Observation Classification for Earth Surface Temperature Retrieval

Claire Bulgin[(1)] (cbulgin@staffmail.ed.ac.uk), Chris Merchant[(1)]
[(1)]School of Geosciences, University of Edinburgh, Edinburgh, UK

Observation classification including cloud detection is a fundamental pre-processing step for remote sensing of Earth surface properties including sea, land, ice and lake surface temperatures. We present here a cloud detection scheme based on Bayesian methods to derive a per-pixel probability of cloud-free conditions. This improves on pre-determined threshold based cloud detection enabling the user to specify cloud screening stringency. We present here two applications of our Bayesian cloud detection scheme, the first within the context of the SEN4LST project comparing cloud screening over land to a manually generated cloud mask and existing operational cloud detection schemes. The second focuses on the performance of the cloud detection scheme in high latitude regions as part of the SST CCI project. We develop the algorithm to include a third class (clear over ocean, cloud, clear over ice) and evaluate the ability of the classifier to identify both cloud and ice pixels.

Potential of IR in Bayesian framework for cloud detection over land

1. Introduction: The Synergistic use of the Sentinel Missions for Estimating and Monitoring Land Surface Temperature (SEN4LST) will develop existing land surface temperature (LST) algorithms to improve LST estimation, exploiting high-resolution complimentary data from instruments onboard the Sentinel 2 and 3 satellites. We assess the performance of currently available cloud clearing algorithms for AATSR against cloud masks generated by expert inspection, and analyze the impact of their performance on LST observations. We evaluate three different cloud-clearing schemes, the operational AATSR mask based on a series of threshold tests, the SYNERGY cloud detection method using neural networks and GlobAlbedo cloud detection based on Boolean logic. In addition, we apply Bayesian cloud detection restricting observations only to infra-red wavelengths. The purpose is to assess the degree to which infra-red observations used in a Bayesian framework could supplement cloud detection over land (which usually relies heavily on reflectance channels).

2. Cloudmask Performance: We compare the performance of the 3 cloud masks and IR-Bayesian for 21 test scenes. Figure 1 shows an example case for Abracos Hill, South America on 26th June 2005. We see that the GlobAlbedo mask misses a significant amount of cloud whilst the IR-Bayesian and operational algorithms are more conservative in their clear sky identification than the manual mask. Table 1 shows the overall performance statistics for each mask. The SYNERGY and IR-Bayesian cloud masks have the highest True Skill Score (TSS) at 84.83% and 75.43% and Percentage of Perfect classification (PP) at 94.72% and 91.39% respectively. The operational cloud mask has the highest False Alarm Rate (FAR) at 16.65% often flagging surface features as cloud. The GlobAlbedo mask has the lowest Hit Rate (HR) at 56.23%.

Statistic	Operational Cloud Mask	SYNERGY Cloud Mask	GlobAlbedo Cloud Mask	IR-Bayesian Classifier
PP (%)	82.76	94.72	89.54	91.39
HR (%)	84.50	88.19	56.23	80.98
FAR (%)	16.65	3.36	0.69	5.55
TSS (%)	68.05	84.83	55.54	75.43

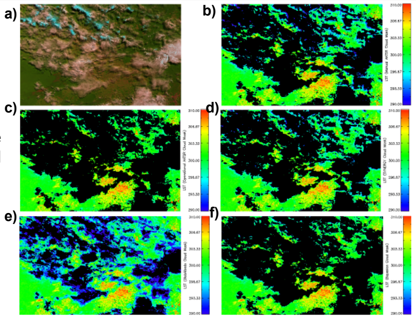

Figure 1: Abracos Hill, 26/06/2005 case study including an RGB image (a), manual mask (b), operational cloud mask (c), SYNERGY cloud mask (d), GlobAlbedo cloud mask (e), and Bayesian cloud mask (f). Cloud masks are plotted over LST estimates from SEBS.

Table 1: Cloud mask performance statistics with reference to the manual cloud mask across 21 test scenes. Statistics are Percentage of Perfect classification (PP), Hit Rate (HR), False Alarm Rate (FAR) and True Skill Score (TSS).

3. LST Impacts: Figure 2 shows the impact of the cloud masks on LST. White blocks (containing 10x10 pixels) indicate large temperature differences where the tested mask does not capture cloud in the manual mask. Grey blocks are where the tested masks give a false alarm of cloud. The operational, SYNERGY and IR-Bayesian masks show small positive biases in LST around cloud edges likely to be caused by masking areas of cloud shadow. Table 2 shows LST impact statistics across the 21 test scenes. They SYNERGY and IR-Bayesian masks have the highest percentage of pixels with no impact on LST (68.95 and 65.36% respectively). The GlobAlbedo mask gives the largest number of blocks where an LST retrieval is make for a cloudy region (6.24%) and the operational mask has the highest percentage of falsely masked blocks (6.61%). The competitiveness of the simple two-channel IR-Bayesian method over these test cases is striking.

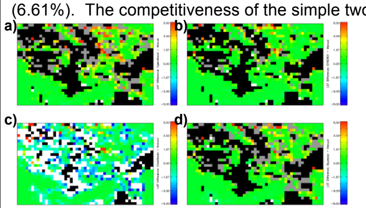

Figure 2: Abracos Hill, 26/06/2005 LST impacts. Coloured pixels indicate LST differences resulting from cloud masking discrepancies. Plots show the operational mask (a), the SYNERGY mask (b), the GlobAlbedo mask (c) and the IR-Bayesian mask (d).

Statistic	Operational Cloud Mask	SYNERGY Cloud Mask	GlobAlbedo Cloud Mask	Bayesian Cloud Mask
No Impact on LST	42.83	68.50	63.62	65.36
LST retrieved for cloudy blocks	1.79	1.22	6.24	2.11
Falsely masked blocks	6.61	2.71	0.11	4.30

Table 2: LST impact statistics across the 21 test scenes. No impact on LST shows blocks of 10x10 pixels where the mask or LST agree. Cloudy blocks are where the manual mask shows cloud but the tested schemes do not. Falsely masked blocks are where the tested masks flag cloud not in the manual mask.

Classification of Cloud, Clear and Ice at High Latitudes

1. Introduction: Cloud detection at high latitudes for sea surface temperature (SST) retrieval is more difficult than at lower latitudes due to the presence of sea-ice at temperatures similar to neighboring open water and strong thermal gradients in SST. Within the context of the SST Climate Change Initiative (CCI) we have extended our two-way Bayesian classifier for the Advanced Along Track Scanning Radiometer (AATSR) to include a third class at high latitudes. We derive a probability of clear over ocean, clear over ice and cloud. We assess the ability of the classifier to improve identification of clear sky pixels over ocean and also examine the classifier competency in correctly identifying ice pixels for ice surface temperature retrieval which is particularly difficult during the night with no reflectance data.

2. Three-way Classification: The Bayesian classifier provides a probability of clear, ice and cloud by comparing satellite observations with prior knowledge of each state. We model the clear-sky conditions for clear over ice and ocean using fast radiative transfer models (RTTOV 10 for the infrared and VisRTM for the visible channels) using numerical weather prediction (NWP) data from the ECMWF. Cloudy sky probabilities are calculated empirically and ingested as look-up tables. We make use of both spectral and textural features (treated as independent) in the probability calculation. At nighttime we use the spectral features from the 3.7, 11 and 12 µm channels and during the day we use the 0.6, 0.8, 1.6, 11, and 12 µm channels. We also use the 11 µm local standard deviation (in a 3x3 pixel block) at both times of day. Figures 3 and 4 show the RGB image and corresponding clear over ocean and ice probabilities for a day and nighttime scene taken from the SST CCI multi match-up database (MMD). In both cases the identification of clear-sky pixels over ocean compare well with the RGB image. At night the classifier shows some skill in identifying the ice floes at the base of the image. During the day, the addition of the visible channels increases the competency of the three-way classifier in being able to correctly identify sea ice.

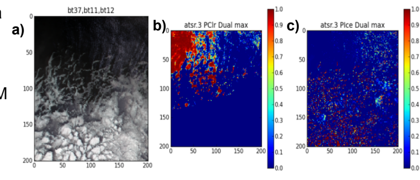

Figure 3: MMD match-up 29588380 April 2009. A) Nighttime RGB image of the 3.7, 11 and 12 µm channels. B) Probability of clear over ocean. C) Probability of clear over ice.

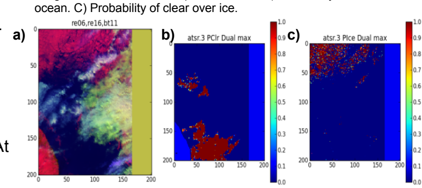

Figure 4: MMD match-up 29588610 April 2009. A) Day time RGB image of the 0.6, 0.8 and 11 µm channels. B) Probability of clear over ocean. C) Probability of clear over ice.

3. Classifier Performance: Table 3 shows the three-way classifier performance statistics assessed against a manually classified dataset of cloud, clear and ice scenes from SST CCI MMD match-ups, in comparison with the original two-way classifier. For the purposes of this comparison we evaluate only the classification of clear scenes with respect to other (cloud or ice) and do not directly evaluate the performance of the ice detection. At nighttime the three-way classifier has a slightly lower true skill score (89.44%) than the two-way classifier (91.56%) which is the result of an increase in the false alarm rate from 8.49% to 10.56% indicating more conservative cloud screening. Figure 3 suggests that this extended classifier shows some skill in ice detection which may be enhanced with the addition of IR textural features such as the 11 µm nadir minus forward view LSD. During the day with the addition of the 0.6 and 0.8 µm channels we see a significant improvement in the cloud detection. The hit rate increases from 97.19% to 98.2% comparable with the two-way classifier (98.61%). The false alarm rate decreases significantly from 7.06% to 0.74% giving an overall true skill score of 97.46% compared with 90.96% for the two-way classifier.

Statistic	Day 2-way (1.6, 11, 12 µm)	Day 3-way (1.6, 11, 12 µm)	Day 3-way (0.6, 0.8, 1.6, 11, 12 µm)	Night 2-way (3.7, 11, 12 µm)	Night 3-way (3.7, 11, 12 µm)
PP (%)	97.67	96.56	98.36	98.73	98.41
FAR (%)	7.64	7.06	0.74	8.49	10.56
HR (%)	98.61	97.19	98.20	100	100
TSS (%)	90.96	90.14	97.46	91.56	89.44

Table 3: Cloud mask performance statistics for AATSR for all SST CCI MMD matches for various day and nighttime channel combinations. Shows Percentage of Perfect classification (PP), Hit Rate (HR), False Alarm Rate (FAR) and True Skill Score (TSS).