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Interactive Comment

Interactive comment on “Bayesian cloud detection for MERIS, AATSR, and their combination” *by* A. Hollstein et al.

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General comments:

The paper "Bayesian Cloud Detection for MERIS, ATSR and their combination“ introduces a cloud detection algorithm based on classical Bayesian theory.

The topic meets the aim and scope of the paper. It is well written and structured. All Figures and Tables are in good quality and support the text. Some important features are not adequately explained or description is lacking.

The introduced approach is highly statistically and is based on artificial truth data. While this paper shows interesting methods, the approach includes many risks.

Improvements could include a more physical-based selection of features, building separate Bayesian classifiers for individual surface types to account for highly variable background impact.

Specific comments:

Introduction:

Please mention whether this approach is daytime only!

Line30: What is the Synergy product? Please refer here to chapter 6. I would also recommend explaining chapter 6 earlier in a section after introducing.

Section2 Bayesian inference for cloud masking:

You state that by using a background probability of 0.5 you avoid circular arguments for building climatological time series because the result will otherwise eventually shift to the climatological value. However, this is also the case by using this value of 0.5. The cloudiness will then shift to 50% cloudiness instead to a climatological a-priori value.

Section 3:

There are good reasons to use external data for cloud masking. Firstly, cloud masks are usually based on contrast between measured property and an assumed clear-sky value. Estimating the assumed clear-sky value requires auxiliary data, such as surface reflectivity, surface temperature or several atmospheric profiles. Secondly, the underlying surface have an impact on the measured signal itself due to simple radiative transfer considerations. Thin cloud signals include high amount of surface and atmosphere impact. The same cloud will lead to different results over different surface types. You may see this not only in the global pattern of skill score, but also in the global maps of cloudiness itself.

For most cases it is not possible to closure with a sufficient accuracy from a reflectance value in a visible channel to a probability of cloudiness of a pixel. The location may be

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over a bright desert, snow or a dark ocean. The reflectance is also highly sensitive to viewing geometry, which can be very different. You may calculate a cloud probability from your truth data set for each feature set, but this likely tells you more about the regional and geometrical distribution of these truth data.

With your approach of strongly independent feature, you may also come into trouble particular for climate purposes. To give a simple example: Assuming we have in reality no trends in cloudiness over a decade. Also assuming that one major feature is reflectance in a visible channel, which is true in reality. You will have being built a strongly independent background joint probability, which among others separates cloud and cloud free according the reflectance in this channel (the brighter the more likely a cloud). If the surface type, and thus also the surface reflectivity changes, the visible reflectance will also change, and thus you will "detect“ an artificial trend in cloud cover. This trend will be stronger for thin clouds, because surface impact is much higher. Examples for surface changes are urbanization and the increase of forest areas, this is not negligible.

This question is related to the "accuracy vs. stability“ dilemma for generating climate data sets. Task is to find the right balance. It is of course not well applicable to use highest accurate surface value changing every week with varying accuracy. However, ignoring surface impact at all lowers accuracy heavily.

Section4 Construction of feature sets:

Please, add a description, which measured property you use for each channel (reflection, radiance or brightness temperature).

Please, explain how you build the pseudo-channel features. (Example: How is 12um x 0.55 um defined?). I can identify 40 bins for a feature from Figures 3 and 4. How do you define the range? Is there any stretching (Gamma stretching etc..) . This could be important for the "x“ pseudo-channels. Can you explain how a channel 442 um x 412 um can provide information about cloudiness? (see Table 2)

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The random search of feature incorporates risks, which may come from unwanted correlation. To give an example from a different field: You may find a high correlation of measured radiance in a window channel to water vapor, even there is no direct impact of water vapor to the signal. Reason is that Sea surface temperature is correlated to atmospheric water vapor. Correlation is high, but the retrieval will fail if dry air is advected over Warm Ocean.

Please discuss the risks of such a non-physical (you say non-educational or statistical) approach.

Line 245: “The experienced expert is not surprised..”: Many pseudo channels look really surprising to me. . . (But I first need clear description how they built..)

Section5:

To Figures 3 and 4: I am wondering if really all areas of the 2d histograms were filled with data before smoothing. If not, why are the areas slightly reddish and not white (or masked out) which would mirror identical probability of cloudy and cloud-free?

Why did the areas around [35,5] decrease after Gaussian smoothing?

Here, I’d wished to interpret the results, but you didn’t give an explanation how you built dx(442nm,12um). (see section 4 comment)

The examples in the images separate after smoothing very well both features in cloudy and non-cloudy regimes. Thus, also a naive Bayesian approach would lead to similar results with less preparation and computational effort. Could you show a different example to illustrate the advantage of the joint (classical) approach?!

The right images only consist on 1000 measurements. How did you pick the samples out of billions of pixels from many different scenes, surface types, seasons, cloud types, etc..? Is this a sufficient number to build a cloud mask for all the different types?

Section 6:

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This section should be in the beginning of this paper because it is needed for understanding of some points in the earlier sections. I would also recommend extending the explanation of the Synergy cloud mask, because the citation does not seem to be a peer-review paper.

Please also mention the processing time difference between Synergy cloud mask and the Bayesian approach to defend the need of a faster retrieval.

Section 7:

Please explain which of the cloud masks do you intent to select for CCI?

Line 419: " ... can be used to reproduce...cloud mask ..“: The skill score for all examples seems to be low in comparison to other cloud masks. Figure 6 shows HSS of less of 0.6 for large parts of Asia and North America. This means an approx. POD of about 75% this is much too low for a cloud mask. This is even more the case if one considers that the skill score here is computed for a comparison of results from the same retrieval as the truth data. Please discuss this! Please provide also POD and the other measures for a better interpretation.

If you have a feature set what has no skill to distinguish between dust and clouds, when you can correct the Bayesian coefficients as often as you want. You cannot solve this problem statistically.

Around line 450: Are missing data really a problem for MERIS/AATSR?

Minor comments:

Line 1: "A broad range of different of Bayesian“ -> delete "of“

Line 63: cloudyness -> cloudiness

Interactive comment on Atmos. Meas. Tech. Discuss., 7, 11045, 2014.