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MODIS-based GPP, PAR, fC4, and SANIRv estimates from SLOPE for CONUS, 2000-2019

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Summary

This dataset contains estimated gross primary productivity (GPP), photosynthetically active radiation (PAR), soil adjusted near infrared reflectance of vegetation (SANIRv), the fraction of C4 crops in vegetation (fC4), and their uncertainties for the conterminous United States (CONUS) from 2000 to 2019. The daily estimates are SatelliTE Only Photosynthesis Estimation (SLOPE) products at 250-m resolution. There are three distinct features of the GPP estimation algorithm: (1) SLOPE couples machine learning models with MODIS atmosphere and land products to accurately estimate PAR, (2) SLOPE couples gap-filling and filtering algorithms with surface reflectance acquired by both Terra and Aqua MODIS satellites to derive a soil-adjusted NIRv (SANIRv) dataset, and (3) SLOPE couples a temporal pattern recognition approach with a long-term Crop Data Layer (CDL) product to predict dynamic C4 crop fraction. PAR, SANIRv and C4 fraction are used to drive a parsimonious model with only two parameters to estimate GPP, along with a quantitative uncertainty, on a per-pixel and daily basis. The slope GPP product has an $R^2 = 0.84$ and a root-mean-square error (RMSE) of 1.65 gC m⁻² d⁻¹.

For each of the four variables (GPP, PAR, fC4, and SANIRv) and their uncertainties, the daily data are provided for each of 14 tiles for each day for the years 2000 thru 2019 with the following exceptions: (1) fC4 data are provided for the years 2000-2014 only. All fC4 uncertainty data is aggregated over all years and provided in 14 total files, one file per tile; and (2) there are no data files for GPP Uncertainty and SANIRv Uncertainty for January 2000, 1-16 February 2000, and 22-25 June 2001.

There are 612,416 files in GeoTIFF (.tif) format with this dataset.

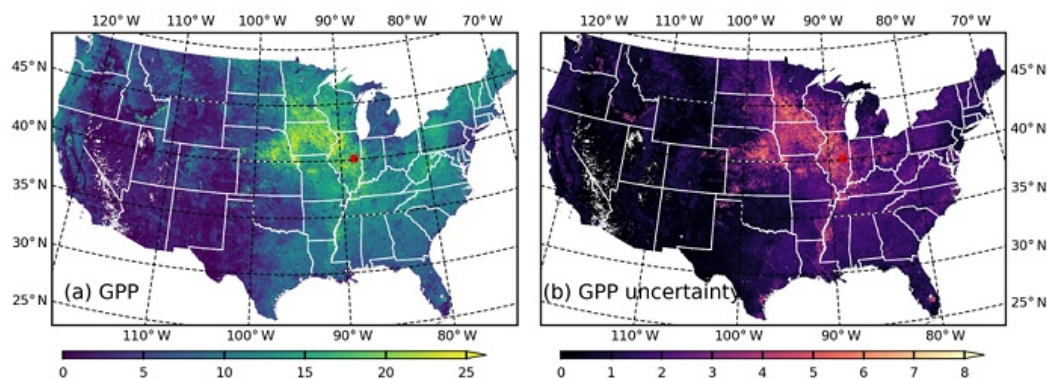


Figure 1. Spatial distribution of (a) GPP (gC m²/d) and (b) GPP uncertainty (gC m²/d) across the CONUS at 250-m resolution for 10 July 2020 (image source: Jiang et al. 2021).

Citation

Jiang, C., and K. Guan. 2020. MODIS-based GPP, PAR, fC4, and SANIRv estimates from SLOPE for CONUS, 2000-2019. ORNL DAAC, Oak Ridge, Tennessee, USA. <https://doi.org/10.3334/ORNLDAAC/1786>

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1. Dataset Overview

This dataset contains estimated gross primary productivity (GPP), photosynthetically active radiation (PAR), soil adjusted near infrared reflectance of vegetation (SANIR_v), the fraction of C4 crops in vegetation (fC4), and their uncertainties for the conterminous United States (CONUS) from 2000 to 2019. The daily estimates are SatelliTE Only Photosynthesis Estimation (SLOPE) products at 250-m resolution. There are three distinct features of the GPP

estimation algorithm: (1) SLOPE couples machine learning models with MODIS atmosphere and land products to accurately estimate PAR, (2) SLOPE couples gap-filling and filtering algorithms with surface reflectance acquired by both Terra and Aqua MODIS satellites to derive a soil-adjusted NIR_v (SANIR_v) dataset, and (3) SLOPE couples a temporal pattern recognition approach with a long-term Crop Data Layer (CDL) product to predict dynamic C4 crop fraction. PAR, SANIR_v and C4 fraction are used to drive a parsimonious model with only two parameters to estimate GPP, along with a quantitative uncertainty, on a per-pixel and daily basis. The slope GPP product has an $R^2 = 0.84$ and a root-mean-square error (RMSE) of $1.65 \text{ gC m}^{-2} \text{ d}^{-1}$.

For each of the four variables (GPP, PAR, fC4, and SANIR_v) and their uncertainties, the daily data are provided for each of 14 tiles for each day for the years 2000 thru 2019 with the following exceptions: (1) fC4 data are provided for the years 2000-2014 only. All fC4 uncertainty data is aggregated over all years and provided in 14 total files, one file per tile; and (2) there are no data files for GPP Uncertainty and SANIR_v Uncertainty for January 2000, 1-16 February 2000, and 22-25 June 2001.

Project: Carbon Monitoring System (CMS)

The NASA Carbon Monitoring System (CMS) is designed to make significant contributions in characterizing, quantifying, understanding, and predicting the evolution of global carbon sources and sinks through improved monitoring of carbon stocks and fluxes. The System will use the full range of NASA satellite observations and modeling/analysis capabilities to establish the accuracy, quantitative uncertainties, and utility of products for supporting national and international policy, regulatory, and management activities. CMS will maintain a global emphasis while providing finer scale regional information, utilizing space-based and surface-based data and will rapidly initiate generation and distribution of products both for user evaluation and to inform near-term policy development and planning.

Related Publications

Jiang, C., K. Guan, G. Wu, B. Peng, and S. Wang. 2021. A daily, 250 m and real-time gross primary productivity product (2000–present) covering the contiguous United States, Earth System Science Data 13:281–298. <https://doi.org/10.5194/essd-13-281-2021>

Related Dataset

Hagen, S., Harris, N., Saatchi, S.S., Pearson, T., Woodall, C.W., Ganguly, S., Domke, G.M., Braswell, B.H., Walters, B.F., Jenkins, J.C., Brown, S., Salas, W.A., Fore, A., Yu, Y., Nemani, R.R., Ipsan, C., Brown, K.R., 2016. CMS: Forest Carbon Stocks, Emissions, and Net Flux for the Conterminous US: 2005-2010. ORNL DAAC. <https://doi.org/10.3334/ORNLDAAC/1313>

Acknowledgments

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2. Data Characteristics

Spatial Coverage: Contiguous US

Spatial Resolution: 250 m

Temporal Coverage: 2000-01-01 to 2019-12-31

Temporal Resolution: Daily

Study Area: Latitude and longitude are given in decimal degrees.

Sites	Westernmost Longitude	Easternmost Longitude	Northernmost Latitude	Southernmost Latitude
CONUS	-155.573	-52.216	50.000	20.000

Data File Information

There are 612,416 datasets in GeoTIFF (.tif) format with this dataset. For each of the four variables (GPP, PAR, fC4, and SANIR_v) and their uncertainties, the daily data are provided for each of 14 tiles, for each day, for the years 2000 thru 2019 with the following exceptions:

- fC4 data are annual data and are only provided for the years 2000-2014. All fC4 uncertainty data for all years are provided in 14 total files, one file per tile.
- There are no data files for GPP Uncertainty and SANIR_v Uncertainty for January 2000, 1-16 February 2000, and 22-25 June 2001.

The files are named as **Variable.YYYY.MM.DD.tile.tif** and **Variable_Uncertainty.YYYY.MM.DD.tile.tif**, where ...

- *Variable* = GPP, PAR, SANIR_v or fC4 (Table 1)
- *YYYY.MM.DD* = date in year, month, day
- *tile* = one of 14 tiles: h08v04, h08v05, h08v06, h09v04, h09v05, h09v06, h10v04, h10v05, h10v06, h11v04, h11v05, h12v04, h12v05, and h13v04 (Figure 2).

Example file names:

GPP.2001.01.01.h08v04.tif, GPP_Uncertainty.2002.01.01.h08v04.tif
 PAR.2000.01.01.h08v04.tif, PAR_Uncertainty.2000.01.01.h08v04.tif

Table 1. Variables in the GeoTIFF files

Variable	Description	Unit	Range	Scale factor	Frequency
GPP	Gross Primary Productivity	$\text{gC m}^{-2} \text{ d}^{-1}$	0–32.5	0.001	Daily
GPP_Uncertainty	GPP uncertainty derived from SLOPE model parameter uncertainties quantified by the evaluation against AmeriFlux ground truth; the uncertainty of predicted dynamic C4 fraction quantified by the evaluation against CDL C4 fraction	$\text{gC m}^{-2} \text{ d}^{-1}$	0–32.5	0.001	Daily
PAR	Photosynthetically Active Radiation	$\text{MJ m}^{-2} \text{ d}^{-1}$	0–15	0.001	Daily
PAR_Uncertainty	PAR uncertainty quantified by the standard deviation of four machine learning models	$\text{MJ m}^{-2} \text{ d}^{-1}$	0–15	0.001	Daily

		d ⁻¹			
SANIRv	Soil adjusted near infrared reflectance of vegetation	1	0–0.6	0.0001	Daily
SANIRv_Uncertainty	SANIRv uncertainty quantified by the standard deviation of a 7-day time window	1	0–0.6	0.0001	Daily
fC4	Dynamic C4 crop fraction derived from a temporal pattern recognition approach applied to a long-term Crop Data Layer (CDL) product	1	0–1	0.0001	Annual
fC4_Uncertainty	fC4 uncertainty quantified by the evaluation against CDL C4 fraction	1	0–1	0.0001	Static

Data File Details

All data are projected in the standard MODIS Land Integerized Sinusoidal tile map projection (Figure 2). Each processing tile is 4800 pixels by 4800 pixels, representing approximately 1200 km by 1200 km land region. The nodata (filled) value is -9999, and each GeoTIFF has a single band.

3. Application and Derivation

This product is developed to address a critical gap in estimating GPP over continental scales using remotely sensed data sources. The estimate method leverages a number of MODIS land and atmosphere products.

4. Quality Assessment

Uncertainty data are provided with this dataset.

Uncertainty of GPP is estimated as

$$dGPP = (fC4 \times PAR \times SANIRv) \times dc_{C4} + [(1 - fC4) \times PAR \times SANIRv] \times dc_{C3} + [(c_{C4} - c_{C3}) \times PAR \times SANIRv] \times dfC4 + \{[c_{C4} \times fC4 + c_{C3} \times (1 - fC4)] \times SANIRv\} \times dPAR + \{[c_{C4} \times fC4 + c_{C3} \times (1 - fC4)] \times PAR\} \times dSANIRv,$$

where dc_{C4} and dc_{C3} are model parameter uncertainties quantified by the evaluation against AmeriFlux ground truth. $dfC4$ is the uncertainty of predicted dynamic C4 fraction quantified by the evaluation against the Crop Data Layer's C4 fraction. $dPAR$ is the uncertainty of PAR quantified by the standard deviation of four machine learning models. $dSANIRv$ is the uncertainty of $SANIRv$ quantified by the standard deviation of a 7-day time window. Refer to Jiang et al. (2021) for additional details.

5. Data Acquisition, Materials, and Methods

The data were produced using the SLOPE GPP estimation algorithm which has three distinct features: (1) SLOPE couples machine learning models with MODIS atmosphere and land products to accurately estimate PAR, (2) SLOPE couples efficient gap-filling and filtering algorithms with surface reflectance acquired by both Terra and Aqua MODIS satellites to derive a soil-adjusted NIRV ($SANIRv$) dataset, and (3) SLOPE couples a temporal pattern recognition approach with a long-term Crop Data Layer (CDL) product to predict the dynamic fraction of C4 crops in total vegetation. PAR, $SANIRv$ and C4 fraction are used to drive a parsimonious model with only two parameters to estimate GPP, along with a quantitative uncertainty, on a per-pixel and daily basis. SLOPE was calibrated using the GPP data derived from AmeriFlux site observations.

All data are projected in the standard MODIS Land Integerized Sinusoidal tile map projection (Figure 2). Each processing tile is 4800 pixels by 4800 pixels, representing approximately 1200 km by 1200 km land region.



Figure 2. MODIS tiles covering the CONUS.

Estimating GPP

GPP was estimated by combining data from Terra and Aqua MODIS satellite instrument with a Crop Data Layer (CDL) product. Because MODIS provides long-term and real-time (2000–present) observations of red (Red_{Ref}) and NIR (NIR_{Ref}) reflectance and atmospheric conditions with high spatial (250 m for reflectance and 1 km for atmosphere) and temporal (daily) resolutions, MODIS can be used to generate an observation-based GPP product. The GPP model used for this dataset was

$$GPP = [c_{C4} \times fC4 \times c_{C3} \times (1 - fC4)] \times PAR \times SANIRv,$$

where c_{C4} and c_{C3} are model parameters representing C3 and C4, respectively, vegetation cover. The remaining parameters are described below. See Jiang et al. (2021) for details of these calculations.

NIRV and $SANIRv$

Near-infrared reflectance of vegetation ($NIR_{V,Ref}$), defined as the product of the normalized difference vegetation index (NDVI) and observed NIR reflectance (NIR_{Ref}), has recently been presented as a proxy of GPP (Badgley et al., 2017).

$$NIR_{V,Ref} = NDVI \times NIR_{Ref} = [(NIR_{Ref} - Red_{Ref}) / (NIR_{Ref} + Red_{Ref})] \times NIR_{Ref}$$

where $NIR_{V,Peak}$ is the maximum value of the multi-year average $NIR_{V,Ref}$ time series on a per-pixel basis.

Moreover, a soil-adjusted measure of near-infrared reflectance of vegetation ($SANIRv$) is available from MODIS.

$$SANIRv = [(NIR_{V,Ref} - NIR_{V,Soil}) / (NIR_{V,Peak} - NIR_{V,Soil})] \times NIR_{V,Peak},$$

$SANIRv$ does not change substantially with $NIR_{V,Peak}$ but is more sensitive to low $NIR_{V,Ref}$ values. $SANIRv$ was set to 0 when $NIR_{V,Ref} \leq NIR_{V,Soil}$. In

general, SANIR_v is supposed to be smooth within a short time period; therefore, the standard deviation within the ±3 day temporal window was calculated as uncertainty.

PAR

SLOPE adopts several machine learning approaches to compute PAR using forcing data mainly from Terra and Aqua MODIS Atmosphere and Land products. Machine learning approaches were used to upscale the ground truth to satellite data. The ground truth was from the Surface Radiation Budget (SURFRAD) Network (Augustine et al., 2000), including seven long-term continuous sites across the CONUS. Daily-mean shortwave radiation (SWR) and PAR on the surface were calculated from site observations at 1-3 min intervals from 2000 through 2018. Daily mean top-of-atmosphere SWR (SWR_{TOA}) was calculated using latitude and day-of-year (DOY) information (Allen et al., 1998). Subsequently, atmospheric transmittance (t_{SWR}) and proportion of PAR in SW (p_{PAR}) were calculated as $\text{SWR} / \text{SWR}_{\text{TOA}}$ and PAR / SWR .

fC4 and CDL data

A National Land Cover Database (NLCD; Homer et al., 2004; <https://www.mrlc.gov/>) along with a crop-specific land cover product Cropland Data Layer (CDL; Boryan et al., 2011; <https://nassgeodata.gmu.edu/CropScape>) were used to derive the fraction cover of C4 crop in vegetation (fC4). The fraction of C4 crop in vegetated areas was first derived using existing CDL data. NLCD land cover types were categorized into vegetated areas and non-vegetated areas with 30 m resolution. The fraction of vegetated areas in total area was subsequently calculated for each 250-m pixel. Similarly, CDL crop types were categorized into C4-planted areas and non-C4 areas with 30 m resolution. The fraction of C4 crops in total area was subsequently calculated for each pixel. The ratio of the fraction of C4 crops in total area to the fraction of vegetated areas in total area was calculated to derive the fraction of C4 crops in vegetated areas (fC4) at 250-m resolution. Since NLCD data were not available for every year, an assumption was made that 1 year of NLCD data can represent adjacent years.

Refer to Jiang et al. (2021) for additional details.

6. Data Access

These data are available through the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (DAAC).

[MODIS-based GPP, PAR, fC4, and SANIR_v estimates from SLOPE for CONUS, 2000-2019](#)

Contact for Data Center Access Information:

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- Telephone: +1 (865) 241-3952

7. References

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