Are there clouds in the sky?

Reproducing the MODIS cloudmask using MODIS level 1 Radiance Data

Clouds are generally cooler and more reflective than the earth's surface. The MODIS cloud mask uses this principle to test for cloud presence based on reflectances and brightness temperatures measured at different wavelengths of light by the Moderate Resolution Imaging Spectroradiometer, which orbits Earth on the Terra and Aqua Satellites (both built by NASA).

This project aims to compare several bits of the MODIS 48-bit cloudmask with cloud determining tests performed on raw MODIS level 1 data. These tests were written using the Modis Algorithm Theoretical Basis Document as a guide (Ackerman et al, 2010), as well as Ackerman 1997, with the aim to examine how closely they reproduce the output of the final mask product.

I wrote tests for five bits of the mask: Bit 13, Bit 18, Bit 19, Bit 21, and Bit 24 and tested them on the skies over Great Britain using raw data from four different days.

The study area

I ran the tests on similar satellite passes on four separate days:

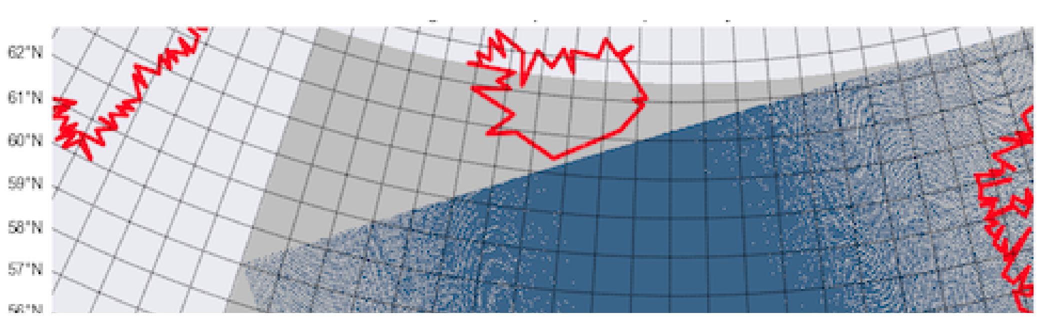
January 4, 2014 at 13:25

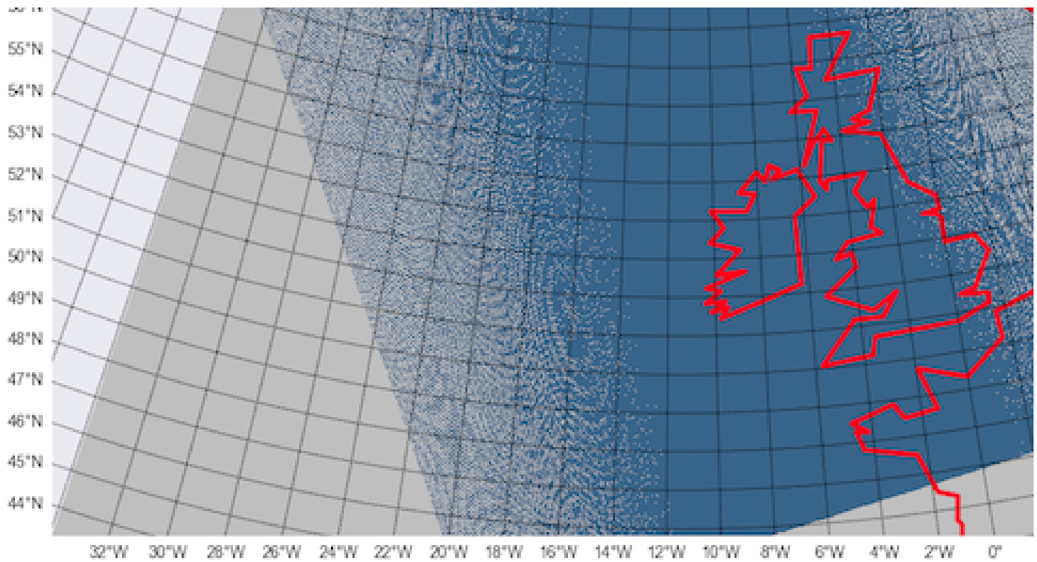
February 10, 2014 at 13:15

June 6, 2014, at 13:20

March 5, 2015, at 13:20

Though the passes differ slightly in spatial extent (according to time of satellite passing), all four cover Great Britain. The image below represents the spatial extent of the passes. For the cloudmask tests, I focused on analyzing the area around Great Britain, so I set the extent of the maps between 49 - 59 ° latitude and -11 - 3° longitude.





Data products used

In this analysis, I used 3 different types of NASA data products. All 3 can be downloaded at https://ladsweb.nascom.nasa.gov/data/search.html (https://ladsweb.nascom.nasa.gov/data/search.html), under the Aqua MODIS Satellite heading. The products are as follows:

-Level 1B calibrated radiances (MYD021KM, Aqua Level 1 Product) - contains radiance data at different bands of the MODIS for a given pass (denoted by date and time recorded in filename). A reference table of band number correspondences to wavelength can be found here: (https://en.wikipedia.org/wiki/Moderate-Resolution_Imaging_Spectroradiometer (https://en.wikipedia.org/wiki/Moderate-Resolution_Imaging_Spectroradiometer))

-Geolocation (MYD03, Aqua Level 1 Product) - Contains georeferencing information for a given pass (denoted by date and time recorded in filename, which can be matched with other products for the same pass).

-MYD35_L2 (MODIS Level 2 Cloud Mask and Spectral Test Results, Aqua Atmosphere Level 2 Product) - Contains the results of the MODIS cloudmask.

My aim in this analysis was to compare the MYD35_L2 cloudmask with the results of tests run on MYD021KM data. The visual comparison of both products (the MODIS cloudmask and my recreation of it) is enabled by plotting both using the same geolocation file.

The principle of brightness temperature: bits 13, 18, 21

discuss brightness temperature here

The principle of reflectance: bits 19 and 24

reflectance

Bit 13: Brightness temperature

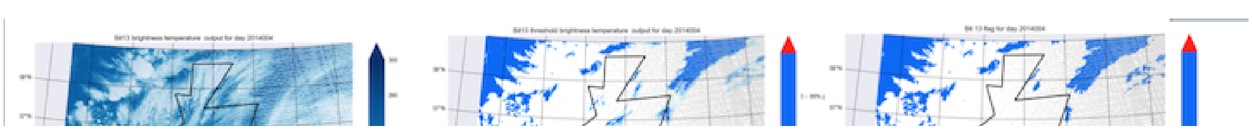
Bit 13 in the MODIS mask is a Group 1 test that uses brightness temperature at 11 microns (MODIS band 31, emissive channel 10) to determine the presence of thick high clouds (the colder the brightness temperature, the higher the chance of cloud presence). The test is difficult to use over land because surface emissivity varies considerably with soil and vegetation type, making it hard to discriminate colder background temperatures (eg. snow) from cloud. (According to Ackerman 1997, the test is most effective over ocean at night.) Ackerman uses the following thresholds: 267 K, 270 K and 273 K, with 270 K being the threshold value below which the pixel fails the clear-sky condition.

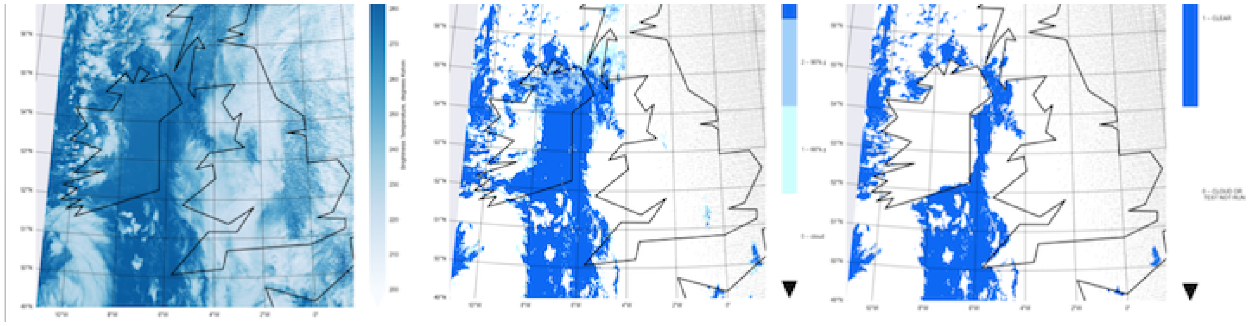
I recreated this test using a script that extracts radiance (W/m^2/micron/sr) at a wavelength of 11 microns for all pixels in a given MODIS level 1 file (filename designation MYD021), then finds brightness temperature from this radiance by solving the Planck function for brightness temperature using this radiance. (The Planck inversion functon was written by Phil Austin).

This script returns an array of brightness temperatures, which can be plotted using the MYD03 geolocation file. It is then possible to write a script that takes an array of brightness temperatures as an input and returns a probability of cloudiness based on the Ackerman thresholds as follows (BT = Brightness Temperature). There are 4 categories of probabilities, with 0 representing cloudy sky and 3 representing a 99% probability clear sky, as listed below:

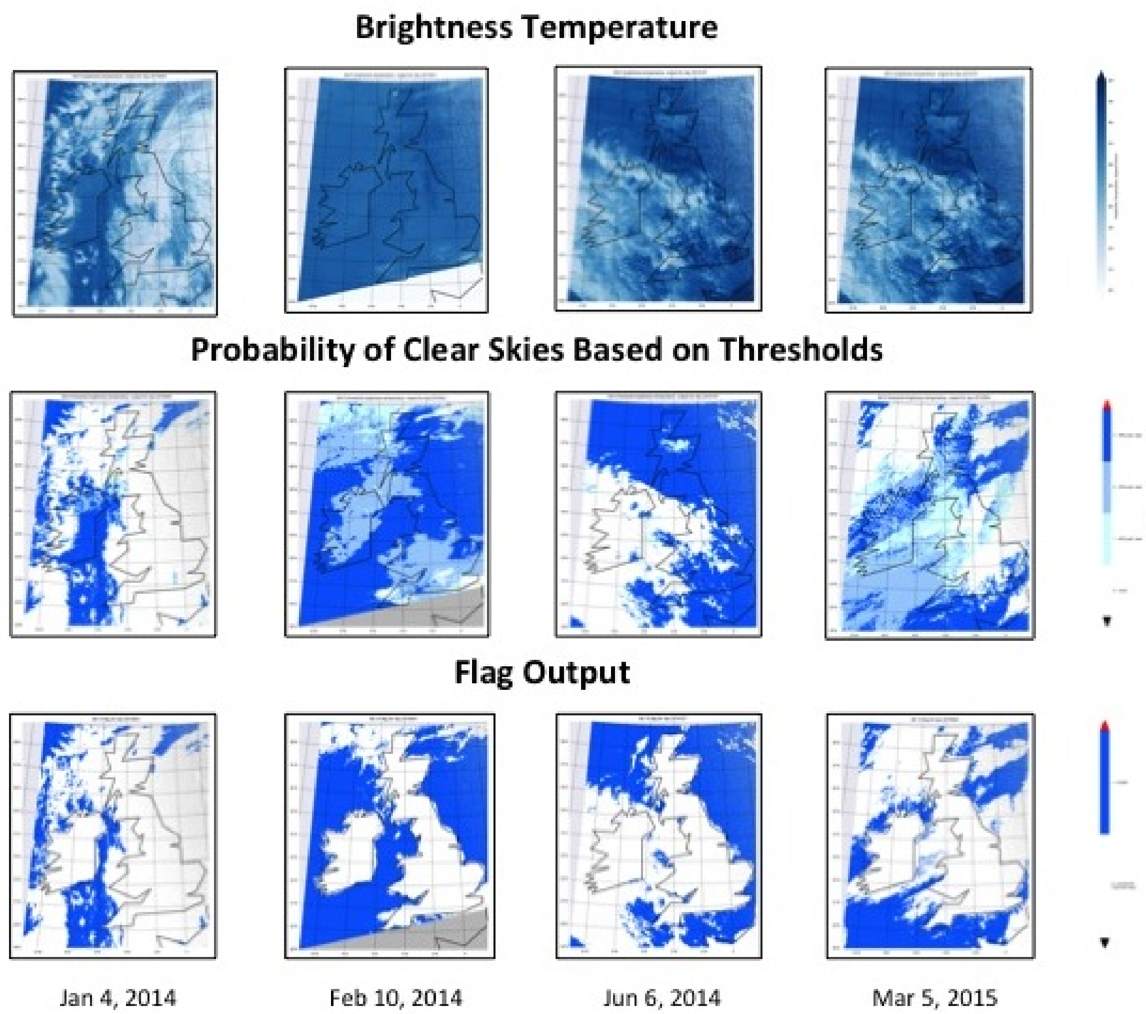
```
BT < 267..................... 0 - cloud (white on the map)
267 <= BT < 270 ..............1 - 66% probability clear
270 <= BT < 273 ..............2 - 95% probability clear
BT > 267......................3 - 99% probability clear (dark
blue on the map)
```

I then compared the output of the threshold categorization with the bit 13 flag in the MODIS cloudmask. The MODIS cloudmask flag is binary, with 1 representing a clear sky and 0 representing the presence of cloud (in some cases, a 0 may indicate that the test was not run).
After this, all files (brightness temperature array, threshold array, and cloudmask array) can be reprojected (using Phil's reproject_numba code) and plotted with the help of the geolocation array) The following image represents a comparison of the scene January 4, 2014 at 13:25 with its threshold categorization and cloudmask.





An overview of the same comparison for all 4 days can be seen below:



Quantifying differences between my tests and the MODIS mask: histograms

From this we can see that, as expected, the Bit 13 test does not appear to be run over land - the landmass always has a value of 0. Therefore, in order to quantify the difference between my categorization and the cloudmask, I need to compare the histogram of the 4 different cloud cover categories with the flag over open ocean. I did this over a small area: 57-58 ° N, 8-10 ° W. Because the mapping files are reprojected, I had to round both the flag and threshold arrays to get discrete numbers in every reprojected cell for the purposes of the histogram. I created bar graph histograms of both the binary flag (values 0 and 1) and the category flags (0 1 2 3) by modifying P.Austin's histogram code. I also had the script print all found histogram values and proportions, which I am summarizing in the following tables:

January 4, 2014				
threshold	0	1	2	3
proportion of map	0.6228	0.093	0.077	0.2072
threshold group	0/1	2/3		
	0.7158	0.2842		
flag	0	1		
proportion of map	0.7524	0.2476		

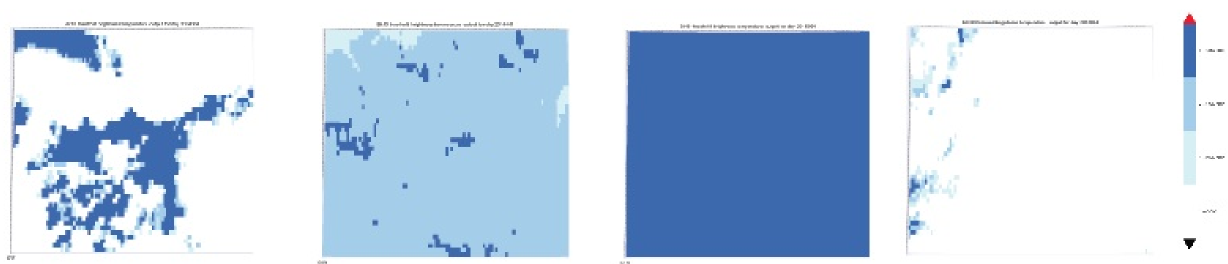
February 10, 2014				
threshold	0	1	2	3
proportion of map	0	0.0316	0.9222	0.0462
threshold group	0/1	2/3		
	0.0316	0.9684		
flag	0	1		
proportion of map	0.2074	0.7926		

June 6, 2014				
threshold	0	1	2	3
proportion of map	0	0.0154	0.0122	0.9724
threshold group	0/1	2/3		
	0.0154	0.9846		
flag	0	1		
proportion of map	0.0172	0.9828		

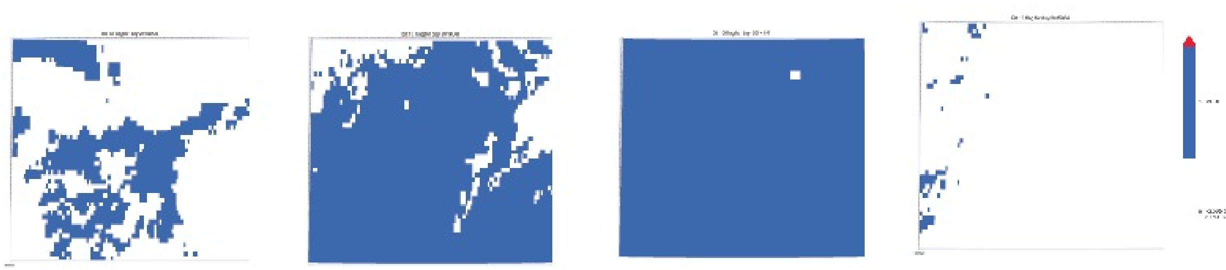
March 5, 2015				
threshold	0	1	2	3
proportion of map	0.9138	0.0464	0.035	0.0048
threshold group	0/1	2/3		
	0.9602	0.0398		
flag	0	1		
proportion of map	0.9696	0.0304		

To compare my threshold categories with the flag, I compared threshold categories 2 and 3 (>95% probability of clear sky) with the clear sky flag. From a first glance at the above table, we see that on January 4, June 6, and March 5, the threshold-category prediction of clear skies agrees relatively well with the clear-sky flag- on March 5 and June 6 the predictions are more or less identical (The biggest difference is on January 4, where the flag predicts clear skies for 24.7% of the studied area, while my categories predict clear skies for 28.4% of the studied area.) On February 10, however, the predictions differ considerably. To see why this is, I created maps of the threshold categories as well as the flag for just the histogrammed area (57-58 ° N, 8-10 ° W).

Probability of Clear Skies Based on Thresholds



Flag Output



Jan 4, 2014 Feb 10, 2014 Jun 6, 2014 Mar 5, 2015

When looking at these images, I noticed two features in the representation. First, the proportions listed in the histogram tables do not perfectly match the maps produced (This can be easily seen from Jun 6, where the map shows the full area as category 3, while the histogram shows a small amount of data in categories 1 and 2). This can be attributed to slightly different rounding scheme in each case - when reprojecting raw data onto a new grid, it's binned in each cell of the grid, and the raw data points binned into each cell are then averaged and then assigned a value. The category map seen above is produced from an already-binned brightness temperature map, while the histogram is produced by rebinning the category map and then rounding to produce integer values. This helps to account for the discrepancy between the two representations of the data.

The other interesting feature regards the difference between the cloudmask and my threshold categorization. The instance where my categorization differs most from the cloudmask (on February 10) is also the day with the largest proportion of the data in the intermediate threshold categories. On all other days, over 80% of the data can be binned into one of the extreme categories - 0 for cloud, or 3 for 99% clear. On February 10, 92.2% of the data is in category 2, meaning that it is closer to the cutoff boundary for the final cloudiness/clear sky categorization. In such cases, the NASA cloudmask algorithm uses other factors to help decide whether a pixel is cloudy or clear - for example, the presence of definitively cloudy pixels nearby (If a 'borderline clear' pixel is surrounded on all sides by 'definitively cloudy' pixels, it's very likely that the pixel is also cloudy). My algorithm does not do this, and so does not have extra information to help find clouds. Because the NASA cloudmask shows a larger proportion of cloud than my categorization, it is likely that these secondary tests were used.