DAAC Home > Get Data > Science Themes > Vegetation and Forests > User guide

Gridded Estimates of Woody Cover and Biomass across Sub-Saharan Africa, 2000-2004

Get Data

Documentation Revision Date: 2020-08-10

Dataset Version: 1

Summary

This dataset provides maps of woody (tree and shrub) cover and biomass across Sub-Saharan Africa at a resolution of 1 km for the period 2000-2004. Canopy cover observations and remote-sensing data related to woody vegetation were used to predict woody cover across Africa. Predicted woody cover, canopy height, and tree allometry were used to estimate woody biomass for Sub-Saharan Africa. Canopy cover observations were assembled from field measurements and Google Earth imagery collected from 2000-2004. Remote-sensing data related to the structural attributes of woody vegetation were derived from MODIS optical data and Q-SCAT (Quick Scatterometer) microwave measurements. Canopy height estimates were derived from spaceborne lidar and tree allometry equations were retrieved from GlobAllomeTree.

There are 2 files in GeoTIFF (*.tif) format.

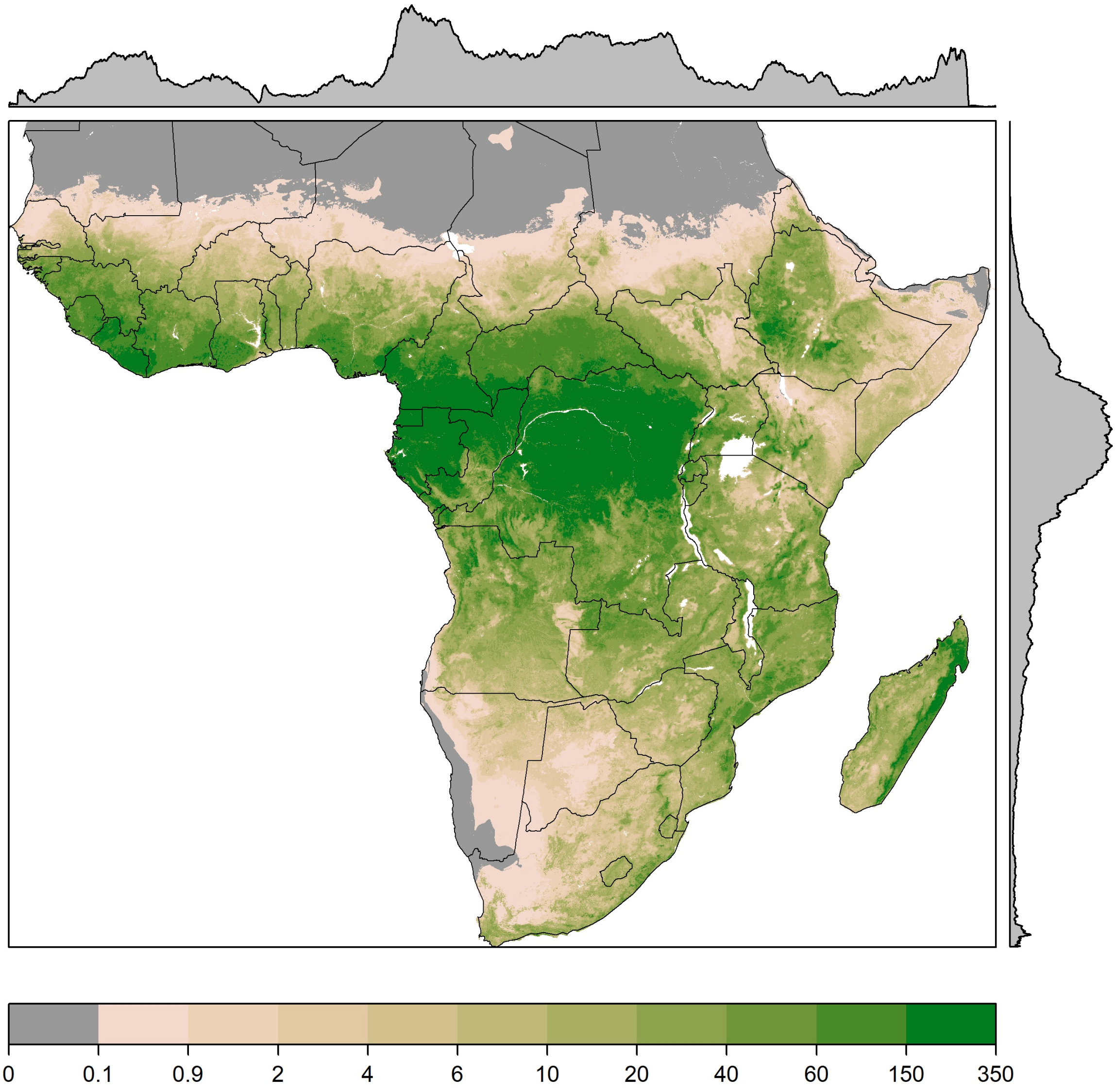

Figure 1. Estimates of woody biomass (tree and shrubs) at 1-km resolution in megagrams per hectare (Mg ha-1). Biomass was estimated from canopy cover, canopy height, and tree allometry. Source: C.W. Ross

Citation

Hanan, N.P., L. Prihodko, C.W. Ross, G. Bucini, and A.T. Tredennick. 2020. Gridded Estimates of Woody Cover and Biomass across Sub-Saharan Africa, 2000-2004. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/1777

Table of Contents

1. Dataset Overview

This dataset provides maps of woody (tree and shrub) cover and biomass across Sub-Saharan Africa at a resolution of 1 km for the period 2000-2004. Canopy cover observations and remote-sensing data related to woody vegetation were used to predict woody cover across Africa. Predicted woody cover, canopy height, and tree allometry were used to estimate woody biomass for Sub-Saharan Africa. Canopy cover observations were assembled from field measurements and Google Earth imagery collected from 2000-2004. Remote-sensing data related to the structural attributes of woody vegetation were derived from MODIS optical data and Q-SCAT (Quick Scatterometer) microwave measurements. Canopy height estimates were derived from spaceborne lidar and tree allometry equations were retrieved from GlobAllomeTree.

Acknowledgments:

This work was supported by the NASA Carbon Cycle Science grant NNX17AI49G.

2. Data Characteristics

Spatial Coverage: Sub-Saharan Africa

Spatial Resolution: 1 km

Temporal Coverage: 2000-01-01 to 2004-12-31

Temporal Resolution: One time, five-year average

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

Site	Westernmost Longitude	Easternmost Longitude	Northernmost Latitude	Southernmost Latitude
Sub-Saharan Africa	-20.60774	61.52528	22.00811	-34.81449

Data File Information

This dataset includes 2 files in GeoTIFF (*.tif) format.

Table 1. File names and descriptions.

File Name	Units	Description
woody_biomass.tif	Mg ha-1	an estimate of woody biomass in megagrams per hectare
woody_cover.tif	percent	the proportion of a cell predicted to have woody cover

Data File Details

Missing values are represented by -3400 in **woody_biomass.tif** and 255 in **woody_cover.tif**. Each file contains 6289 rows and 7515 columns. The projection used is "World_Sinusoidal", EPSG:54008.

3. Application and Derivation

These data were produced to support studies investigating the role of woody vegetation in ecology, carbon cycle, biogeochemistry, and land surface-atmosphere interactions of the African continent.

4. Quality Assessment

Canopy Cover Evaluation & Comparison with Existing Products

When estimating woody cover from Google Earth imagery, the ambiguous crown identification was recorded to estimate the error in measurements (± 3.7% woody cover).

Model training was performed on 775 field-based canopy cover measurements, and model evaluation was performed by comparing predicted cover against a held-out validation set, which consisted of 259 field-based measurements. Model evaluation with the independent validation set indicated that the model explained 67% of the variation in woody canopy cover, corresponding to a root mean square error (RMSE) of 10.8%.

Canopy Height Evaluation

Model evaluation indicated that local calibration error was 4.1 m ($R^2 = 0.84$) and wall-to-wall model RMSE was 6.6 m ($R^2 = 0.64$). See Simard et al. (2011) for a thorough description of model development and error assessment.

Woody Biomass Evaluation

Woody biomass estimates were compared with existing woody biomass estimates for Africa at the national level (Table 2). Total aboveground biomass for each country was converted to carbon using a conversion factor of 0.5. While estimates of carbon stocks were in general agreement with other satellite-based estimates, the values provided in this dataset are lower on average.

Table 2. Comparison between woody biomass carbon stock estimates (Mt C) available from different sources.

Country	Land Area (km^2)	This Study	Bouvet et al. (2018)	Saatchi et al. (2011)	Baccini et al. (2012)	Avitabile et al. (2016)
Angola	1275231	1673	2786	3322	4742	2041
Benin	116837	123	180	162	212	33
Congo	341223	2768	3358	3209	3333	4098
DemRepCongo	2332349	16581	17746	18195	21867	19966
Burundi	26968	60	51	73	74	22
Cameroon	467694	3305	3393	3700	3650	4322
Chad	1315774	142	509	NA	NA	NA
CentAfrRep	623022	2569	2583	2428	3404	1762
Djibouti	22104	1	30	7	5	8
Equatorial Guinea	26964	287	316	363	253	454
Eritrea	123952	36	115	53	40	34
Ethiopia	1142267	1446	2260	2003	1812	822
Gambia	10970	5	32	9	14	2
Gabon	264143	2719	3377	3448	2624	4453
Ghana	240131	573	522	601	680	325
Guinea	248210	680	1262	807	855	234
Cote d'Ivoire	323831	1131	944	1105	1282	584
Kenya	580858	387	977	804	519	273
Liberia	96334	766	878	1003	904	1172
Libya	1807520	0	41	NA	NA	NA
Madagascar	625517	1333	1941	1906	NA	1202
Mali	1307669	182	417	NA	NA	NA
Mauritania	1106930	7	40	NA	NA	NA
Mozambique	822837	1246	1964	2302	NA	889
Malawi	120965	115	153	218	269	76
Niger	1237580	15	85	NA	NA	NA
Nigeria	919182	1367	1855	1572	1655	675
Guinea-Bissau	34474	71	94	88	105	25
Rwanda	25236	73	61	72	73	31
South Africa	1388689	466	829	1706	NA	493
Lesotho	34843	23	13	43	NA	15
Botswana	622179	79	337	329	NA	131
Senegal	202015	76	195	192	181	48
Sierra Leone	73252	313	276	346	407	215
Somalia	635865	118	989	397	237	248
Sudan	2580717	720	1439	979	1701	231
Togo	57521	94	76	108	125	26
Tanzania	946097	1172	1800	2010	2710	800
Uganda	241018	424	421	495	591	217
Burkina Faso	280518	89	251	151	146	44
Namibia	887156	84	622	281	NA	168
Swaziland	19235	17	31	47	NA	15
Zambia	770823	906	1642	2086	2816	1012

Zimbabwe	411819	226	607	764	670	154
Total	26738519	44473	57498	57384	57956	47320

5. Data Acquisition, Materials, and Methods

Canopy Cover Observations

A dataset of 1034 canopy cover estimates for trees and shrubs was assembled from field-based measurements across Africa and supplemented in under-sampled regions (desert margins and moist tropical forests) by visual analysis of high-resolution imagery (Fig. 2). Most of the field measurements were compiled in 2000-2004 in African savannas (Sankaran et al., 2005). Additional field measurements were provided from three field surveys: 69 points in the Kruger National Park, South Africa (Bucini et al. 2010), 12 points in Uganda (Mitchard et al. 2009), and 49 points in Zambia. Plots falling within the same 1 km pixel were averaged, resulting in 803 field-based data points.

Google Earth (GE; http://earth.google.com) imagery collected between 2000 and 2005 was used to estimate woody cover at 173 locations, including forest and seasonal woodlands, deserts, and agricultural areas. A 1-km by 1-km geo-rectified grid was overlaid on the GE images divided into 16 cells (250 m^2), and an 8 x 8 point sub-grid was deployed within each cell. The fractional cover of a cell was estimated by the presence and absence of woody plant crowns under the digital point samples.

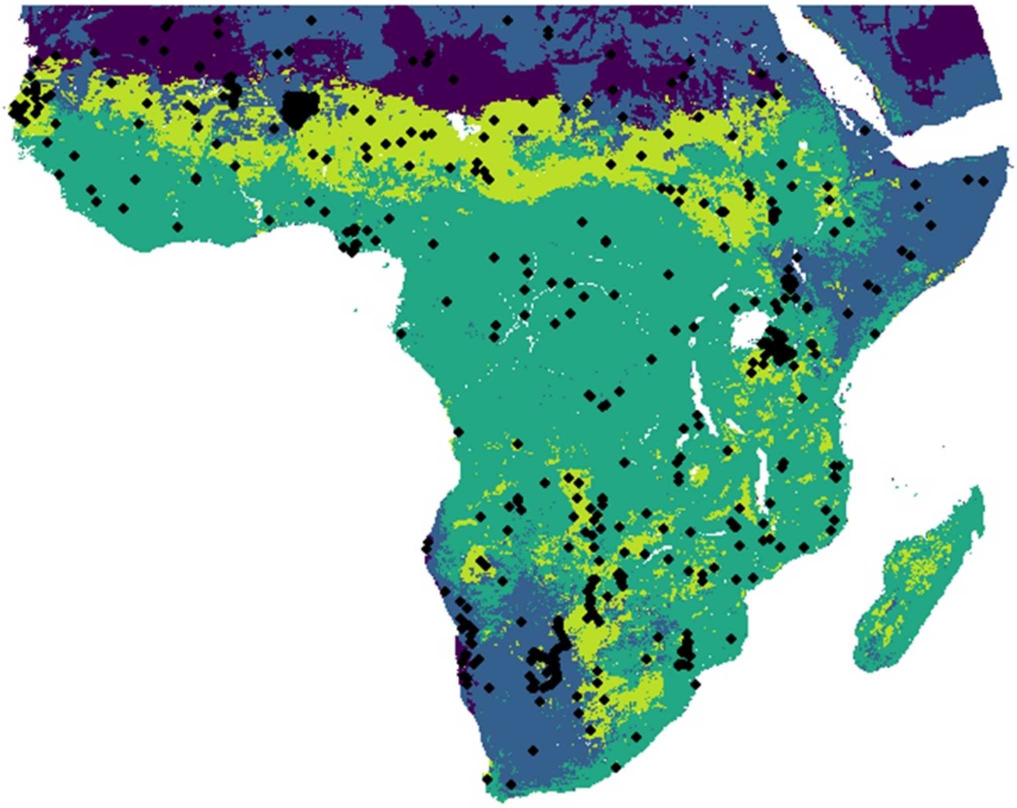

Figure 2. Distribution of sites (N = 1,034) contributing woody cover data including field data (Sankaran et al, 2005) and estimates from high-resolution satellite imagery. (Source C. W. Ross)

Canopy Cover Covariates

Remote-sensing data were compiled from both optical and microwave sensors operating from 2000-2004 and were limited to metrics linked to structural attributes of woody vegetation. MODIS composite reflectance was used to minimize cloud and atmospheric contamination, resulting in monthly average reflectance data at 1-km resolution. Monthly average red (R) and near-infrared (NIR) reflectance were used to calculate monthly average normalized difference vegetation index (NDVI=(NIR-R)/(NIR+R)), mean annual NDVI (“ND_mean”) and the difference between growing season and dry-season mean NDVI (“ND_diff”), which provides information related to phenological variability.

Imagery from Q-SCAT (Quick Scatterometer) available in three-day composites at 2.25-km resolution for years 2000-2004 was processed into average monthly composite and resampled at 1-km resolution. Two metrics were calculated from the data: the annual averaged backscatter (“QS_mean”) and the standard deviation (“QS_sd”) in the HH polarization.

The combination of optical data from MODIS and microwave backscatter from Q-SCAT offered two optical remote sensing metrics (ND_mean, ND_diff) and two microwave metrics (QS_mean, QS_sd) covering Sub-Saharan Africa and projected to a common 1 km spatial resolution sinusoidal grid projection.

Predicting Woody Cover

Fractional woody cover (y) located within pixel i was modeled as conditionally binomial

$y_i \sim Binomial(p_i,100)$ (1)

$\mathrm{logit}(p_i) = \alpha + x_i\beta$ (2)

where p_i is the probability of success (expected proportional woody cover) out of 100 trials for pixel i, x is the vector of remote-sensing covariates for pixel i, α is the intercept, and β is the vector of effect terms for the remote-sensing covariates. Remote-sensing covariates were standardized $[(x_i - x)/\sigma(x)]$ to improve convergence during the model fitting stage and to allow for an easier prior specification.

Each model was fit using a subset of the complete dataset (75%; N = 775) and then using the remaining held-out data (25%; N = 259) to calculate the out-of-sample predicted fit as the log predictive density (Eq. 3):

$lpd = log\int [y_{val} |\theta][\theta]|y_{train}]d\theta$ (3)

where *lpd* is a local and proper scoring function for Bayesian validation (Gelman et al., 2014), and is approximated from Markov chain Monte Carlo (Eq. 4), θ is the set of all unknown parameters to be estimated by the model.

$lpd = \log[y\_val \mid y\_train] \approx \log\sum\_(k=1)^K \; y\_val \mid y\_train]/K$ (4)

where *k* is a single iteration and *K* is the total number of MCMC iterations (Hooten and Hobbs, 2015). The model with the highest *lpd* was considered to be the optimal predictive model and was used to estimate parameters for spatial mapping of woody percent cover.

The three optimally-predictive model sets provide ensemble predictions of tree cover for every terrestrial location in sub-Saharan Africa using different combinations of variables derived from MODIS optical data and Qscatt microwave measurements. The final multi-model ensemble prediction approach is summarized in Table 3.

The posterior prediction scores were calculated from three MCMC chains comprised of 1000 iterations each after discarding an initial 1000 iterations as burn-in. After selecting the optimally predictive model based on *lpd*, that model was fit using only the training data to obtain posterior distributions of all model parameters from three MCMC chains comprised of 1000 iterations each after discarding an initial 1000 iterations as burn-in.

Table 3. Multi-model ensemble prediction approach for different mean annual rainfall (MAP) climate zones of Sub-Saharan Africa.

Bioclimate Zone	MAP Range (mm/year)	Ensemble Estimation Approach	Index
Desert	MAP < 100	TC = 0%	0
Arid savanna	100 < MAP < 600	3-model median (median[1,2,3])	1
Semi-arid savanna	600 < MAP < 1000	3-model average (mean[1,2,3])	2
Mesic savanna & forest	1000<MAP	2-model average (mean[1,3])	3
Sankaran constraint on maximum TC predictions	100 < MAP < 1000	Use Sankaran potential TC if < multi-model TC prediction	4

Canopy Height

The source of canopy height estimates was Simard et al. (2011). They derived global canopy height at 1-km resolution from 2005 Geoscience Laser Altimeter System (GLAS) aboard ICESat (Ice, Cloud, and land Elevation Satellite) and covariates. Canopy height was integrated into the Spatial Data Access Tool (ORNL DAAC, 2017) for reprojection and download. Gridded canopy height data are available for download at https://webmap.ornl.gov/ogc/dataset.jsp?dg_id=10023_1.

When canopy height was not available where canopy cover was greater than 0%, linear regression was used to model and predict canopy height as a function of long-term mean-annual precipitation (Fick and Hijmans, 2017). Unavailable canopy height values were primarily confined to semi-arid and arid regions with low mean annual precipitation, where trees and shrubs tend to have relatively low canopy cover and short stature due to water constraints. Canopy height was then re-projected to the same coordinate system and resolution as the canopy cover data.

Allometric Relationships to Calculate Biomass

Global tree allometry data were retrieved from GlobAllomeTree (www.globallometree.org) and subset to calculate the relationship between biomass, tree height, and canopy cover in Africa:

$B/C = \mathrm{expi}(-1.19909+\ln(H)*1.27841$ (5)

where *B/C* is woody biomass (kg) per square meter of canopy cover, and *H* is height.

Continental-scale biomass estimates were then obtained:

$Biomass = (wc/100)*10{,}000*B/C$ (6)

where *Biomass* is tree and shrub biomass (Mg ha-1), *wc* is predicted woody cover (%), and *B/C* is obtained from Eq. 5.

6. Data Access

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

Gridded Estimates of Woody Cover and Biomass across Sub-Saharan Africa, 2000-2004

Contact for Data Center Access Information:

- E-mail: uso@daac.ornl.gov
- Telephone: +1 (865) 241-3952

7. References

Avitabile, V., Herold, M., Heuvelink, G.B.M., Lewis, S.L., Phillips, O.L., Asner, G.P., Armston, J., Ashton, P.S., Banin, L., Bayol, N., et al. (2016). An integrated pan-tropical biomass map using multiple reference datasets. Glob. Change Biol. 22, 1406–1420. https://doi.org/10.1111/gcb.13139

Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P.S.A., Dubayah, R., Friedl, M.A., et al. (2012). Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nat. Clim. Change 2, 182–185. https://doi.org/10.1038/nclimate1354

Bouvet, A., Mermoz, S., Le Toan, T., Villard, L., Mathieu, R., Naidoo, L., and Asner, G.P. (2018). An above-ground biomass map of African savannahs and woodlands at 25m resolution derived from ALOS PALSAR. Remote Sens. Environ. 206, 156–173. https://doi.org/10.1016/j.rse.2017.12.030

Bucini, G., Hanan, N.P., Boone, R.B., Smit, I.P.J., Saatchi, S.S., Lefsky, M.A., Asner, G.P., Hanan, N.P., Boone, R.B., Smit, I.P.J., et al. (2010). Woody Fractional Cover in Kruger National Park, South Africa: Remote Sensing–Based Maps and Ecological Insights. https://doi.org/10.1201/b10275

Fick, S.E., and Hijmans, R.J. (2017). WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37, 4302–4315. https://doi.org/10.1002/joc.5086

Gelman, A., Hwang, J., and Vehtari, A. (2014). Understanding predictive information criteria for Bayesian models. Stat. Comput. 24, 997–1016. https://doi.org/10.1007/s11222-013-9416-2

Hooten, M.B., and Hobbs, N.T. (2015). A guide to Bayesian model selection for ecologists. Ecol. Monogr. 85, 3–28. https://doi.org/10.1890/14-0661.1

Mitchard, E.T.A., Saatchi, S.S., Woodhouse, I.H., Nangendo, G., Ribeiro, N.S., Williams, M., Ryan, C.M., Lewis, S.L., Feldpausch, T.R., and Meir, P. (2009). Using satellite radar backscatter to predict above-ground woody biomass: A consistent relationship across four different African landscapes. Geophys. Res. Lett. 36. https://doi.org/10.1029/2009GL040692

Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T.A., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S., et al. (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. Proc. Natl. Acad. Sci. 108, 9899–9904. https://doi.org/10.1073/pnas.1019576108

Sankaran, M., Hanan, N.P., Scholes, R.J., Ratnam, J., Augustine, D.J., Cade, B.S., Gignoux, J., Higgins, S.I., Roux, X.L., Ludwig, F., et al. (2005). Determinants of woody cover in African savannas. Nature 438, 846. https://doi.org/10.1038/nature04070

Simard, M., N. Pinto, J. B. Fisher, and A. Baccini (2011), Mapping forest canopy height globally with spaceborne lidar, J. Geophys. Res., 116, G04021, https://doi.org/10.1029/2011JG001708.

OAK RIDGE National Laboratory

Privacy Policy | Feedback | Help

Home

About Us
Mission
Data Use and Citation Policy
User Working Group
Partners

Get Data
Science Themes
NASA Projects
All Datasets

Submit Data
Submit Data Form
Data Scope and Acceptance
Data Authorship Policy
Data Publication Timeline
Detailed Submission Guidelines

Tools
MODIS
THREDDS
SDAT
Daymet
CARVE Data Viewer
Soil Moisture Visualizer
Land - Water Checker

Resources
Learning
Data Management
News

Contact Us