Machine learning and FLUXNET-based Carbon and Water Fluxes (MF-CW)

Description:

FLUXNET eddy covariance (EC) sites offer temporally continuous carbon and water flux data for a large number of sites encompassing a wide range of ecosystems and climate types across the globe. However, the EC measurements only represent the status of carbon and water fluxes around the tower footprint; they need to be upscaled to regional or global scales so that we can explore the dynamics of carbon and water fluxes over broad regions. The datasets of Machine learning and FLUXNET-based Carbon and Water Fluxes (MF-CW) include the exponential GPR-based optimal estimates and the corresponding standard deviation (SD) of monthly GPP, ET, and WUEeco at 0.5-degree resolution over the global vegetated lands, and the average and median estimates of using 24 machine learning methods (see list below), FLUXNET in-situ observations of CO_2 and water vapor fluxes, satellite-derived observations and climate reanalysis data. The methodology, validation, and spatial and temporal patterns of these datasets are detailed in the paper.

List of Machine Learning Algorithms utilizing:

1 Linear: ET(✓), GPP(✓), WUEeco(✓)
2 InteractionsLinear: ET(✓), GPP(✓), WUEeco(✓)
3 RobustLinear: ET(✓), GPP(✓), WUEeco(✓)
4 StepwiseLinear: ET(✓), GPP(✓), WUEeco(✓)
5 FineTree: ET(✓), GPP(✓), WUEeco(✓)
6 MediumTree: ET(✓), GPP(✓), WUEeco(✓)
7 CoarseTree: ET(✓), GPP(✓), WUEeco(✓)
8 LinearSVM: ET(✓), GPP(✓), WUEeco(✓)
9 QuadraticSVM: ET(✓), GPP(✓), WUEeco(✓)
10 CubicSVM: ET(✓), GPP(✓), WUEeco(✗)
11 FineGaussianSVM: ET(✓), GPP(✓), WUEeco(✓)
12 MediumGaussianSVM: ET(✓), GPP(✓), WUEeco(✓)
13 CoarseGaussianSVM: ET(✓), GPP(✓), WUEeco(✓)
14 BoostedTrees: ET(✓), GPP(✓), WUEeco(✓)
15 BaggedTrees: ET(✓), GPP(✓), WUEeco(✓)
16 GPR_RationalQuadratic: ET(✓), GPP(✓), WUEeco(✓)
17 GPR_SquaredExponential: ET(✓), GPP(✓), WUEeco(✓)
18 GPR_Matern5_2: ET(✓), GPP(✓), WUEeco(✓)
19 GPR_Exponential: ET(✓), GPP(✓), WUEeco(✓)
20 NarrowNeuralNetwork: ET(✓), GPP(✓), WUEeco(✓)
21 MediumNeuralNetwork: ET(✓), GPP(✓), WUEeco(✓)
22 WideNeuralNetwork: ET(✓), GPP(✓), WUEeco(✓)
23 BilayeredNeuralNetwork: ET(✓), GPP(✓), WUEeco(✓)
24 TrilayeredNeuralNetwork: ET(✓), GPP(✓), WUEeco(✓)

To be continued →

Fair Data Use Policy:
We make the datasets available to the research community as we believe that the dissemination of the datasets can be helpful to advancement in science. If you plan to use our datasets in a manuscript or project, we request that you inform us early in your work. If our datasets are essential to your results or findings, co-authorship will be appropriate.

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Metadata:
Spatial resolution: 0.05-degree
Spatial extent: globe
Temporal resolution: monthly
Temporal extent: 1982-2016
File format: GeoTIFF Map projection: Geographic
Scale factor: none
Units: GPP (g C m^{-2}), ET (kg H_2O m^{-2}), and WUE_{eco} (g C kg^{-1} H_2O)

For each variable (GPP, ET, WUE), there are four folders: *Mean* (the mean estimate of all the ML methods), *Median* (the median estimate of all the ML methods), *Optimal* (the optimal estimate), and *SD* (the standard deviation, which can be used as an estimate of uncertainty).

Citation:
Li, F., Xiao, J., Chen, J., Ballantyne, A., Jin, K., Li, B., Abraha, M., John, R. (2023) Global water use efficiency saturation due to increased vapor pressure deficit. *Science*, 381, 672-677. DOI: 10.1126/science.adf5041.

Download:
Global Ecology Group Data Repository: http://globalecology.unh.edu/data/MF-CW.html. Please visit our webpage for any updates to this product.

Note that you can download the entire dataset (GPP, ET, WUE; 1982-2016) at one time by downloading the .tar.gz file.