BAYESIAN IMAGE CLASSIFICATION AT HIGH LATITUDES

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ABSTRACT

The European Space Agency created the Climate Change Initiative (CCI) to maximize the usefulness of Earth Observations to climate science. Sea Surface Temperature (SST) is an essential climate variable to which satellite observations make a crucial contribution, and is one of the projects within the CCI program. SST retrieval is dependent on successful cloud clearing and identification of clear-sky pixels over ocean. At high latitudes image classification is more difficult due to the presence of sea-ice. Newly formed ice has a temperature close to the freezing point of water and a dark surface making it difficult to distinguish from open ocean using data at visible and infrared wavelengths. Similarly, melt ponds on the sea-ice surface make image classification more difficult. We present here a three-way Bayesian classifier for the AATSR instrument classifying pixels as 'clear-sky over ocean', 'clear-sky over ice' or 'cloud' using the 0.6, 1.6, 11 and 12 micron channels. We demonstrate the ability of the classifier to successfully identify sea-ice and consider the potential for generating an ice surface temperature record from AATSR which could be extended using data from SLSTR.

1. BAYESIAN IMAGE CLASSIFICATION FOR SST RETRIEVAL

Probabilistic cloud detection uses Bayes' theorem to calculate the probability of an observation class (clear-sky or cloud) given the satellite observations and prior knowledge of the background state [1]. In its general form this can be expressed as Eq. 1 where it is assumed that the prior background information is independent of the prior probability of a given class.

$$P(c|\boldsymbol{y^o},\boldsymbol{x_b}) = \left[1+\frac{P(\bar{c})P(\boldsymbol{y_o}|\boldsymbol{x_b},\bar{c})}{P(c)P(\boldsymbol{y_o}|\boldsymbol{x_b},c)}\right]^{-1} \tag{1}$$

P denotes probability, **y** is the observation vector and **x** is the state vector. Subscripts 'o' and 'b' denote the observed and background states respectively. We apply this cloud detection algorithm to data from the Advanced Along-Track Scanning Radiometer (AATSR) instrument, using the 1.6, 11 and 12 µm channels during the day. Over the oceans, the probability of the observations given the background state is split into two components: spectral and textural denoted by superscripts 's' and 't' in Eq. 2. The textural probability density function (PDF) is constructed from the standard deviation in the 11 µm channel in a 3x3 pixel box centred on the pixel to be classified.

$$P(\boldsymbol{y}_o|\boldsymbol{x}_b,c) = P(\boldsymbol{y}_o^s|\boldsymbol{x}_b,c)P\boldsymbol{y}_o^t|\boldsymbol{x}_b,c) \tag{2}$$

Clear-sky PDFs are simulated using the RTTOV 10.2 [2] and VisRTM [3] radiative transfer models for the infrared and visible channels respectively. Surface properties and atmospheric profiles are constrained using ERA-Interim ECMWF global reanalyses data. Cloud spectral PDFs and all textural PDFs are empirical, constructed offline using multiple years of data from the AATSR mission. The prior probabilities of cloud and clear conditions are set using a global map of cloud probabilities.

2. PERFORMANCE IN REGIONS OF SEA ICE

Figures 1 and 2 give examples of the Bayesian cloud detection performance in high latitude regions. When we establish a binary mask (clear/cloud) from the Bayesian scheme for SST retrieval purposes we want sea-ice to be classified as 'cloud' or 'not clear'. Figure 1 shows a region of sea-ice shadowed by cloud. In the baseline classifier we find that both areas highlighted by the white boxes have a high clear-sky probability but would be unsuitable for inclusion in a sea surface temperature (SST) record.

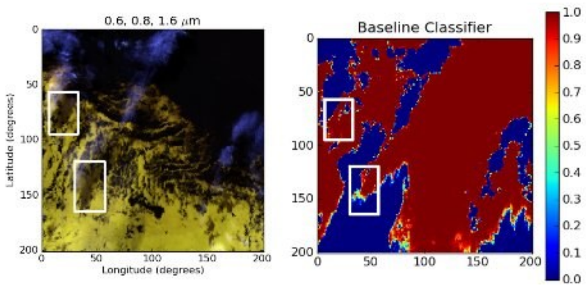

Figure 1: False colour image and baseline Bayesian classifier performance for a region of sea-ice shadowed by cloud, marked by white boxes.

Figure 2 shows a region of mixed ice. The baseline classifier correctly identifies some of the thicker ice

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towards the top and left hand side of the feature but wrongly classifies the mixed ice on the bottom right of the image as clear-sky over ocean.

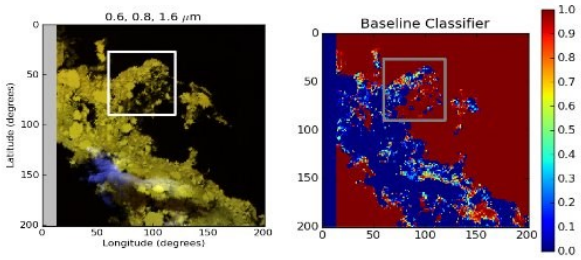

Figure 2: False colour image and baseline Bayesian classifier performance for a region of mixed ice, marked by white boxes.

Table 1 summarises the baseline classifier performance with reference to a number of manually classified scenes from the SST Climate Change Initiative match up database. Critically, 21.64% of all ice targets are misclassified as clear-sky over ocean which will affect SST retrieval.

		Bayesian Classification	
		Cloud	Clear
Validation Data	Cloud	38804	1906
	Clear	151	8037
	Ice	4857	1341
	Cloud	95.32 %	4.68 %
	Clear	1.84 %	98.16 %
	Ice	78.36 %	21.64 %
Classifier Accuracy		85.02 %	

Table 1: Baseline classifier performance for sea-ice affected regions with reference to manually classified cloud, ice and clear scenes. Table presents results as total number and percentage of cases.

3. CLASSIFIER DEVELOPMENTS

In order to improve classifier performance for detecting clear-sky over ocean scenes a third class 'clear-sky over ice' was added for SST retrieval at high latitudes. The Bayesian scheme can be generalised to 'n' number of classes as shown in Eq. 3 [4,5].

$$P(class_x|\boldsymbol{y}_o, \boldsymbol{x}_b) = \frac{P(class_x)P(\boldsymbol{y}_o|\boldsymbol{x}_b, class_x)}{\sum n\, P(class_n)P(\boldsymbol{y}_o|\boldsymbol{x}_b, class_n)} \tag{3}$$

Clear-sky over ice observations were modelled using the RTMs described in Section 1, with ERA-Interim skin temperatures (rather than SST) used to constrain surface temperature with a fixed error of 5 K. Ice surface emissivity and reflectance is modelled based on observations of sun crust/compact snow surfaces [5].

Two further modifications to the classifier were made, first replacing the textural measurement in the 11 µm channel with the texture in the 1.6 µm channel which gave improved separation between the cloud and ice classes. We also include an additional visible channel in the spectral PDF (0.6 µm). Prior probabilities of the cloud, clear and ice classes remain constant at 0.8, 0.1 and 0.1 respectively.

4. THREE-WAY CLASSIFIER PERFORMANCE

Figure 3 shows the performance of the modified classifier over the region of sea-ice in shadow presented in Section 2. Here we see that the modified classifier now correctly identifies the entire ice sheet (shown by yellow colours in the false colour image) and the areas in both boxes affected by cloud shadow are no longer classified as clear-over ocean pixels.

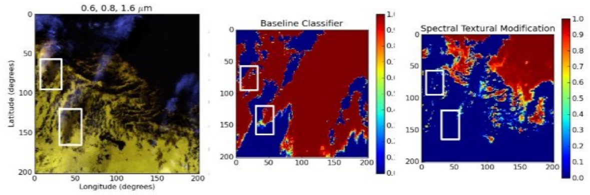

Figure 3: Modified Bayesian classifier (referred to as spectral textural modification) performance over a region of ice in shadow. First two panels are as Figure 1 for reference.

Figure 4 shows the performance of the modified classifier over mixed ice. In this example the certainty of the classifier has improved, with the thicker area of sea-ice no longer classified as clear-sky over ocean. In the bottom left of the highlighted box, the classifier now correctly identifies individual leads in the mixed ice sheet.

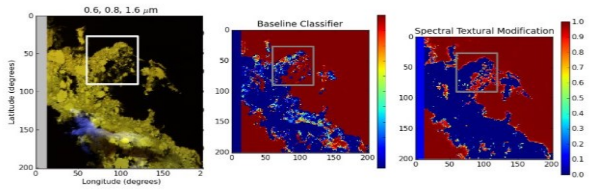

Figure 4: Modified Bayesian classifier (referred to as spectral textural modification) performance over a region of mixed ice. First two panels are as Figure 2 for reference.

Table 2 summarises the performance of the classifier with reference to the manually classified observations in the validation dataset. All ice misclassifications are now as cloud which is preferable for SST retrieval. The Bayesian classifier also shows some skill at correctly identifying sea-ice with 77.72 % of observations correctly classified and a ~11 % increase in overall classifier accuracy.

		Bayesian Classification		
		Cloud	Clear	Ice
Validation Data	Cloud	39943	685	82
	Clear	83	8102	3
	Ice	1381	0	4817
	Cloud	98.12 %	1.68 %	0.2 %
	Clear	1.01 %	98.95 %	0.04 %
	Ice	22.28 %	0.0 %	77.72 %
Classifier Accuracy		95.95 %		

Table 2: Modified Bayesian classifier performance with reference to manually classified cloud, ice and clear scenes. Table presents results as total number and percentage of cases.

Ice detection remains most difficult in cases of new/thin ice with low surface reflectance (not represented in the ice validation pixels defined above). Development and testing of classifier performance under these conditions needs to be further pursued but is challenging due to the difficulty in identifying these regions in remote sensed imagery at infrared and visible wavelengths.

5. CONCLUSIONS AND FUTURE DEVELOPMENTS

The modified Bayesian classifier in sea-ice affected regions shows improved skill in identifying clear-sky over ocean scenes. The probabilistic method could be used to identify sea-ice for ice surface temperature retrieval and would be applicable to the Sea and Land Surface Temperature Radiometer (SLSTR) on Sentinel 3. Further development is needed to apply this algorithm to the ATSR-1 and ATSR-2 instruments where observations in the 0.6 µm channel are either unavailable or limited and ensure sampling consistency over the entire data record.

6. REFERENCES

[1] Merchant, C. J., Harris, A. R., Maturi, E., & MacCallum, ,S. (2005). Probabilistic physically based cloud screening of satellite infrared imagery for operational sea surface temperature retrieval. *Quarterly Journal of the Royal Meteorological Society.* **131**, 2735-2755.

[2] Hocking, J., Rayer, P. & Saunders, R. (2011). RTTOV v10 Users Guide. *Technical Report EUMETSAT Satellite Application Facility on Numerical Weather Prediction (NWP SAF).* DOC ID: NWPSAF-NO-UD-023.

[3] Mackie, S., Merchant, C. J., Embury, O., & Francis, P. (2010). Generalized Bayesian cloud detection for satellite imagery. Part 2: Technique and validation for daytime imagery. *International Journal of Remote Sensing.* **31**, 2595-2621.

[4] Mackie, S. (2009). Exploiting Weather Forecast Data for Cloud Detection. *PhD Thesis.* University of Edinburgh, School of Geosciences.

[5] Bulgin, C. E., Eastwood, S., Embury, O., Merchant, C. J., Donlon, C. (2013). The Sea Surface Temperature Climate Change Initiative: Alternative Image Classification Algorithms for Sea-Ice Affected Oceans. *Remote Sensing of Environment Climate Change Initiative Special Issue.* Submitted Jan 2013.