

Soil C Storage in Relation to Satellite Climate Constraints

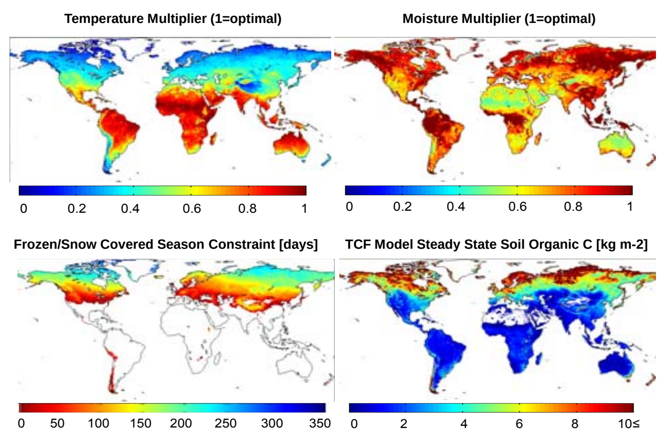


Fig. 3: Long term (2003 - 2006) mean annual soil temperature and moisture constraints (top) to soil respiration. These maps were derived exclusively from AMSR-E and MODIS observations. **(a)** The dimensionless temperature multiplier [T_{mult}; 0-1] is an exponential function of mean daily soil temperature from AMSR-E [**1**]. **(b)** The soil moisture multiplier (W_{mult}) is a convex-parabolic function of soil wetness from AMSR-E. W_{mult} is assigned a value of 1 where vegetation optical depth >1.5. **(c)** The frozen season constraint was derived from a combination of AMSR-E and SSM/I algorithms. **(d)** TCF model steady state surface SOC content is derived for conditions described by (a) – (d).

Disturbance Modifies Soil Carbon Pool Size

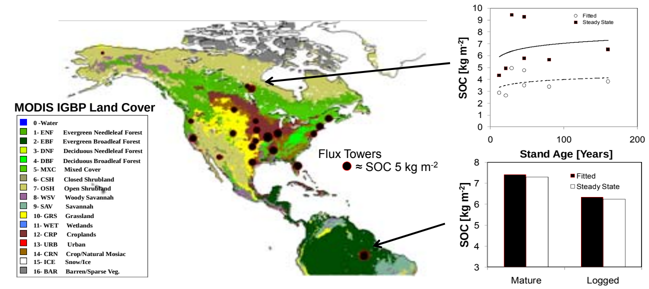
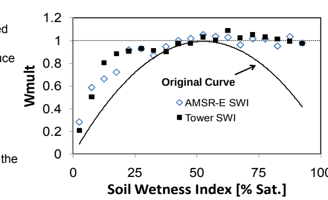


Fig. 4: Model effective surface (<10 cm depth) SOC pools for 33 flux tower locations. Two methods of inferring effective pool size were compared: 1) Effective SOC was calculate using tower observed ecosystem respiration by assuming that maximum observed rates for each site were only temperature limited (not moisture limited); 2) The model was solved for steady state SOC using long term average (2003-2006) GPP, temperature, and growing season length. Note that method 2 assumes ΣNEE =0, whereas, method 1 does not.

Ecosystem Respiration Responds to Soil Wetness

Fig. 5: Effective R_{eco} moisture response curves obtained by normalizing tower R_{eco} for temperature effects and substrate limitation (method 1 in Fig. 4 caption) to produce an estimated moisture multiplier (W_{mult}). Data points represent averages of daily data (2003-2006) from 33 tower locations within 5 % SWI bins. Shown are the original model functional response, SWI from tower precipitation, and SWI from AMSR-E soil moisture. The tower and AMSR-E curves are not significantly different (X^2= 6.8; df = 17, p>0.01), but the two curves differ from the original (X^2 = 52.9; df = 17, p<0.01).



Conclusions

- Satellite based soil moisture and temperature from AMSR-E and GPP from MODIS, combined within a simple TCF model framework, capture global SOC storage patterns relative to soil inventory data, and R_{eco} temporal dynamics at 33 flux tower locations.
- AMSR-E surface wetness corresponds significantly with surface wetness calculated from TRMM precipitation for the majority of the TRMM domain. Significant correspondence decreases where vegetation optical depths ≥1.5 (Fig. 1-2).
- The TCF algorithms produce realistic steady state SOC pools using AMSR-E derived indices of surface freeze-thaw status, soil moisture and temperature, and MODIS GPP (Fig. 3).
- Effective SOC pools can be inferred from tower observations and TCF model dynamics that correspond well (R = 0.57; p<0.01) with the steady state solutions. Pool sizes follow expected patterns with disturbance history (Fig. 4).
- Tower R_{eco} responds to soil wetness as indicated by AMSR-E and TRMM. The respective response curves calculated from AMSR-E and TRMM are indistinguishable from on another but are different from the original model curve under wet conditions. The wet end of the soil moisture curve may not be well represented by the available flux towers or by precipitation data alone (Fig. 5).

References

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Acknowledgements

The authors gratefully acknowledge the work of the FLUXNET/Ameriflux principle investigators in collecting data making it generally available. A full list of all 33 locations and PIs is not possible here due to limited space, but please contact the corresponding author if you are interested in this information.