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Atmospheric
Measurement
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Discussions

Interactive comment on "Development of a neural network model for cloud fraction detection using NASA-Aura OMI VIS radiance measurements" *by* G. Saponaro et al.

Anonymous Referee #5

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GENERAL COMMENTS

The manuscript presents a cloud detection application for the NASA-Aura Ozone Monitoring Instrument (OMI). The identification of the cloudy pixels is based on two types of neural networks trained to predict the cloud fraction estimates from Aqua-MODerate Resolution Imaging Spectrometer (MODIS) data. The method is applied to four OMI orbits.

The authors present the proposed methodology in a concise and clear manner. However, presented results are clearly insufficient for a paper presenting an algorithm for a new satellite, since they do not clearly show if the proposed algorithm solve the problem

it is intended for.

The manuscript might be acceptable for publication after major revisions as outlined below.

SPECIFIC COMMENTS:

1) The main problem of the paper is that both the training and validation of the algorithm seem to be a simple exercise and not an exhaustive study aimed at obtaining a robust cloud detection for OMI. The authors show some results for a limited dataset and as the abstract admits "The developed neural network approach performs generally well in the training. Highly reflective surfaces, such as ice, snow, sun glint and desert, or atmospheric dust mislead the neural network to a wrong predicted cloud fraction.". Since the use of neural networks for cloud detection has been already presented in previous works, a thorough development of the models and analysis of the results are required.

2) The authors apply SVD to reduce the number of reflectances at 751 wavelengths to a set of 20 values. They say that they tested several numbers of non-zero eigenvalues such as 5, 10 and 20, but they do not explain how they measure the different performances nor provide any classification accuracy results. The eigenvalues of the SVD decomposition explaining the variance of the transformed data should be shown, and the performance analysis used to select 20 dimensions has to be described and shown.

3) By using SVD for dimensionality reduction, one is preserving the maximum variance in the projected dataset, however some spectral channels with low variance (e.g. in some absorption bands) can be relevant for cloud detection. Other dimensionality reduction approaches such as partial least squares (PLS) should be explored and compared with SVD.

4) Again, for the selection of the model structure, the authors say that to determine

the optimal number of nodes in the hidden layer, several tests were made. However, no information is given about the procedure followed to arrive to the 25 hidden nodes for the back-propagation (BP) algorithm, and the 240 nodes for the extreme learning machine (ELM) algorithm.

5) The author say that "Data was first analyzed by observing each orbit individually, then by separating land- and water-covered pixels and discarding the ice-covered ones." Than means that they are intentionally excluding difficult ice/snow cases from the training, which explains the poor results obtained in highly reflective surfaces, such as ice or snow. In order to train a neural network performing well in most critical cloud detection cases, an effort must be done to include these cases in the training set.

6) Also, results are analyzed independently for land and water surfaces, but a better option is to develop different models for land and ocean due to their different characteristics.

7) The authors do not explain how many samples use for training the models nor how many samples per class they have in the training and validation set. In fact, they do not clearly describe any validation set nor the procedure they follow to validate the trained models (cross-validation, v-fold, ...?). All this information has to be clearly stated in the results section.

8) Also, in the results section, the authors say that "The algorithm fails in distinguishing cloud-free pixels ... due to the lack of cloud-free pixels in the training dataset.". That is probably due to an unbalanced number of cloudy and cloud-free samples in the training set, which produces biased models. However, this is not an explanation for the poor results, it simply reveals a drawback in the generation of the training set that must be solved before training the final models.

9) In the opinion of this reviewer, the training set has been generated almost randomly and with very few orbits. Therefore, comprehensive training and validation sets must be generated and all the results have to be repeated on a higher number of orbits to

show the validity of the approach.

10) Another aspect that the authors present as the main novelty of the paper is the comparison between back-propagation and extreme learning neural networks. However, the comparison is very limited since the authors only present the results of both methods. For example, the first layer of the extreme learning machines can be interpreted as a feature extraction. The analysis of the meaning of the SVD features and the first layer of ELM could be an interesting study of this paper.

11) Also, the authors say that "results show that the ELM-based solution achieved higher cloud screening accuracy than the back-propagation algorithm" but in the opinion of this reviewer this conclusion is not justified by the presented results.

12) Finally, regarding the computation required by each neural network, the authors repeat during all the paper that the back-propagation based scheme is extremely time consuming in the training phase when compared to the ELM training approach. However, the training phase is performed only once ant the critical computing time is the testing time, which determines the time consumed for generating the cloud mask in a given orbit during the satellite operation.

TECHNICAL CORRECTIONS:

p1651, l17: "presence of clouds mask" -> "presence of clouds".

p1652, l7: "Here we use real data obtained from MODIS, with a spatial resolution which is much smaller than that of OMI." The sentence is misleading since the spatial resolution of MODIS is actually higher.

p1657, l16: Radiances are actually converted to TOA reflectance and hence some values can be higher than one.

p1668, l30: Preusker et al. (2008) reference cites a pdf file of a project report. More updated references from these authors presenting cloud screening algorithms based on neural networks can be found in international conferences.

Sincerely, The reviewer

Interactive comment on Atmos. Meas. Tech. Discuss., 6, 1649, 2013.