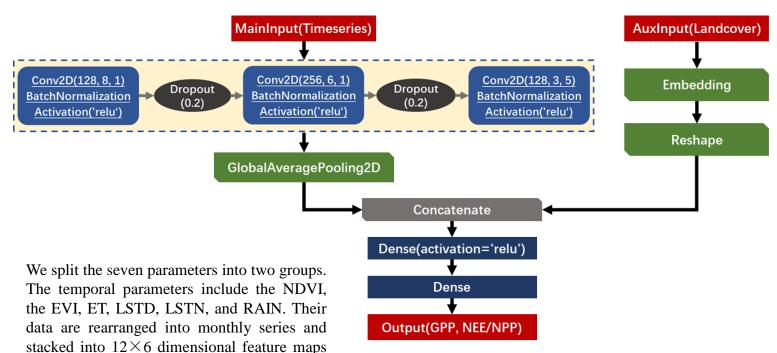


to form the MainInput. The FCN block then performs as an automatic multi-scale pattern

detector to precept these feature maps.

Model Architecture and Input Datasets

The model was developed based on a Deep Learning (DL) neural network. It incorporated two inputs—the MainInput and the AuxInput—as well as a Fully Convolutional neural Network (FCN) block, an embedding block, and a Multi-Layer Perceptron (MLP) block. All the inputs can be acquired from Google Earth Engine to benefit from cloud data storage and processing.



Paramet er	GEE Dataset	Time Range	Resolution	GEE ImageCollection ID
NDVI	MODIS 16-day NDVI	02/2000- now	500 m	MODIS/ MCD43A4_006_ NDVI
EVI	MODIS 16-day EVI	02/2000- now	500 m	MODIS/ MCD43A4_006_ EVI
ET	MODIS 8-day ET	02/2000- now	1000 m	MODIS/NTSG/M OD16A2/105
LSTD LSTN	MODIS 8-day LST	02/2000- now	1000 m	MODIS/ MOD11A2
Precipita tion	JAXA GSMaP 3-hour precipitation	03/2000- now	0.1°	JAXA/GPM_L3/ GSMaP/v6/ reanalysis (before 03/2014) /operational (after 03/2014)
Forest Type	ESA Global Landcover	2009	300 m	ESA/GLOBCOV ER_L4_200901_ 200912_V2_3

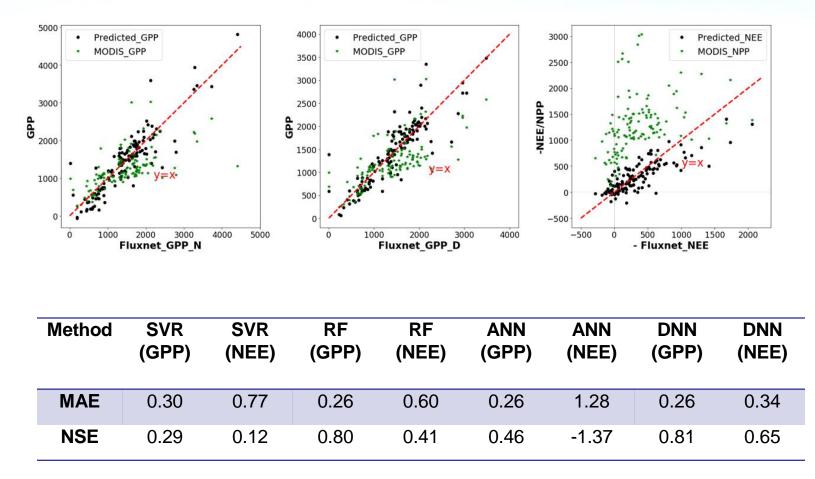
www.aircas.ac.cn



Model Performance and Comparison with Traditional Machine Learning Methods

The model was pretrained with MODIS GPP and NPP and transferred to Fluxnet GPP and NEE. After four levels of transfer learning, the model can finally predict FLUXNETconsistent forest GPP and NEE globally.

- The Mean Absolute Error (MAE) is used to show the overall performance of the model, and for easier interpretation, we apply it on normalized data obtained with the z-score method to exclude the influence of data range.
- The Nash-Sutcliffe model Efficiency coefficient (NSE) ranges from $-\infty$ to 1, with 1 corresponding to a perfect match and 0 denoting estimation as accurate against the benchmark mean.



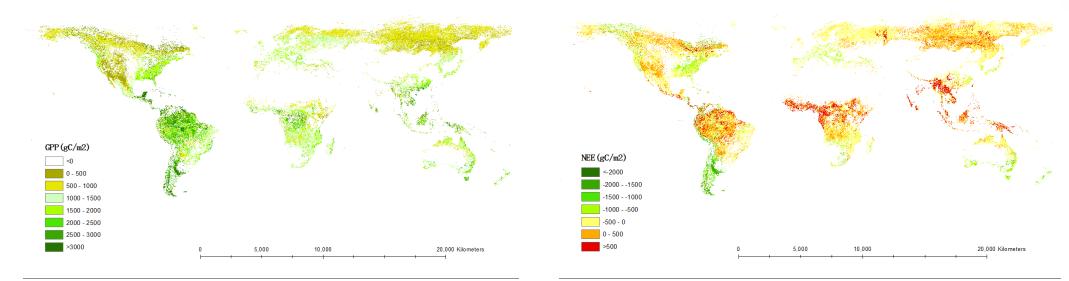
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Predicted Global Forest GPP and NEE using the New Model

GPP in 2018





	2003 (PgC/m ²)	2018 (PgC/m ²)
GPP	63.48668	66.93591
NEE	-1.76478	-2.00268

Note that there are many point-like carbon sources in the tropical region, which may be prediction errors caused by cloud-contaminated input data or insufficient model ability owning to inadequate training data in tropical region. They could also be real carbon sources caused by wild fire or deforestation.

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