A Machine Learning Approach to Determine Surface Radiative Fluxes based on CERES Observations

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Introduction

The Clouds and Earth's Radiant Energy System (CERES) project provides satellite-based observations of the radiative fluxes and clouds systems. CERES climate quality data products typically take several months of calibration and validation before release to the public. The Fast Longwave and Shortwave Radiative Flux (FLASHFlux) data product was developed to provide key data for the applied sciences and educational users within a week of observation. FLASHFlux achieves this by using simplified calibration, an operational meteorological product from Global Modeling and Assimilation Office (GMAO), and its own surface parameterizations model. The CERES FLASHFlux provides two data products: 1) an hourly Level 2 Single Scanner Footprint (SSF) data separately for Terra and NOAA-20 observations, and 2) a daily Level 3 Time Interpolated and Spatially Averaged (TISA) 1º x 1º gridded data that combines Terra and NOAA-20 observations.

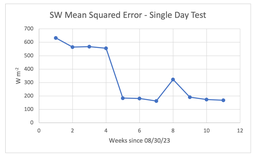
Currently, FLASHFlux uses the Langley Parameterized Shortwave Algorithm (LPSA) and Langley Parameterized Longwave Algorithm (LPLA) to derive its surface fluxes. A new Machine Learning based approach using Artificial Neural Networks to derive Surface LW & SW fluxes based on training data from the CERES Clouds Radiative Swath (CRS) product is being investigated to replace LPSA and LPLA. We test ANN produced fluxes against surface fluxes produced from the Fu-Liou model used in CRS and the LPSA/LPLA used in FLASHFlux SSF. Furthermore, we investigate Leave-One-Feature-Out Importance (LOFO) to evaluate the significance of each feature in our training and provide insight for future models.

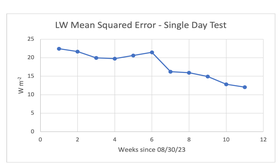
Model Improvement

* 4 training days across all models

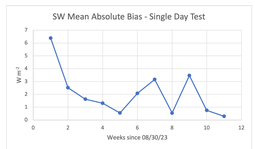
Shortwave (Day) | Longwave (Day)

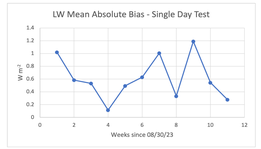
Mean Squared Error





Bias





Our initial run for SW surface flux down included the training variables TOA insolation, solar zenith angle, cloud fraction, cloud optical depth, precipitable water vapor, aerosol optical depth, and altitude.

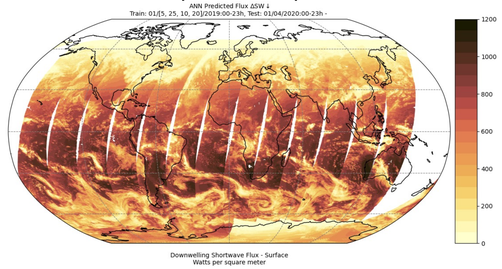
Our final run included all the above variables except for cloud optical depth, we instead ran the exponential function of the weighted average of the log value of COD for each of the 2 cloud layers, we also included TOA reflected shortwave in our features.

Our initial run for LW surface flux down included the training variables effective temperature, cloud fraction, cloud optical depth, precipitable water vapor, potential temperature gradient, cloud temperature, and altitude.

Our final run (daytime and nighttime) included all the above variables and near surface air temperature, aerosol optical depth, temperature at surface and 500 hPA and 850 hPa, surface pressure, cloud fractions and temperatures and optical depths for each layer, and cloud base temperature.

ANN Surface Fluxes

Surface SW Down (Jan 4, 2020)

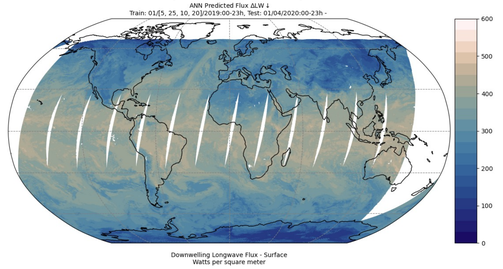


January Terra SW Daytime

Monthly Global Average: 518.831 W m^{-2}
Standard Deviation of Daily Global Averages: 5.653 W m^{-2}

Training Features:
Top of Atmosphere Insulation, Solar Zenith Angle, Cloud Fraction, exponential of weighted average of natural log Cloud Optical Depth, Precipitable Water Vapor, Aerosol Optical Depth, Altitude, Top of Atmosphere Reflected Shortwave Flux

Surface LW Down Day (Jan 4, 2020)

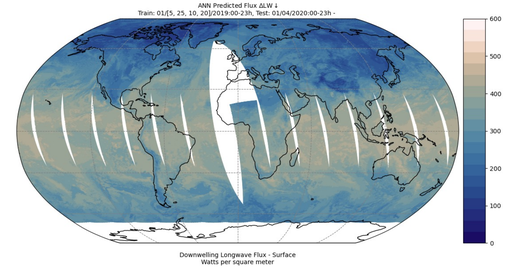


January Terra LW Daytime

Monthly Global Average: 342.047 W m^{-2}
Standard Deviation of Daily Global Averages: 1.566 W m^{-2}

Training Features:
Effective Temperature, Cloud Fraction, Cloud Optical Depth, Precipitable Water Vapor, Potential Temperature Gradient, Cloud Temperature, Altitude, Near Surface Air Temperature, Aerosol Optical Depth, Surface Temperature, Temperature at 500 hPa, Temperature at 850 hPa, Surface Pressure, Cloud Base Temperature

Surface LW Down Night (Jan 4, 2020)



January Terra LW Nighttime

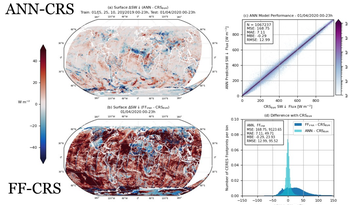
Monthly Global Average: 332.136 W m^{-2}
Standard Deviation of Daily Global Averages: 1.458 W m^{-2}

Training Features:
Effective Temperature, Cloud Fraction, Cloud Optical Depth, Precipitable Water Vapor, Potential Temperature Gradient, Cloud Temperature, Altitude, Near Surface Air Temperature, Aerosol Optical Depth, Surface Temperature, Temperature at 500 hPa, Temperature at 850 hPa, Surface Pressure, Cloud Base Temperature

Model Comparisons

Surface SW Down

ANN-CRS



FF-CRS

Testday: 01/04/2019

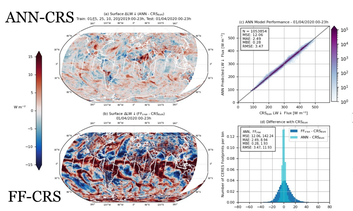
Terra Daytime
ANN-CRS Total January Stats:

Mean Squared Error	163.284
Mean Absolute Error	7.036
Mean Bias Error	0.152
RMS Error	12.778

For Surface SW Down Daytime, we can see a tighter range of differences and a smaller bias relative to FF. Our differences are consistently small across all flux values. We are investigating the cause behind the systematic differences for the area along the sub-Sahara and Central Asia.

Surface LW Down Day

ANN-CRS



FF-CRS

Testday: 01/04/2019

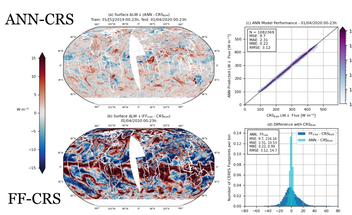
Terra Daytime
ANN-CRS Total January Stats:

Mean Squared Error	12.331
Mean Absolute Error	2.504
Mean Bias Error	0.251
RMS Error	3.512

For Surface LW Down Daytime, we also see a tighter range of differences and a smaller bias relative to FF. Our differences are consistently small across all flux values. The bottom plot highlights the differences between FLASHFlux and CRS. These differences are at least partly attributed to differing meteorological inputs.

Surface LW Down Night

ANN-CRS



FF-CRS

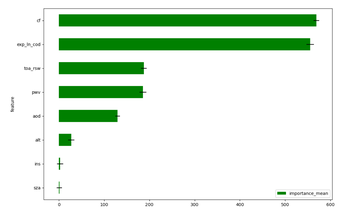
Testday: 01/04/2019

Terra Nighttime
ANN-CRS Total January Stats:

Mean Squared Error	9.497
Mean Absolute Error	2.298
Mean Bias Error	0.244
RMS Error	3.082

For Surface LW Down Nighttime, we can see a tighter range of differences and a smaller bias relative to FF. Our differences are consistently small across all flux values. Some areas over continents and areas involving cloud patterns can be improved.

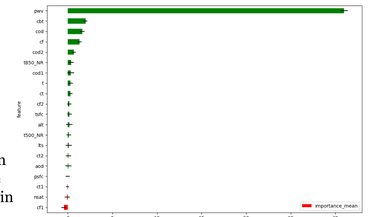
LOFO Variable Importance



Shortwave Training Features

A heavy focus for the initial stages of model improvement was feature selection. Some methods in consideration to determine variable importance were permutation feature importance, partial dependence plots, and SHAP values. Due our needs of quick setup and versatility in model types we can implement it on, we decided to use Leave-One-Feature-Out (LOFO) Importance as our feature importance method.

This involves retraining the model repeatedly based on the number of features in our dataset, and leaving one variable out in each retrain, calculating the difference in loss when we leave that variable out. A loss increase (green), usually indicates we have a very important variable, a loss decrease (red), that indicates the variable is hurting our model performance. Running LOFO over different variable configurations also gives us insight into whether multiple variables cross-correlate and how this affects the model.



Longwave Training Features

Conclusions & Future Goals

- The ANN models surface fluxes compares reasonably well to the full Fu-Liou radiative transfer models.
- The LOFO methods allow us to narrow down the training features parameters and produce surface flux models that has low mean square error and bias to the Fu-Liou.
- July runs have shown similar accuracy, next step is to produce seasonal months of data and validate the ANN surface fluxes to surface sites measurements.
- We are also investigating a separate clear-sky and cloudy-sky only models using this method to study clouds radiative effect.
- The ANN surface models will be available in the future version of the CERES Fast Longwave And Shortwave Flux (FLASHFlux) near real time data product.

Acknowledgements: We used aerdem4's LOFO importance repo: https://github.com/aerdem4/lofo-importance.
This work was funded by the NASA CERES Project, Norman Loeb PI.