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A cloud mask methodology for high resolution remote sensing data combining information from high and medium resolution optical sensors

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ABSTRACT

This study presents a novel cloud masking approach for high resolution remote sensing images in the context of land cover mapping. As an advantage to traditional methods, the approach does not rely on thermal bands and it is applicable to images from most high resolution earth observation remote sensing sensors. The methodology couples pixel-based seed identification and object-based region growing. The seed identification stage relies on pixel value comparison between high resolution images and cloud free composites at lower spatial resolution from almost simultaneously acquired dates. The methodology was tested taking SPOT4-HRVIR, SPOT5-HRG and IRS-LISS III as high resolution images and cloud free MODIS composites as reference images. The selected scenes included a wide range of cloud types and surface features. The resulting cloud masks were evaluated through visual comparison. They were also compared with ad-hoc independently generated cloud masks and with the automatic cloud cover assessment algorithm (ACCA). In general the results showed an agreement in detected clouds higher than 95% for clouds larger than 50 ha. The approach produced consistent results identifying and mapping clouds of different type and size over various land surfaces including natural vegetation, agriculture land, built-up areas, water bodies and snow.

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1. Introduction

Earth observation remote sensing studies largely depend on the availability of accurate cloud masks. Clouds not only limit the amount of valid land surface information in a scene, undetected cloudy pixels affect atmospheric correction procedures, aerosol retrievals and compromise the estimation of biophysical parameters. They pose a limitation in land cover classification. Cloud covers obstruct the training selection process for supervised and unsupervised classification algorithms and also hinder the interpretation of results (cluster labeling) in unsupervised classifiers.

Given the relevance of the problem, low and moderate resolution sensors such as AVHRR and MODIS have integrated cloud masking algorithms and have delivered cloud masks as one of their products. These algorithms have been mainly based on empirically tuned thresholds from a number of spectral channels with brightness temperature having a dominant role in the process (Stowe et al, 1999; Ackerman et al., 1998). In last years, several studies have proposed more sophisticated alternatives to adapt, refine and/or substitute the cloud masking approaches originally developed for these sensors. These strategies include for instance the use of neural networks (Jang et al., 2006), linear unmixing techniques and time series analysis (Gómez-Chova et al., 2007; Lyapustin et al., 2008) and parallel Markovian segmentation (Kussul et al., 2005).

The number of cloud mask studies for high resolution sensors has been sensibly smaller. Since high resolution remote sensing studies have mostly focused on smaller areas covered by a few scenes, the rejection and substitution of cloudy images and the manual delineation of clouds have been common options. When simple image replacement was not possible, thermal channelbased spectral thresholding has been the most common automatic cloud masking approach. For instance, the Landsat 7 ETM+ automatic cloud cover assessment (ACCA) established a set of threshold-based filters and prior knowledge on land surface properties for cloud detection (Irish, 2000; Irish et al., 2006). Some studies have developed modifications and adaptations of the original ACCA algorithm to other sensors such as ASTER (Hulley and Hook, 2008) or SPOT and IRS-LISS (Soille, 2008).

Today, the fast development of earth observation and aerospace industry has lead to a growing number of high resolution earth observation sensors (Sandau et al, 2008). The combination of imagery from several high resolution sensors presents an opportunity for high resolution land cover mapping for large areas (Cihlar, 2000). While thermal bands represent the superior alternative for cloud making, the payload of several of these earth observation sensors does not include thermal channels in which cloud masking strategies have previously relied. Under this new scenario, there is a clear need for the development of cloud masking methodologies suited for the next generation of high resolution earth observation sensors. The new approaches must be able to operate without thermal bands and for large amounts of data from various high resolution sensors.

Recently some studies have proposed novel strategies for this problem using approaches such as Markov random fields, object oriented techniques (Le Hégarat-Mascle et al., 2009), and wavelet transforms, morphological operations and multitemporal analysis (Tseng et al., 2008). Some studies also anticipate the opportunities for cloud mask detection of the combination of observations from future high resolution sensors (Hagolle et al., 2010).

Building upon these studies, and in the context of large area land cover mapping activities, this study proposes a cloud making approach for the identification and delineation of clouds. The approach is designed for single date high resolution images for which thermal information is not available and relies on the complementary information provided by a second sensor with a higher revisit period. For demonstration purposes, this study uses high resolution images from SPOT4-HRVIR, SPOT5-HRG and IRS-LISS III and cloud free MODIS composites from almost simultaneously acquired dates as reference images.

The method is fully automatic and is suited for cloud masking of large amounts of scenes from various sensors.

This cloud masking approach relies on techniques widely used in remote sensing applications. However, our specific implementation of these techniques allows further exploiting the potential of sensor combination for this specific remote sensing challenge. The manuscript is divided in two sections. The first section describes a cloud identification procedure in which the combination of high and medium resolution remote sensing data provides a first approximation of cloudy pixels is provided. The second part proposes a simple, robust and automatic region growing-based cloud delineation alternative from the cloudy pixels identified in the previous stage.

2. Data

The performance of the method was evaluated for seven high resolution scenes from three sensors: SPOT4-HRVIR, SPOT5-HRG and IRS-LISS III (Table 1). The three sensors have four wavelengths green, red, near-infrared (NIR) and short wave infrared (SWIR) (Müller et al., 2009). The images were resampled to 25 m rasters in LAEA/ETRS89 projection (Annoni et al., 2003). The selected scenes included a wide range of different cloud types and surface features covering locations around Europe (Table 2). The original radiometrically calibrated and atmospherically corrected red wavelength reflectance MODIS daily images were provided by the German Aerospace Center in 250 m rasters in LAEA/ETRS89 projection.

Table 1	1
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List of high resolution images.

Ideally, the input data for the method would have included BRDF corrected surface reflectance for the MODIS data and atmospherically corrected surface reflectance for the high resolution data. However in order to evaluate the robustness of the approach we have worked with sub-optimal non corrected MODIS BRDF data and non atmospherically corrected high resolution data. It is to be expected that would only retrieve more accurate results.

Cloud free MODIS composites were created for the extent of each of the high resolution scene. In order to create a red wavelength (620–670 nm) cloud free composite, daily 250 m resolution images both from Terra and Aqua sensors were successively included starting from the acquisition date of the high resolution image. The acquisition window for the composites covered a maximum of 17 days (8 days before and after the high resolution acquisition date). The 17 days window avoids major land cover changes during that period and it showed to be sufficient to obtain cloud free MODIS composites.

Several alternatives are possible for compositing the daily MODIS scenes. The most obvious being using the cloud mask provided for MODIS data. However MODIS cloud mask is only 1 km spatial resolution. Furthermore, since cloud mask might not always be present for other moderate resolution sensors, we applied a simple pixel selection criteria based on maximum normalized difference vegetation index (NDVI) (Tucker et al., 1981). For each pixel, the value in the red wavelength corresponding to the daily pixel with the highest NDVI value of the daily MODIS images of the composite was selected. The NDVI presents high values for surfaces with high contrast between NIR and red signatures. Since clouds have similar signatures in NIR and red bands cloudy pixels will have low NDVI values. On the contrary, cloud free pixels will present in most cases higher NDVI values. A limitation of the maximum NDVI criteria is that water bodies usually present lower NDVI values than clouds. This was overcome by applying a in-house water mask to inland water bodies, water surfaces and sea.

Because of their thickness and size, the NDVI values of low clouds at 250 m are not necessarily as low as those of other cloud types. This represents a limitation for the compositing strategy. However, this solution still showed consistent results for cloud free pixel selection within the composites.

3. Methods

3.1. Preprocessing

Our implementation of the seed identification process depends on a one to one relationship between pairs of pixels in the high resolution images and the corresponding MODIS cloud free composites. In order to achieve this correspondence, the high resolution and MODIS images were co-registered in a common grid for a better pixel to pixel comparison. Subsequently the high resolution images were resampled to 250 m pixel size. This operation was carried out applying a spatial filter resembling the MODIS point spread function (Tan et al., 2006). This spatial filter aggregates

Id	Sensor	High resolution image date	Location	Cloud type	Scene description
1	IRS-LISS III	20060702	Alpine region	Large and small clouds over mountainous areas	Mountainous area (snow and ice cover)
2	IRS-LISS III	20060724	Spain	Medium and small size clouds	Agriculture, bare soil and natural vegetation
3	SPOT5-HRG	20061108	Greece	Medium size clouds	Mountainous area with high reflectance bare soil slopes
4	IRS-LISS III	20060812	Spain	Medium size clouds	Bare soils and agriculture fields
5	IRS-LISS III	20060817	Greece	Clusters of small clouds	Agriculture, bare soil and natural
6	IRS-LISS III	20060905	France	High density of small clouds	Agriculture and natural
7	SPOT4-HRVIR	20060925	Bulgaria	Medium and small size clouds	Agriculture, bare soil and natural vegetation

Table 2

Parameters from confusion matrices for each scene, top table: results for ad-hoc cloud mask generated with maximum likelihood classifier; bottom table: results for ad-hoc cloud mask generated with classification tree.

High resolution image date	Commission disagreement	Omission disagreement	Kappa coefficient	% Clouds in cloud mask	% Clouds in reference cloud mask
20060702	12.27	0.29	0.90	4.294	4.042
20060724	9.87	0.20	0.89	1.693	1.657
20061108	1.92	0.23	0.85	1.15	1.29
20060812	17.70	0.68	0.86	4.60	4.70
20060817	1.69	0.28	0.89	1.308	1.566
20060905	0.39	1.60	0.78	2.912	4.456
20060925	0.37	1.30	0.80	2.701	3.951
20060702	43.60	0.01	0.71	4.294	2.43
20060724	5.47	0.62	0.81	1.693	2.18
20061108	6.13	0.57	0.78	1.15	1.29
20060812	28.60	1.48	0.70	4.60	4.70
20060817	0.39	1.14	0.69	1.308	2.43
20060905	0.52	1.09	0.84	2.912	3.96
20060925	0.10	1.32	0.80	2.701	3.98

the high resolution pixels in the most comparable way with respect to the MODIS pixel. Given the considerable difference in spatial resolution (from 25 to 250 m), this operation is particularly important, since only a proper aggregation of the 25 m resolution pixels will result in a sound relationship between pixels in both images. Although this PSF is originally designed as a weighting function in a spatial convolution for MODIS observation geometry, the differences introduced by applying it to LAEA/ETRS89 images represent a lower order of magnitude than the result of the aggregation process and should not introduce significant differences.

3.2. Cloud patch identification

The cloud patch identification phase extracts cloudy pixels through a scene-specific adaptive threshold. These cloudy pixels represent the initial patches from which the seeds for the subsequent region growing process are obtained and are a first approximation of the cloud mask. It is expected that, given guasi-contemporaneous acquisition dates, there will be no major land cover changes. Surface features will present similar spectral signatures in cloud free MODIS composites and resampled high resolution images. Hence digital numbers for cloud free pixel in both image types will be largely correlated, while digital numbers for cloudy pixels will deviate from that correlation. Under normal acquisition circumstances it is expected that this correlation is linear or close to linear. Following this logic it is assumed that the correlation between recorded values of the cloud free pixels in the cloud free MODIS composites and resampled high resolution images from overlapping acquisition dates can be modeled with a linear regression. Pixels that deviate from linear relationship can be considered as cloudy.

The cloud patch identification routine delineates a large proportion of cloud free pixels in the resampled high resolution image. These pixels are the base for building a reference linear regression model. They are identified based on the density distribution of pixel-pairs in the scatterplot defined by the resampled high resolution image and the cloud free MODIS composite (Fig. 1). Under the assumption that clouds do not dominate the scene and can occur over any land surface, cloudy pixels will be distributed over a wide region of the spectral space. It is therefore, safe to consider that they will present lower spatial densities than the larger amount of cloud free pixels, concentrated on a pixel cloud of the spectral space. Therefore, the identification of the linear regression will be more reliable for scenes with large proportions of cloud free pixels. On the other hand, the identification of the linear relationship between cloud free pixels will become more complicated for scenes heavily dominated by clouds.

The identification of cloud free pixels for the reference linear regression is based on the estimation of pixel density in the 2-D spectral space. There are various alternatives for density estimation in spatial point pattern analysis literature. Methods such as quadrats, nearest neighbor and kernel methods have been extensively used for point density estimation (Bailey and Gatrell, 1995; Silverman 1986). With different levels of complexity all these methods calculate the number of events within a certain region or neighborhood. As these regions decreases the density estimation becomes a more local parameter and the above mentioned methods provide similar results.

We estimated density at local level by simply counting the number of times a pixel occurs in the same location (zero neighborhoods). Subsequently, only the pixels occurring in the same location of the spectral space (point density larger than 1) are selected to build the linear regression. This represents a robust alternative to identify the majority of the cloudy pixels in the scenes required to build a reference linear regression.

As previously mentioned, cloudy pixel values in the resampled high resolution image will be sensibly different from those estimated from the established linear regression. Hence a threshold based on the standard deviation of the linear regression identifies the pixels with large squared errors (Fig. 1). As this threshold is based on the values of all pixels in the scene it provides a more robust alternative than thresholds purely relying on individual pixel digital numbers. For the cases tested in this study, the process was implemented in the red band and a three standard deviation parameter provided a reliable separation of cloudy pixels.

3.3. Cloud delineation

Region growing operations have been widely used in remote sensing and image processing in the last 20 years (Dreyer, 1993; Ryherd and Woodcock, 1996; Stuckens et al., 2000). Region growing processes group pixels into larger regions based on predefined criteria (Gonzalez and Woods, 2002)(Please check the following references Cihlar et al. (2000), Hulley et al. (2008), Dreyer et al. (1993), Ryherd et al. (1996) Gonzalez et al. (2002) Hartigan et al. (1979) Irish et al. (2000), Roy et al. (2009) have been changed to Cihlar (2000), Hulley and Hook (2008), Dreyer (1993), Ryherd and Woodcock (1996), Gonzalez and Woods (2002), Hartigan and Wong (1979) Irish (200), Roy and Boschetti (2009) to match with the reference list) and allow a detailed delineation of borders.

Taking the original cloud patches as input, this process extracts the seeds from which the output clouds are grown. The combination of region growing routines with other classification strategies substantially improves the result of the latter. The cloud patch



Fig. 1. Red wavelength scatterplot for resampled high resolution image (*Y* axis) and cloud free MODIS composite (*X* axis). The upper plate displays the pixel-pair density within the scatterplot. The middle plate shows the pixel-pairs selected for the linear regression and the adaptive thresholds. The lower plate shows the cloudy pixels after the region growing process.

identification routine can be designed to provide a conservative estimation of initial cloud seeds. However, the gradual transition from cloud to cloud free pixels cannot be fully captured by a simple linear border. The region growing process results in a redistribution of pixels previously labeled as cloudy during the cloud patch identification and allows a fine delineation of clouds (Fig. 1, bottom plate). Using the cloud patches generated during the cloud patch identification stage the region growing process is implemented on the original 25 m spatial resolution.

This region growing was implemented on the SWIR bands (1550–1700 nm). After several tests with different band combinations, it was found the SWIR band provide a simple and fast solution while still offering a high contract between cloudy and cloud free pixels. The lack of 250 m spatial resolution SWIR MODIS band prevented its initial use for the cloud patch identification stage. The alternative application of a 500 m spatial resolution band was discarded because it would have implied decreasing the capacity of the method for detecting smaller clouds.

Each patch of cloud seeds is treated individually during the processing. For each cloud patch, k-means clustering (Hartigan and Wong, 1979) separates the pixels into two clusters for the pixels of the high resolution image falling under the patch. The cluster with highest pixel values was taken as cloud seed (Fig. 2). This clustering operation filters out 25 m resolution pixels that could have been included within the cloud patch in the process of reestablishing the spatial resolution of the cloud patch from 250 to 25 m. The stopping criterion for the region growing process was defined based on the spectral information of each seed. For each seed obtained from a cloud patch, the average and the standard deviation were computed. Pixels within 8-neighborhood were



Fig. 2. Region growing process. (A) cloud patch at 250 m; (B) cloud patch at 25 m; (C) k-means for each cloud patch; (D) cluster with highest pixel values selected as cloud seed; E: cloud grown from cloud seed at 25 m spatial resolution.

successively included provided their pixel values did not depart from the average more than 2.5 times the standard deviation.

4. Validation methodology

Because of the unfeasibility of obtaining precise simultaneous cloud information the validation of a cloud mask remains a challenging task. Available reference cloud products present their own inherent limitations, and can often be less accurate that the product they should serve to evaluate.

Given this lack of fully reliable datasets for cloud mask validation, the quality assessment of a cloud mask must be regarded as a product comparison rather than a product validation.

In this study we implemented a number of complementary comparisons between different independent cloud mask products. The combination of these analyses serves as an assessment of the strength of our cloud mask approach.

Cloud masks were first evaluated through visual comparison with the original high resolution satellite images. In the absence of irrefutable reference information, visual analysis has been usually applied for the validation of cloud masks (Irish, 2000; Soille, 2008; Tseng et al., 2008; LeHégarat-Mascle et al., 2009). Visual interpretation is often considered the best possible approach for the classification of remotely sensed images (Roy and Boschetti, 2009).

In a second stage, the cloud masks were also compared against two ad-hoc independently generated cloud masks. The two "adhoc" cloud masks were generated using a supervised classification algorithm. One of them used a parametric (maximum likelihood) and a non-parametric (classification tree). Training data was generated by manually delineating cloud and cloud free polygons for each scene. Therefore two ad-hoc cloud masks were generated for each scene. As previously mentioned, this ad-hoc comparison cloud mask cannot be regarded as a reference as such, since it does not necessarily have higher precision than our cloud mask and its accuracy is unknown. However the degree of agreement of two cloud masks created with different approaches provides valuable information about the performance of both cloud masks.

The agreement between both cloud masks was first characterized through a two-way (cloud-cloud free) confusion matrix. This matrix shows the percent of cloudy pixels in both cloud masks, the commission disagreement (i.e. the probability that a pixel mapped as cloudy in our cloud mask is not cloudy in the reference cloud mask), the omission disagreement (i.e. the probability that a pixel mapped as cloud free in our cloud mask is cloudy in the reference cloud mask). The kappa coefficient (Congalton, 1991) provided an additional statistical measure of the agreement, correcting for chance agreement, between the two cloud masks.

Additionally, individual clouds were labeled to evaluate the number of detected clouds in our cloud masks also detected in the ad-hoc comparison cloud masks. This evaluation provides some insights about the capacity of the cloud mask for the detection of clouds of various sizes.

In a subsequent analysis, the proportions of cloudy pixels within a spatial kernel in both cloud masks were compared via a scatterplot. Similar approaches have been previously proposed in validation approaches for burned areas (Roy and Boschetti, 2009). This analysis provides additional information to the confusion matrix, since it allows a closer look into the nature of the discrepancies of both cloud masks. This type of geographical analyses is sensitive to the kernel size (Unwin, 1996). In our case, a 9-pixel kernel was applied to all the cloud masks.

Finally, in order to further assess the performance of our cloud mask approach, their results were compared against those of the automatic cloud cover assessment (ACCA) algorithm. The automatic cloud cover assessment (ACCA) algorithm developed for the ETM+ Landsat 7 system (Irish et al., 2006). ACCA establishes a number of spectral thresholds, from which several of them rely on the thermal band. The ACCA cloud mask was implemented for five cloudy ETM+ scenes. These five scenes correspond to locations in France, Italy, Poland, Slovakia, Serbia and United Kingdom. They include a variety of cloud types over different land surfaces. For the same scenes cloud masks using the presented approach were also created using only ETM+ bands 2, 3, 4 and 5 (LISS and SPOT4/5 equivalent).

5. Results and discussion

A visual comparison of the cloud masks generated for the seven scenes with the original high resolution spectral bands (Fig. 3) shows that clouds of different sizes are detected and delineated over land surfaces such as natural vegetation, agriculture land, built-up areas, and snow and water bodies. This visual interpretation shows that the main differences between our cloud mask and the ad-hoc reference cloud masks are because of the cloud edges.

The information extracted from the confusion matrices showed a high convergence with the independently generated cloud masks, with high kappa coefficients and low commission and omission disagreements in cloud estimation (Table 3). As observed in the visual analysis, the lowest values in kappa coefficient between cloud masks are in scenes with large number of small clouds. In these scenes the pixels at the edge of clouds can account for a large proportion of the cloudy area. Nevertheless, these divergences are a consequence of the different precisions inherent to different cloud masking methodologies and can hardly be interpreted as misclassification of any of the cloud masks.

The scatterplots of the proportion of cloudy pixels within a given spatial kernel in both cloud masks provide some additional information (Fig. 4). The one-to-one line defines the total agreement between both masks. Points above the line indicate overestimation of our cloud masks the ad-hoc reference cloud mask while points below the line indicate overestimation with respect to the ad-hoc reference cloud mask. The analyzed scenes presented cases of over and underestimation, which indicates the cloud mask methodology is not affected by bias in one direction, and the differences mostly depend of each specific scene. The distance of the points from the one-to-one line indicates discrepancies between our cloud mask and the ad-hoc reference cloud mask. Short distances are mainly because of differences in cloud edges, while large distances correspond to large differences in the cloud estimation and undetected clouds in one of the masks. Fig. 4 displays the scatterplots for four of the scenes. These scatterplots show that high point densities consistently occur near the one-to one line and points far away from the line tend to have very low point densities. The slope, intercept and correlation coefficients of the linear regressions built from the points are presented in Table 4. These parameters provide an indication of the agreement between both cloud masks and the dispersion of the points. Slopes close to one and intercepts close to zero point to full agreement. High correlation coefficients show low point dispersion. Again the largest discrepancies (lowest correlation coefficients slopes and intercepts far from one and zero, respectively) occur for scenes with small clouds, in which the differences in the estimation of edge cloud pixels is a major part of the cloudy area in relative terms.

An object-based comparison of the number of clouds identified by the generated cloud masks taking the ad-hoc cloud masks as a reference shows a high degree of agreement for cloud identification (Table 5). The agreement increases for large clouds: While clouds smaller than 50 pixels the percent agreement can be as low as 10% in one of the scenes, nearly 90 percent of the clouds larger than 100 pixels are detected in both cloud masks.



Fig. 3. Snapshots of the high resolution scenes and corresponding cloud masks. (A) Original high resolution image (SWIR wavelength); (B) cloud patches; (C) Region grown cloud mask.

The comparisons of the cloud masks (generated with ETM+ band 2, 3, 4 and 5) with the ACCA cloud masks (generated with 7 ETM+ bands) for five LANDSAT seven scenes show a strong agreement. Fig. 5 displays snapshots of our cloud mask and ACCA cloud mask for two of the Landsat seven scenes. Main differences occur in border delineation. The use of additional spectral information in ACCA, specially the thermal band, allows, in some cases a more precise delineation of cloud borders. The aggregated figures for the five Landsat scenes analyzed explain that the percentage of clouds detected in both cloud masks increase with the cloud size. For clouds larger than 50 ha, 95% of the clouds detected by ACCA are also detected by our cloud masks (Table 5).

Table 3

Slope, intercept and correlation coefficient of the linear regression calculated from the proportion of pixels within 9×9 kernels labeled as cloud by our cloud mask (horizontal axis) and the ad-hoc reference cloud mask (vertical axis).

High resolution image date	Slope	Intercept	Correlation coefficient
20060702	1.0179	0.1071	0.9395
20060724	1.0222	0.175	0.9357
20061108	1.0168	0.168	0.8955
20060812	0.9632	0.375	0.9120
20060817	0.9814	0.289	0.8857
20060905	0.6646	0.47	0.6803
20060925	0.7870	0.42	0.7742

There are a number of relevant aspects in the design and implementation of this method to be considered for its application. The method is designed for partially cloudy scenes. It is assumed that scenes in which the cloud cover clearly dominates the image will not be valid for any further land cover analysis and therefore rejected. The seed identification process relies on the higher density of cloud free pixels in the spectral plane defined by the cloud free MODIS composite and the resampled high resolution images. These cloud free pixels define the linear regression model from which cloudy pixels are identified as seeds. Whenever the density of cloud free pixels is not higher than that of cloudy pixels the seed identification routine is prone to retrieve erroneous seeds. Nonetheless the method provides reliable seeds even in cases with large number of scatter clouds spatially distributed all over the scene. Under these configurations despite their large number, clouds will be distributed over different land surfaces and still result in lower pixel densities than cloud free pixels.

In the examples presented in this study, clouds are only identified if the cloud signature dominates at least one pixel in the cloud free MODIS composite. The dominance of the cloud signature depends on both the size of the cloud and the contrast of the underneath surfaces. Since cloud patches are extracted from 250 m pixel size images it can be expected that, under some



Fig. 4. Scatterplot of the proportion pixels within 9 × 9 kernels labeled as cloud by our cloud mask (horizontal axis) and the ad-hoc reference cloud mask (vertical axis). The solid line represents the one-to-one line. The color scale represents the point density distribution representing the number of pixels with the same values in both axes.

Table 4

Percentage of agreement in number of cloud detected between our cloud masks and ad-hoc comparison cloud masks. Each column shows the percentage of clouds larger than a given number of pixels (0, 50, 100, 200, 300, 400, 500, and 1000) detected in both masks.

date	Cloud size (11	Cloud size (in pixels)							
	Larger than 0	Larger than 50	Larger than 100	Larger than 200	Larger than 300	Larger than 400	Larger than 500	Larger than 1000	
20060702	45.87	93.78	94.94	97.04	98.08	98.33	98.81	100	
20060724	48.13	94.82	97.84	98.20	98.22	99.05	98.86	100	
20061108	46.23	93.84	96.80	99.12	99.21	99.56	100	100	
20060812	43.52	97.56	98.25	99.01	99.26	99.65	100	100	
20060817	42.84	98.00	98.85	99.25	99.26	98.8	99.07	98.45	
20060905	18.43	81.70	94.47	98.96	99.78	99.87	100	100	
20060925	24.79	95.23	99.65	100	100	100	100	100	

Table 5

Percentage of agreement in cloud detection by cloud size (ha) between our cloud masks (generated with ETM+ bands 2, 3, 4 and 5) and ACCA cloud masks (generated with 7 ETM+ bands).

Clouds larger than (ha)	Percentage of detected clouds				
10	54				
20	75				
30	84				
40	90				
50	95				

conditions, clouds smaller than one 250m pixel (circa 6 ha) size may remain undetected (sub-pixel cloud contamination). This limitation is specific choice of the 250 m cloud free MODIS composites as reference image. If available, images from higher resolution sensors such as AWIFS could be used as cloud free reference images for the cloud patch identification phase. The higher resolution of the cloud free reference image would result in reduction of the minimum size of the cloud patch and an increase in the detection of the smaller clouds. Nevertheless, it must be noted that the region growing process is implemented on the higher resolution image (25 m pixel size image in this study) and therefore, this defines the precision in the delineation of identified clouds. The method presented has not been designed for haze detection. Haze modifies the signature of a given pixel within the normal range of spectral variation of a given land surfaces. The method relies on the identification of uncorrelated signatures between equivalent pixels from two different sensors. Since the correlation is gradually lost in hazy scenes cloud patches cannot be reliably detected. Furthermore, even if cloud patches were identified, the extraction of cloud seeds would be affected by the signature of the underneath surfaces and, given the limited spectral contrast between cloud seeds and cloud free pixels, the cloud seeds may grow out of the limits of the hazy area.

Rapid land cover changes such as forest fires, crop harvesting, and variations in the snow cover result in differences in the digital numbers of the daily images within the acquisition window for the cloud free MODIS composite. As a consequence, depending on the compositing strategy, these changes can affect the relationship between pixels digital numbers in the cloud free MODIS composite and the resampled high resolution images, leading to erroneous estimation of cloud seeds. The compositing strategy selected for this study has consistently provided good results over all the scenes analyzed. It has proved particularly robust dealing with variations of snow cover in mountainous regions. However, alternative compositing strategies could improve the results for



Fig. 5. Four snapshots of Landsat ETM+ scenes and corresponding cloud masks retrieved by ACCA and our cloud mask. Each snapshot corresponds to a different ETM+ scene.

specific areas and situations. For instance, bright surfaces after agriculture harvest can be detected as cloud seeds when harvest occurs during the composite period. The selection of the median of all the cloud free pixels of the daily MODIS images will reduce the risk of selecting bright surfaces as cloud seeds. Furthermore the combinations of compositing approaches depending land surface criteria could be implemented for large area cloud mask initiatives.

As in the case of clouds, cloud shades also pose a limitation for remote sensing land surface analyses. Cloud shades modify pixel digital numbers at different intensity levels hampering automatic interpretation of satellite images. A number of studies have proposed shade detection techniques with highly accurate results (Lissens et al., 2000; Le Hégarat-Mascle et al., 2009; Soille, 2008; Tseng et al., 2008). These studies commonly identify cloud shades from previously defined clouds and take advantage of scene viewing and illumination characteristics. This study is focused on developing a cloud mask methodology. However, any of the strategies presented in these studies can be applied on top of the cloud mask approach as a subsequent step.

Finally, the methodology, as described in this study, uses the red band for the cloud patch identification stage and short wave infrared for the region growing stage. These two bands proved to be an adequate choice given the spatial and spectral resolution of the sensors used in the study. However the number of available bands does not pose a critical limitation for the application of the method. This approach may also be applied in more restrictive situations in which only a single band in high and medium resolutions are available.

6. Conclusion

The cloud masking strategy presented here integrates high and medium resolution satellite imagery to develop a high resolution cloud mask. The combination of a pixel by pixel comparison and a region growing process allows an accurate identification of clouds and their precise delineation. The validation of the cloud masks for a number of high resolution scenes shows a robust performance for clouds of different sizes and over various land surfaces including natural vegetation, agriculture land, built-up areas, water bodies and snow. The approach is not sensor specific and can be applied to various high resolution earth observation sensors without thermal band. Under less restrictive schemes, in which the temporal constrains for the creation of the composites are relaxed this strategy could be also applied to larger number of sensors. This strategy can be operationally implemented in an automatic manner for extensive image datasets of various sensors covering large geographic regions. The methodology, as presented in this study, has been already applied to a pan-European dataset of over 3,500 LISS, SPOT 4 and SPOT 5 scenes. As the number of high resolution earth observation sensors is steadily increasing, sensor-independent methodologies, as the one presented in this study are likely to play a relevant role in future land cover mapping initiatives.

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