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Object-based cloud and cloud shadow detection in Landsat imagery

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ABSTRACT

A new method called Fmask (Function of mask) for cloud and cloud shadow detection in Landsat imagery is provided. Landsat Top of Atmosphere (TOA) reflectance and Brightness Temperature (BT) are used as inputs. Fmask first uses rules based on cloud physical properties to separate Potential Cloud Pixels (PCPs) and clear-sky pixels. Next, a normalized temperature probability, spectral variability probability, and brightness probability are combined to produce a probability mask for clouds over land and water separately. Then, the PCPs and the cloud probability mask are used together to derive the potential cloud layer. The darkening effect of the cloud shadows in the Near Infrared (NIR) Band is used to generate a potential shadow layer by applying the flood-fill transformation. Subsequently, 3D cloud objects are determined via segmentation of the potential cloud layer and assumption of a constant temperature lapse rate within each cloud object. The view angle of the satellite sensor and the illuminating angle are used to predict possible cloud shadow locations and select the one that has the maximum similarity with the potential cloud shadow mask. If the scene has snow, a snow mask is also produced. For a globally distributed set of reference data, the average Fmask overall cloud accuracy is as high as 96.4%. The goal is development of a cloud and cloud shadow detection algorithm suitable for routine usage with Landsat images.

1. Introduction

The long history of Landsat data is one of the most valuable datasets available for studying land cover change and human influences on the land surface (Cohen et al., 1998; Coiner, 1980; Coppin & Bauer, 1994; Seto et al., 2002), especially since the first Thematic Mapper (TM) sensor was launched in 1982, which provided higher spatial resolution and more spectral bands. However, many of the Landsat images are inevitably covered by cloud, especially in the tropics (Asner, 2001). The International Satellite Cloud Climatology Project-Flux Data (ISCCP-FD) data set estimates the global annual mean cloud cover is approximately 66% (Zhang et al., 2004). The presence of clouds and their shadows complicates the use of data in the optical domain from earth observation satellites. The brightening effect of the clouds and the darkening effect of cloud shadows influence many kinds of data analyses, causing problems for many remote sensing activities, including inaccurate atmospheric correction, biased estimation of Normalized Difference Vegetation Index (NDVI) values, mistakes in land cover classification, and false detection of land cover change. Therefore, clouds and cloud shadows are significant sources of noise in the Landsat data, and their detection is an initial step in most analyses (Arvidson et al., 2001; Irish, 2000; Simpson & Stitt, 1998). Generally, clouds can be divided into two categories: thick opaque clouds and thin semitransparent clouds. The thick opaque clouds are relatively easier to identify because of their high reflectance in the visible bands. The identification of thin semitransparent clouds is difficult as their signal includes both clouds and the surface underneath (Gao & Kaufman, 1995; Gao et al., 1998, 2002).

Due to the high spectral variability of clouds, cloud shadows, and the Earth's surface, automated accurate separation of clouds and cloud shadows from normally illuminated surface conditions is difficult. Intuitively, it seems that clouds and cloud shadows are easily separable from clear-sky measurements, as clouds are generally white, bright, and cold compared to the Earth's surface, while cloud shadows are usually dark. Nevertheless, there are clouds that are not white, bright, or cold and cloud shadows even brighter than the average surface reflectance. Part of the difficulty arises from the wide range of reflectances and temperatures observed on the surface (Irish, 2000). One common approach is to screen clouds and cloud shadows manually. However, this approach is time consuming and will limit efforts to mine the Landsat archive to study the history of the Earth's surface.

Over the years, a number of methods were developed for cloud identification. However, most of them are designed for moderate spatial resolution sensors such as Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS). These sensors are usually equipped with more than one thermal band, or with water vapor/CO2 absorption bands, both of which are useful for thin semitransparent cloud detection (Ackerman et al., 1998; Derrien et al., 1993; Saunders &

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Kriebel, 1998). For high spatial resolution sensors like Landsat, with only one thermal band and 6 optical bands placed in atmospheric windows, accurate cloud identification is difficult. And, cloud shadow identification is even more difficult. Clouds cast shadows on any type of land cover. When cloud shadows fall on urban, snow, ice, or bright rocks, they can be very bright compared to the average surface reflectance. Moreover, when the cloud is semitransparent, the darkening effect of the cloud shadow can be subtle, making the cloud shadow hard to detect. Therefore, how to detect clouds, cloud shadows, and especially thin clouds and their shadows in Landsat images is still an important issue in the remote sensing community, particularly as we try to use increasingly automated methods to analyze large volumes of data.

2. Background

Historically, screening of clouds in Landsat data has been performed by the Automated Cloud Cover Assessment (ACCA) system (Irish, 2000; Irish et al., 2006). By applying a number of spectral filters, and depending heavily on the thermal infrared band, ACCA generally works well for estimating the overall percentage of clouds in each Landsat scene, which was its original purpose. However, it does not provide sufficiently precise locations and boundaries of clouds and their shadows to be useful for automated analyses of time series of Landsat images. Additionally, ACCA fails to identify warm cirrus clouds and falsely identifies snow/ice in high latitude areas as clouds (Irish, 2000; Irish et al., 2006). Wang et al. (1999) proposed the use of two multi-temporal Landsat TM images to find clouds and their shadows by image differencing. This method can successfully provide an accurate cloud and cloud shadow mask, but it is highly dependent on the input images. Since the Landsat sensors are not always turned on, it can be months between successive acquisitions. Also, it is possible that the next Landsat observation is still cloudy in the same location as the previous Landsat image, which would further limit the utility of the proposed algorithm. As cloud and snow/ice are very hard to distinguish from each other in high latitude areas, Choi and Bindschadler (2004) suggested a method for detecting clouds over ice sheets by using a shadow matching technique and an automatic Normalized Difference Snow Index (NDSI) threshold. This method matches the possible cloud and cloud shadow edges iteratively to find the optimal NDSI threshold for cloud detection. It works well over ice sheets but it is time consuming and only works for the surface of ice sheets. The Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmosphere correction tool also generates an internal cloud mask (Vermote & Saleous, 2007). It uses two passes. There are four tests in the first pass and a thermal test in the second pass which is similar to ACCA, except that the second pass generates a cloud mask while the second pass of ACCA only provides the percentage of cloud cover. This algorithm needs other ancillary data like the surface temperature provided from National Centers for Environmental Prediction (NCEP) to help generate a coarse resolution surface temperature reference layer for cloud detection. This algorithm has already been used extensively for atmospheric correction of Landsat images and has shown a better method for cloud detection in low and middle latitudes compared to ACCA. However, it may not work well when the clouds cover a large percentage of the image (large amount of leakage were observed) or in sun glint and turbid water conditions (Vermote, 2010). Hégarat-Mascle and André (2009) developed an approach that uses only two bands, Green and Short Wave Infrared (SWIR), to generate a “clear-sky line” and use the distance from the tested points to this line to detect cloud pixels. This method was originally used by Zhang et al. (2002) to correct for haze in Landsat imagery. It has been shown to be accurate for retrieving clouds over vegetated areas, but it fails when the surface reflectance is bright, as is the case for rocks, snow, ice, sand, etc. (Zhang et al., 2002). By implementing a cloud-mask algorithm originally developed for the MODIS Land bands on Landsat data, Oreopoulos et al. (2011) proposed an algorithm that performs on par with the ACCA algorithm without using the thermal band.

Detecting cloud shadow is more difficult than detecting cloud. Previously, cloud shadow identification was based on spectral tests. Though it works sometimes, most of the time it will inevitably include other dark surfaces that have similar spectral signatures (like topographic shadows or wetlands) and exclude cloud shadows that are not dark enough (Ackerman et al., 1998; Hutchison et al., 2009). Recently, geometry-based cloud shadow detection has been shown to be feasible and more accurate. Currently, there are three kinds of geometry-based cloud shadow detection methods in the literature: object matching, lapse rate, and scattering differencing. The object matching algorithm detects cloud shadow by matching cloud shadows with cloud objects (Berendes et al., 1992; Hégarat-Mascle & André, 2009; Simpson & Stitt, 1998; Simpson et al., 2000). The lapse rate method used a constant lapse rate to estimate cloud top height by brightness temperature and use the cloud pixels to cast shadows (Vermote & Saleous, 2007). This latter method works well for thick clouds but is not accurate when the clouds are semitransparent, as the brightness temperature will be a mixture of thin cloud and the surface, making cloud height estimation problematic. As cloud shadow scattering is stronger in the short wavelengths (especially Blue band), Luo et al. (2008) proposed to use this physical characteristic (scattering differences between the short wavelength and NIR or SWIR), combined with the geometry, to produce cloud shadow masks. This new method works well over vegetated area, but is less accurate when the cloud shadow falls on bright surfaces or the cloud shadow comes from a very thin cloud.

In this paper, we provide a new algorithm for detecting both clouds and cloud shadows for Landsat TM and Enhanced Thematic Mapper Plus (ETM+) images that builds on the results of previous approaches. The cloud mask is computed from a probability mask and a scene-based threshold. Cloud shadows are calculated using a combination of previous methods (object matching and lapse rates) and a flood-fill transformation. This algorithm works well in high latitudes, separating clouds from shallow or turbid water accurately, and can also detect thin clouds and their shadows. If a Landsat scene has snow, Fmask also produces a snow mask.

3. The Fmask algorithm

The input data are Top of Atmosphere (TOA) reflectances for Bands 1, 2, 3, 4, 5, 7 and Band 6 Brightness Temperature (BT) (Table 1). For Landsat L1T images, Digital Number (DN) values are converted to TOA reflectances and BT (Celsius degree) with the LEDAPS atmosphere correction tool (Masek et al., 2006; Vermote & Saleous, 2007). Then, rules based on cloud and cloud shadow physical properties are used to extract a potential cloud layer and a potential cloud shadow layer. Finally, the segmented potential cloud layer and the geometric relationships are used to match the potential cloud shadow layer, leading to the production of the final cloud and cloud shadow mask. If the Landsat scene has snow, Fmask will also

Table 1
Landsat TM/ETM+ spectral bands.

TM bands (μm)	ETM+ bands (μm)
Band 1 (0.45–0.52)	Band 1 (0.45–0.515)
Band 2 (0.52–0.60)	Band 2 (0.525–0.605)
Band 3 (0.63–0.69)	Band 3 (0.63–0.69)
Band 4 (0.76–0.90)	Band 4 (0.75–0.90)
Band 5 (1.55–1.75)	Band 5 (1.55–1.75)
Band 6 (10.40–12.50)	Band 6 (10.40–12.50)
Band 7 (2.08–2.35)	Band 7 (2.09–2.35)