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Atmospheric Measurement Techniques Discussions

Interactive comment on "Detecting cloud contamination in passive microwave satellite measurements over land" *by* Samuel Favrichon et al.

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The authors would like to express their gratitude for the reviewing done on the paper "Detecting cloud contamination in passive microwave satellite measurement over land". A detailed response to the reviewer comments on behalf of all authors can be found below.

RESPONSE TO REVIEWER COMMENTS

The manuscript addresses an interesting issue frequently ignored when retrieving Land Surface Temperature (LST) from satellite microwave (MW) data, namely a possibly

non-negligible impact of cloud contamination on MW measurements. The developed neural network (NN) approach to cloud detection in MW data can use various channels available on MW imagers over the years, thereby making it applicable to historical and current satellite sensors. The training data consist of suitably filtered MW data (input) and SEVIRI cloud masks (desired output): ambiguous scenes were removed to avoid training the NNs with incorrect data, which improves the NNs ability to distinguish between cloud-free and cloud contaminated data. The reported results are in good agreement with previous findings, e.g. precipitation detected with Ferraro's (1977) method in MW data agrees well with the fraction of cloud contaminated MW observations detected with a NN and a suitably chosen threshold. The presented NN approach helps to ensure the accuracy of all-weather LST products retrieved from MW data. The manuscript is well structured and generally well written, but needs proofreading. Particularly the abstract has to be improved (formulation, construction of sentences, spelling); however, the other parts of the manuscript also require another round of proofreading and stylistic improvements.

Specific comments: - In the abstract it should say 'Meteosat Second Generation - ...'.

R. Corrected.

- Please check your use of the definite article.

R. Done, thanks for pointing that out.

- In modern English the word 'meanly' has not the meaning that is intended: consider using 'moderately' instead (many occurrences).

R. The term "meanly" is only used in the label of one of the SEVIRI classes ("high semitransparent meanly thick clouds"). As it is the official designation of this type of cloud in the cloud classification we prefer to leave the label unchanged.

- I recommend to make the tables more reader-friendly, e.g. consider using different grey tones for the rows, swap columns 'Cloud type number' and 'SEVIRI class description' in table 2 (so the numbers are directly next to their respective labels), narrower tables 3, 4, 5, 6 (consider using background colours for the rows) .

R. The tables have been revised as suggested by the reviewer in the revised manuscript.

- In table 4, please avoid two lines of text for the labels in the left column

R. The table layout has been changed as suggested.

- In table 5, consider providing the associated SEVIRI class numbers in the left column

R. They have been added.

Figure 1: - Consider using different line styles for low, medium and high clouds

R. Figure modified as suggested by the reviewer.

- Caption : 'The average frequency of each cloud type over these 2 months is indicated in the legend.'

R. Corrected as indicated.

Figure 2: - Insert tick marks for all x and y axes

R. Added to the revised figure.

- Consider using different line styles for low, medium and high clouds

R. Figure modified as suggested by the reviewer.

Sections 3.1 and 3.2: - You write about the data and the training, but there is no information on the NN software you used.

R. We use the Keras library (https://keras.io, 2015).

- I suggest providing figures showing the topologies of the 5-5-1 (and the 5-5-11?) network with appropriate labels - this would be more intuitive for the readers.

R. We appreciate the suggestion, but given that we use a standard multilayer perceptron of one hidden layer well described in numerous papers and text books on neural networks, we deemed unnecessary to include them in the paper.

- Please write which NN training algorithm was used – simple Backprop or something more elaborate?

R. We use backpropagation (Rumelhart et al., 1986) to find the weights minimizing a binary cross-entropy loss function (Dreiseitl and Ohno-Machado, 2003).

- Please provide information on the number of iterations / time required for the results to converge.

R. The number of iterations is in the order of a few hundreds, with a largest number of iterations for the NNs having a largest number of input and outputs nodes, as expected.

- Which stop criterion was used?

R. Early-stopping, with the training haltered when the loss function is not decreasing during 5 consecutive epochs.

- Which hardware was used (e.g. standard office PC)?

R. A standard office laptop with 4 cores and 16 GB of RAM. This, plus all the previous details about the NN are now added in Section 3.2.

Figure 5: - Consider inserting a vertical line at x=0.1 to illustrate the threshold recommended in the text.

R. Figure in the revised manuscript changed as suggested.

Figure 6: - The subplots are too small. Consider showing two columns with the current top subplots as left column and the current bottom subplots as right column. Maybe also reduce geographical region. The colour scheme for SEVIRI clouds is too complex – at least I find it hard to see much in the LR subplot.

R. Figure updated as suggested.

- Caption: please mention that the squares in the figures are explained in the text.

R. Added.

- The last sentence of the conclusions could be more specific (and up-beat).

R. We updated the sentence as: “Overall the classification models developed in this study are potentially useful for numerous applications where it is of interest to identify possible cloud contaminations in observed MW radiances. For instance, in addition to the land surface temperature example, they can also be applied to select clear scenes for accurate MW emissivity estimation (Moncet et al., 2011), or to detect cloudy scenes for the analysis of deep convections (Prigent et al., 2011). ”

References

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Prigent, C., Rochetin, N., Aires, F., Defer, E., Grandpeix, J.-Y., Jimenez, C., and Papa, F., Impact of the inundation occurrence on the deep convection at continental scale from satellite observations and modeling experiments, Journal of Geophysical Research: Atmospheres, 116, 2011.

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