Preliminary Report on Deep Learning-based Daytime Clear-Sky Radiance for VIIRS

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Abstract: A fully connected "deep" neural network algorithm with the Community Radiative Transfer Model (FCDN_CRTM) is proposed to explore the efficiency and accuracy of reproducing the Visible Infrared Imaging Radiometer Suite (VIIRS) clear-sky radiances in five thermal emission M (TEB/M) bands. The model was originally trained and tested in the global ocean clear-sky domain for nighttime and was modified and applied for daytime data in this study. CRTM-simulated brightness temperatures (BTs) were defined as model labels, and the clear-sky pixels were identified by an FCDN-trained clear-sky mask (FCDN_CSM) model. The preliminary result showed that the FCDN_CRTM prediction minus CRTM simulation (F-C) mean biases are only several tens mK for all bands. However, the corresponding standard deviations (STDs) were 4-5 times worse than training and testing data due to the effect of the daytime solar reflection. The evaluation result suggested that further fine-tune model is needed to improve the daytime prediction accuracies by improving input data uniformity, adjusting the model architecture, and selecting possible important features.

Keywords—fully connected "deep" neural network (FCDN), deep learning, community radiative transfer model (CRTM), artificial neural network (ANN), the visible infrared imaging radiometer suite (VIIRS)

I. INTRODUCTION

The Community Radiative Transfer Model (CRTM) was developed at the Joint Center for Satellite Data Assimilation (JCSDA). This fast radiative transfer model is used at the National Oceanic and Atmospheric Administration (NOAA) and in many institutes and universities, both nationally and internationally [1-8]. The model simulates satellite measurements from visible, infrared, or microwave bands and calculates corresponding tangent-linear, adjoint, and Jacobian values for various geophysical and atmospheric parameters to support radiance assimilation and the retrieval of atmosphere and surface states [1,3]. With the development of high spatial and temporal resolution sensors, the efficiency of CRTM simulation is still a key issue for global monitoring of the sensor observations against CRTM simulation (O-M) biases, such as the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the satellites in the Joint Polar Satellite System (JPSS) and the advanced baseline imager (ABI) onboard the geostationary operational environmental satellite-R (GOES-R).

In recent years, the method of an artificial neural network (ANN) has gradually become a popular algorithm and is applied in most science and technical fields, including atmosphere and ocean remote sensing and climate research [9-12]. Using simple, statistical, nonlinear approximation instead of a complicated physical-based model in ANNs renders a more computationally efficient method to achieve a similar job to that of the physical-based model without significant accuracy loss [9-12]. A fully connected deep neural network (FCDN) algorithm has been developed and applied to nighttime CRTM simulation (referred to FCDN_CRTM) in clear-sky condition for the Suomi-National Polar-orbiting Partnership (SNPP) VIIRS in the thermal emission M bands (TEB/M) [13], where a FCDN-based clear-sky mask (FCDN_CSM) [14-15] was used as the clear-sky identification for FCDN_CRTM. The preliminary evaluation

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showed that the FCDN_CRTM with FCDN_CSM is high efficient, accurate and robust, and it is ready for the monitoring of VIIRS radiometric biases in global for nighttime. In this paper, we intent to explore the daytime clear-sky radiances prediction by using the FCDN_CRTM and FCDN_CSM models.

II. MODEL REVIEW FOR DAYTIME

Nighttime FCDN_CRTM used 278 input features, including surface wind speed and type, sensor zenith angle, surface pressure and temperature, and 91-layer temperature, water vapor humility and O3 profiles. The model was designed three hidden layers with 512 x 384 x 64 nodes, and used the CRTM simulated clear-sky brightness temperatures (BTs) in five VIIRS TEB/M bands as reference labels in the output layer. A mean square error (MSE) was used as the model cost function. For the daytime, the solar reflection should be taken account in the model, particularly for the midwave infrared bands (MWIRs, M12 and M13), which related to the solar zenith angle and relative azimuth angle between solar and sensor. In the initial study, the nighttime FCDN_CRTM model was first applied for daytime, together with solar zenith angle and relative azimuth angle included in the input features. Although sun glint angle is also a critical parameter on the effect of solar reflection in the daytime [16], the offline analysis showed that it did not contribute much on the model prediction accuracies when the solar zenith angle, sensor zenith angle and relative azimuth angle were the features in the model.

III. INPUT AND OUTPUT DATA

A. *Data Preprocessing*

To take account the seasonal cycle effects, similar to the nighttime FCDN_CRTM, the input data also included six dispersion data points from 2019 to 2020, including March 10, May 5, August 1, October 12, and November 6 in 2019 and January 15 in 2020, which nearly cover all seasons. These data were selected side by side with the CRTM BTs for five VIIRS TEB/M bands. Roughly 40 million samples were accumulated after data preprocessing.

All training and testing data were limited to less than 90° of the solar zenith angle as daytime input samples. Similar to the CRTM input, the input data were extracted from the VIIRS sensor record data (SDR) product, high-resolution European Centre for Medium-Range Weather Forecasts (ECMWF) data, and the Canadian Meteorology Centre daily sea surface temperature analysis (CMC SST, (https://podaac.jpl.nasa.gov/dataset/CMC0.1deg-CMC-L4-GLOB-v3.0). As using the cosine of the sensor zenith angle as the input feature was more efficient for model training than the angle itself [19], we also used cosines of the solar zenith angle and relative azimuth angle as daytime model input. Therefore, after data preprocessing, total number of the input features is 280 and there are still five BTs for VIIRS TEB/M bands as output.

B. *Daytime Data feature*

Due to the nighttime VIIRS BTs minus CRTM simulation (O-M) in five TEB/M bands are close to Gaussian distribution, all five bands can be trained simultaneously in one FCDN model [19] and the well-trained model can predict high accurate nighttime BTs with respect to CRTM simulation. However, for the daytime, since the solar reflection was an innegligible contributor to sensor BTs in MWIRs, the Gaussian feature of the O-M biases for M12 and M13 will be significantly degraded. Figure 1 showed the differences of the CRTM simulation between daytime and nighttime (CRTM_Day-CRTM_Night) for M12, where the nighttime CRTM simulation was conducted by changing all daytime solar zenith angle to 150°. Thus, the CRTM_Day-CRTM_Night was used to measure how much the solar reflection contribute to the sensor BTs in daytime. Figure 1 clearly showed that the maximum contribution can reach more than 30 K for

M12 in the daytime sun glint area, which it is only small portion in global, but these data have clear physical mean and can be not ignorable. This large contribution will result the larger extent of BTs for M12 than nighttime, and also made the distribution of M12 biases non-Gaussian.

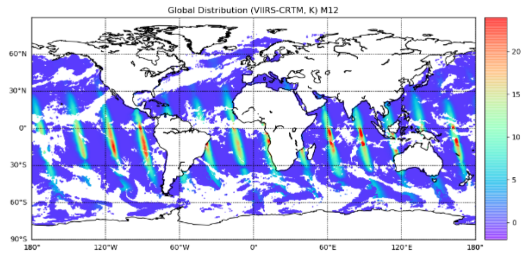

Figure 1. The differences of the CRTM simulation between daytime and nighttime

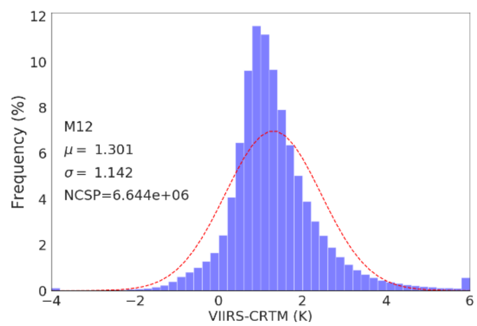

Figure 2. Histogram of the global O-M mean biases for M12 in daytime, 21 February 2020.

An example of the histogram of the O-M biases for M12 for daytime, which was also similar to the result from the NOAA integrated calibration/validation system (ICVS, https://www.star.nesdis.noaa.gov/icvs). The histogram was not consistent with the Gaussian distribution due to massive of large O-M biases existed in the both tails, resulting that the global O-M mean and STD (0.97±1.1 K) are significantly larger than nighttime, mainly due to suboptimal in CRTM solar reflection simulation [21]. This non-Gaussian distribution of O-M biases with outliers was also exist in M13 but became smaller obviously. However, the solar reflection is very minimal for long wave IRs (LWIRs, M14, M15 and M16) and the corresponding O-M biases are all Gaussian distributed, which are consistent with nighttime. This inconsistent distribution in five bands will cause more complex model design and largely hint the model prediction performance.

IV. EVALUATION OF PRELIMINIARY RESULT

Due to more complex of daytime data, in this initial study for daytime model development, we first used a modified nighttime FCDN_CRTM described in previous section to predict daytime data, and try to find possible improvement for the daytime model by evaluating the training, testing and prediction results.

The daytime data preprocessing, training, and testing were similar to the nighttime, and have been discussed in detail in [19]. The only difference is that the number of iterations during daytime model training was more than that of nighttime, indicating that the model weights and biases were harder to reach their optimum due to the more features and more complex input data in daytime.

The well-trained model was used to predict daytime BTs on 21 February 2020. Table 1 showed the preliminary result of the accuracies of the training, testing and prediction data with respect to CRTM simulations. Similar to nighttime, the mean of the FCDN_CRTM minus CRTM (F-C) are very small and only up to several tens mK for all bands. The STDs between training and testing data are comparable, indicating that there is not significant overfitting in the model. In contrast to nighttime analysis, the STDs for both MWIRs are larger than three LWIRs for all three data sets, due to more solar reflection contribution in MWIRs. The STD for M12 is the largest among the five bands. The STD magnitude for M12 is twice more than M13. Interestingly, the magnitudes of STDs were 4-5 times more than the training and testing data, particularly for M12, the STDs was near ~0.86 K, although the STDs were comparable between training and testing data.

As we discussed above, the large STDs in prediction data did not seem overfitting. Inconsistent data distribution and outliers could be one critical factor for the large STDs in the model prediction. To validate this hypotheses, we plot global distribution of F-C for M12 and M15 in Figure 3, and the solar reflection dependence of F-C and corresponding number of pixels dependence in Figure 4, where the CRTM_Day-CRTM_Night showed in figure 1 was used to measure the solar reflection.

Table 1. The F-C mean and STD of the train and test data, and predicted data for 02/21/2020 (F-C: difference between FCDN_CRTM BT and CRTM BT; μ: F-C mean bias; σ: corresponding STD; Unit: mK).

	Train Data		**Test Data**		**Prediction Data**	
	μ	**σ**	**μ**	**σ**	**μ**	**σ**
M12	-41.3	163.4	-8.6	208.0	-1.2	865.2
M13	10.9	85.3	-0.2	95.1	50.5	432.4
M14	8.7	69.6	2.9	52.5	12.9	280.1
M15	2.4	72.5	-2.0	58.2	-1.2	308.4
M16	-0.9	88.4	-4.2	71.0	-1.4	330.0

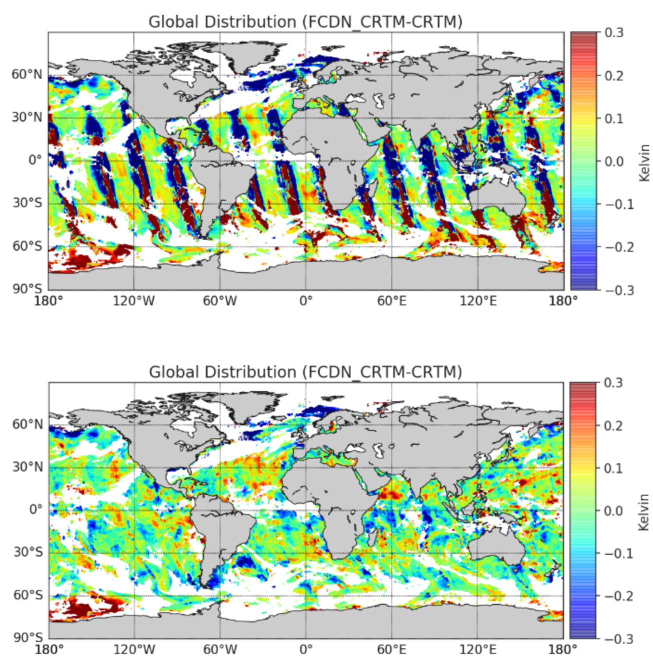

Figure 3. Global distributions of the F-C mean biases for M12 (upper) and M15 (bottom).

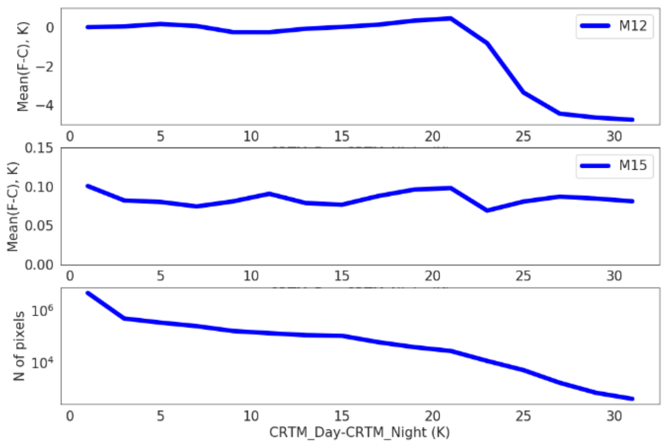

Figure 4. The dependencies of F-C mean biases on solar reflection contribution for M12 (top) and M15(middle), and dependencies of the corresponding number of pixels (bottom)

More noises than nighttime were found for both M12 and M15. There were unrealized positive and negative F-C bias up to 35 K can be found in the sunglint area for M12. The corresponding dependencies of F-C mean biases for M12 on solar reflection contribution (SRC) showed quite flat during the 0 to 20 K of SRC, but became rapidly dependence when SRC was larger than 20 K with only several thousands of pixels per each bin. As we discussed above, both outliers and unbalanced distribution of the input data largely hint the model train and prediction, resulting in large STD and dependencies in M12. It suggested that the nighttime model cannot directly used for daytime.

The initial analysis for daytime model indicated that several potential methods to improve the daytime model prediction. First, increasing input data in sun glint area is needed to improve data unbalanced distribution feature. Second, the cost function used mean square error (MSE) may be not good for non-Gaussian distribution input data. Further test by using different cost functions is desired. Third, as the non-Gaussian distribution data with outliers for MWIRs were trained together with LWIRs, resulting the prediction accuracies of the close-Gaussian LWIR data were worse, separated training for MWIRs and LWIRs can be considered. Finally, the new feature exploring, such as the spatial variability of BT difference [15] may improve the daytime model performance as well.

V. Concusion

An early-developed FCDN-CRTM used for nighttime clear-sky radiance prediction was emplied to explore the prediction performance for daytime data. The preliminary result showed that there were large F-C biases (up to 30 K) in the sun glint area. The unbalanced-distributed five bands also conflicted when all bands were trained simuteniously. All result indicated that the nighttime model cannot directly used for daytime. Several potential methods were considered to improve daytime model, including increasing input data, reviewing cost function, separating train for MWIRs and LWIRs, and exploring new input feature.

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