Improving Radiative Fluxes for the CERES FluxByCldTyp Data Product Using Deep Neural Network

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1. Introduction

The NASA Clouds and the Earth's Radiant Energy System (**CERES**) Project monitor the top-of-the-atmosphere (TOA) radiation budget through a series lower orbit satellites. It provides a suite of data such as **EBAF**, **SSF1Deg**, **SYN1Deg** and **FluxByCldTyp** et al. for more than 20 years (https://ceres.larc.nasa.gov/ data/). These data are essential for climate studies and modeling constrains.

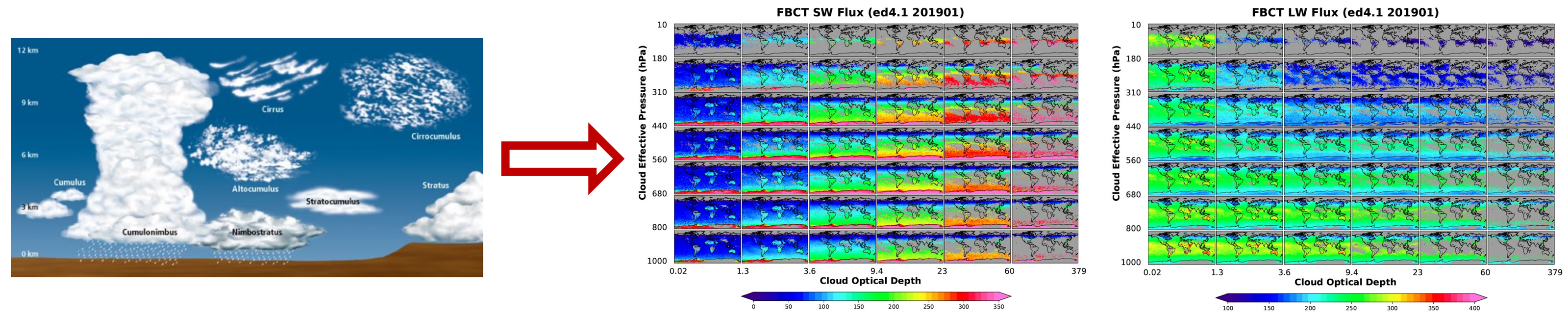

Fig. 1 The CERES FluxByCldTyp (FBCT) Data

contains radiative fluxes and cloud properties by 42 cloud types (6 cloud optical depth bins and 7 cloud effective pressure bins). The accuracy and consistency of the data are critical for climate studies. In this paper, we use deep neural network (**DNN**) to improve the FBCT Ed4 TOA radiative fluxes.

2. Data and Methodology

a. Data:

Input: The CERES Single Scanner Footprint (SSF) Edition 4A footprint data. **Aqua Satellite January 2019**.

As in Fig. 2, each footprint has up to three sub-footprint areas: low cloud, high cloud and clear. Footprint size is about 20-km nadir. Each footprint contains following parameters:

- Time, position, viewing geometry
- Surface maps, scene types
- Meteorological data
- Radiances (MODIS narrowband radiances and CERES broadband radiances) and broadband fluxes
- Cloud properties: cloud fraction, TempEff, TempTop, PressEff, PressTop, Liquid water path, Ice water path, Cloud Radius, Emissivity, Optical Depth, etc.

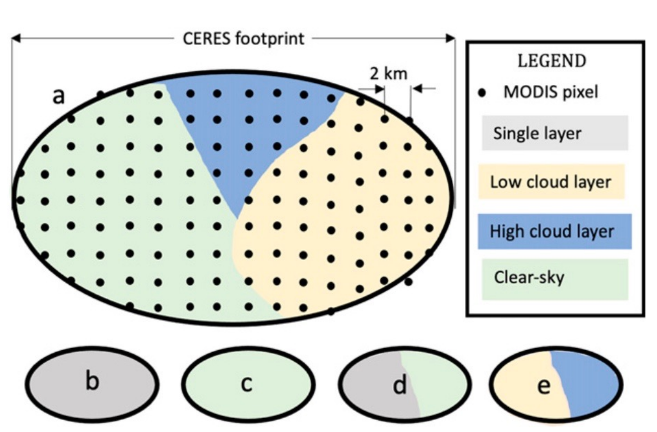

Fig. 2 Schematic of the CERES footprint.

b. Methodology:

Aim: To obtain a corresponding flux for each of the three sub-footprint areas: clear, cloudLow and cloudHigh using DNN.

1) Fig.3 presents the FBCT product flowchart and provides an overview of the inputs and algorithms needed for FBCT processing. This paper will focus on the procedures within the red frame. The rest stay the same.
2) **DNN** will be used to convert MODIS NB radiances to fluxes with or without angular distribution models (ADMs). DNN models are trained on Single scene SSF footprints (case b and c in Fig. 2). The trained DNN model will be applied to SSFs with mixed scenes (case d and e in Fig. 2)
3) **DNN model** as in Fig 3. Besides the input and output layers, it has 5 hidden layers with different nodes from 100 in the first layer to 10 in the 5th hidden layer. The model's hyper-parameters: epoch number is 300, minibatch size is 128, initial learning rate is 0.01 and decreasing with drop rate 0.5, epoch drop rate is 50. The data is split into three groups: 80% training data, 18% development data and 2% test data. Table 1 shows the input parameters for the DNN Model. Both SW and LW use the same clear sky and cloudy sky models. Clear sky has total of 13 parameters including skin temperature plus other 12 parameters that are also used by cloudy sky model. Surface are classified into 7 types: ocean, forest, savannah, grass, dark desert, bright desert, snow/ice. Including other variables like cloud optical depth does not improve performance.

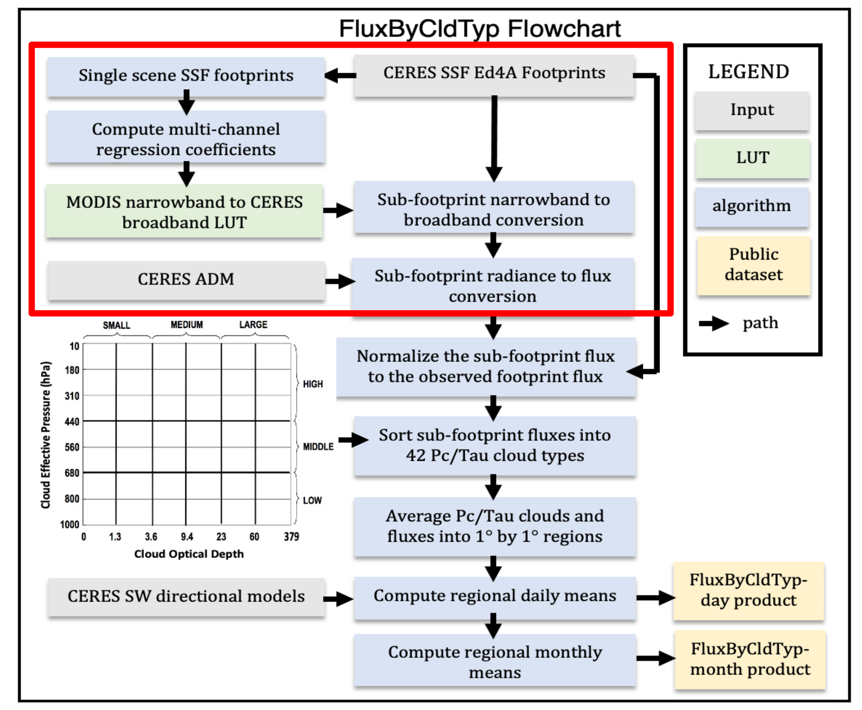

Fig. 3 The CERES FBCT flowchart. The FBCT cloud effective pressure by optical depth cloud-types are shown in the center left and are defined in the same manner as the ISCCP D1 product.

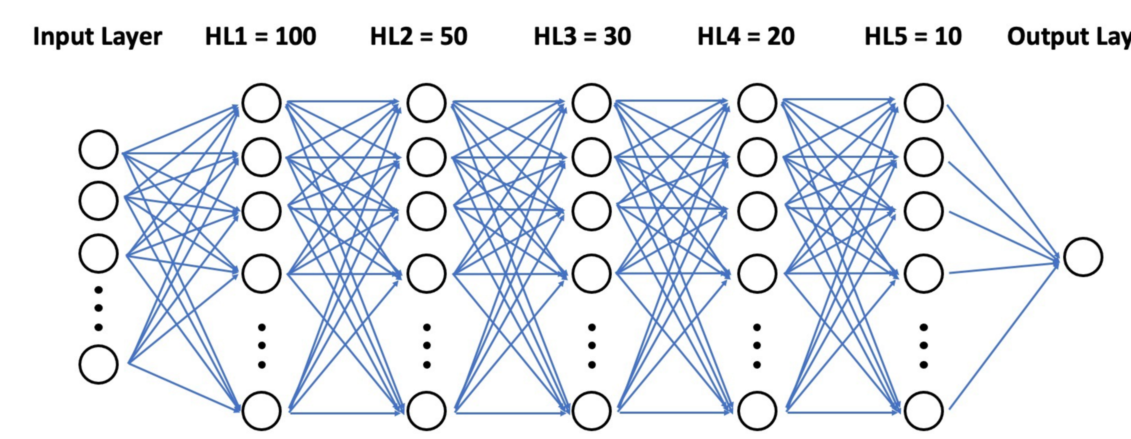

Fig. 4 DNN network diagram with 5 hidden layers and number of nodes for each hidden layer.

	Input Parameters		Total
Clear Sky	5 NB radiances: 0.47µm, 0.65µm, 0.86µm,11µm, 12µm, solar zenith angle (SZA), viewing zenith angle (VZA), relative azimuth angle (RAA), surface type, total precipitable water (TPW), latitude, longitude	Skin Temperature	13
Cloudy Sky			12

Table 1. Input parameters for DNN clear sky and cloudy sky models.

3. Results

As mentioned in section 2b.2, two methods are developed. The first one uses DNN to convert MODIS NB radiances to BB radiance and then convert it to BB flux using ADM (**DNN+ADM**). The second one converts MODIS BB radiances to BB flux directly without ADM (**DNNOnly**). The trained DNN parameters are applied to SSFs with mixed scenes (Fig. 2) to generate BB flux for each scene (sub-footprint). The fluxes from each sub-footprint are summed to form the total footprint flux. It will be compared against the CERES observed footprint level fluxes provided in the SSF Ed4 dataset.

Fig. 5 shows the biases and standard deviations between derived and observed SW and LW fluxes plotted as a function of cloud fraction, cloud effective pressure, cloud effective temperature, cloud optical depth, TPW, SZA, VZA, and surface type. The biases and standard deviations and their variations along the underlying parameters show how well each algorithm does. The smaller values mean improved results. Both **DNN+AMD** and **DNNOnly** show overall improvement over Ed4. The most significant improvement is against the cloud optical depth for both methods. The two DNN methods give similar results. This indicates future FBCT edition can bypass ADM which significantly reduces the code complexity.

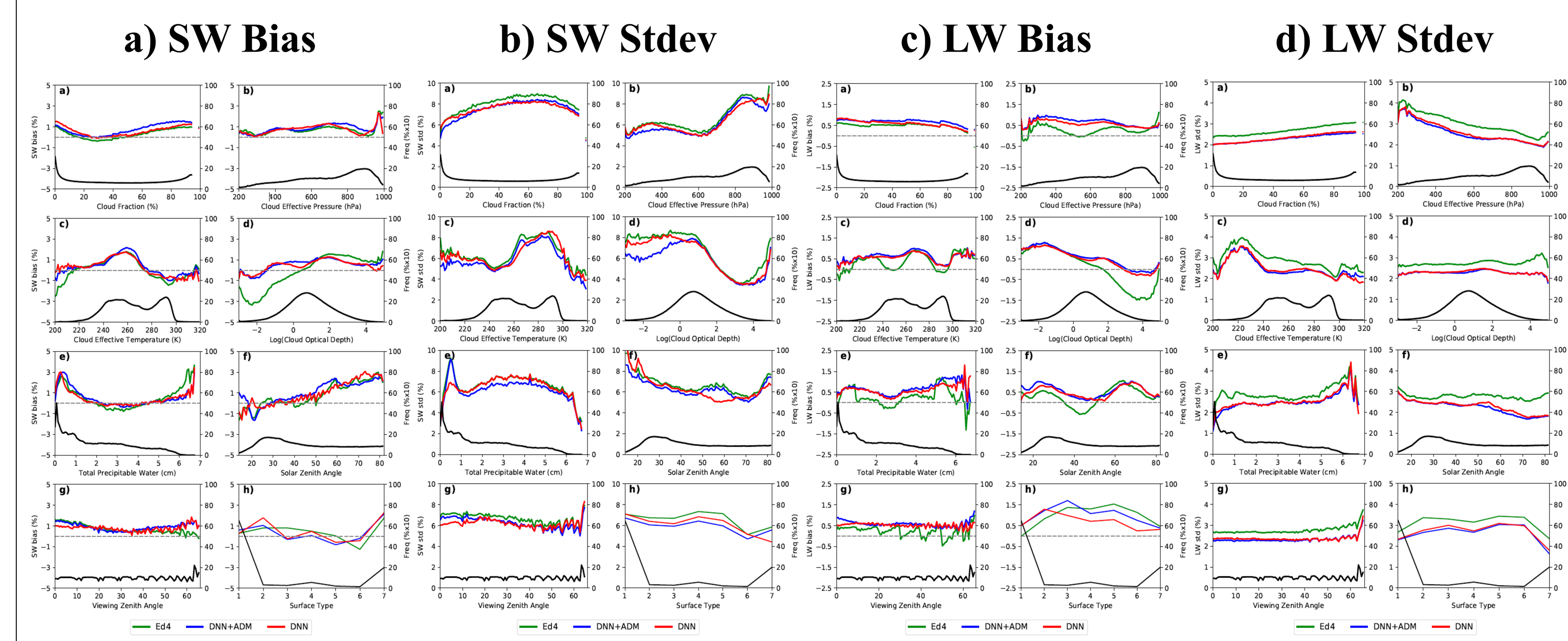

Fig. 5 January 2019 Aqua derived SW and LW fluxes vs CERES observed SSF fluxes biases and Standard deviations dependency on parameters. (Green **Ed4; Blue DNN+ADM; Red DNNOnly**), and **frequency** (%x10, black).

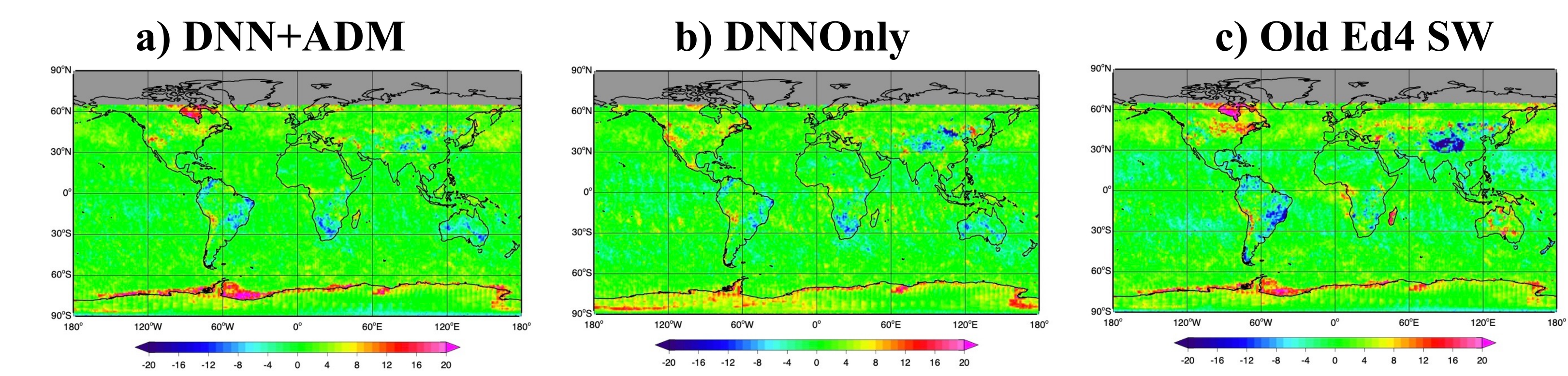

Fig. 6 Derived SW fluxes minus observed fluxes based on mixed scene footprints (unit W/m²).

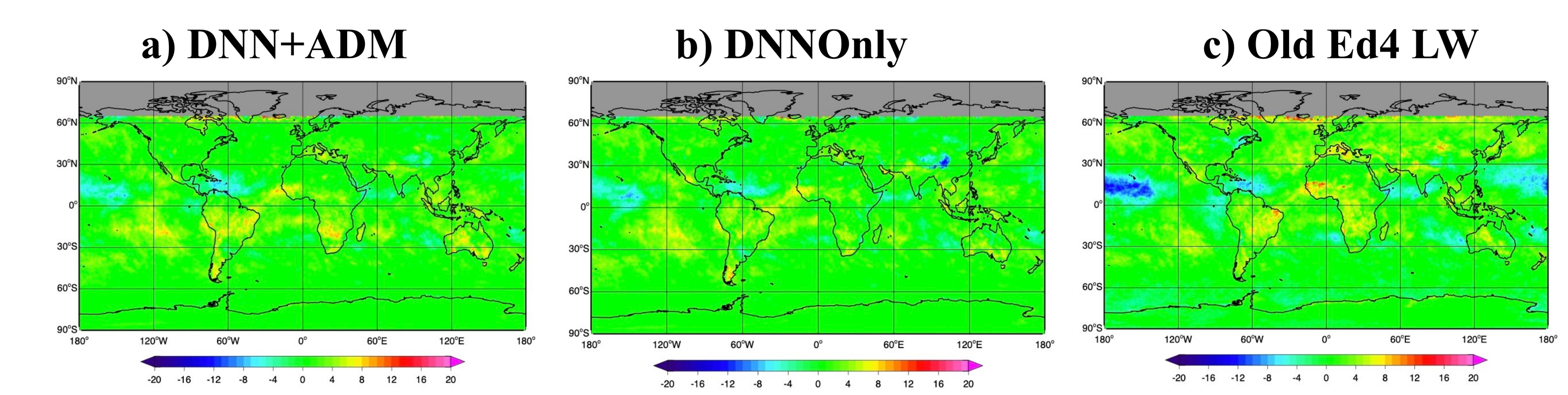

Fig. 7 same as Fig. 6 but for LW.

Fig. 6 and Fig. 7 show the biases of SW and LW fluxes between derived fluxes and CERES observed fluxes. Both **DNN+ADM** and **DNNOnly** show improvement for SW and LW over Ed4. **DNNOnly** SW significantly reduces biases over Hudson bay and Weddell Sea regions. LW fluxes show very small differences between the two new methods. Again, ADM is not required to generate accurate FBCT fluxes. Table 2 shows biases and RMSs (root mean square) for the whole globe corresponding to Fig.5 and Fig. 6. The smaller biases for old Ed4 are the results of cancellation between negative and positive biases.

	Ed4	DNN+ADM	DNN
SW Bias	0.42	0.85	0.60
SW RMS	3.99	3.21	3.15
LW Bias	0.70	1.14	0.97
LW RMS	3.03	2.45	2.33

Table 2. Global mean SW and LW biases and RMSs for Old Ed4, DNN+ADM and DNN cases.

4. Summary and future work

Two methods based on DNN are developed to improve fluxes in FBCT product. They both show improvement over Ed4. The two methods give about the same results and ADM is not required in future FBCT code. Further improvement may come from using different MODIS NB channels.

Reference:

Sun, M., Doelling, D. R., Loeb, N. G., Scott, R. C., Wilkins, J., Nguyen, L. T., & Mlynczak, P. (2022). Clouds and the Earth's Radiant Energy System (CERES) FluxByCldTyp edition 4 data product. Journal of Atmospheric and Oceanic Technology, 39(3), 303-318.