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Automated cloud, cloud shadow, and snow detection in multitemporal Landsat data: An algorithm designed specifically for monitoring land cover change

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ABSTRACT

We developed a new algorithm called Tmask (multiTemporal mask) for automated masking of cloud, cloud shadow, and snow for multitemporal Landsat images. This algorithm consists of two steps. The first step is based on a single-date algorithm called Fmask (Function of mask) that initially screens most of the clouds, cloud shadows, and snow. The second step benefits from the extra temporal information from the remaining "clear" pixels and further improves the cloud, cloud shadow, and snow mask. Three Top Of Atmosphere (TOA) reflectance bands (Bands 2, 4, and 5 — Landsat-7 band numbering) are used in a Robust Iteratively Reweighted Least Squares (RIRLS) method to estimate a time series model for each pixel. By comparing model estimates with Landsat observations for the three spectral bands, the Tmask algorithm is capable of detecting any remaining clouds, cloud shadows, and snow for an entire stack of Landsat images. Generally, this algorithm will not falsely identify land cover changes as clouds, cloud shadows, or snow, as it is capable of modeling land cover change. The multitemporal images also provide extra information for better discrimination of cloud and snow, which is difficult for single-date algorithm. A snow threshold is derived for Band 5 TOA reflectance for each pixel at each specific time based on a modified Norwegian Linear Reflectance-to-Snow-Cover (NLR) algorithm. By comparing the results of Tmask with a single-date algorithm (Fmask) for multitemporal Landsat images located at Path 12 Row 31, significant improvements are observed for identification of clouds, cloud shadows, and snow. The most significant improvement is observed for cloud shadow detection. Many of the errors in cloud, cloud shadow, and snow detection observed in Fmask are corrected by the Tmask algorithm. The goal is development of a cloud, cloud shadow, and snow detection algorithm that results in a multitemporal stack of images that is free of "noise" factors and thus suitable for detection of land cover change.

1. Introduction

Landsat data has been widely used in remote sensing because of its medium spatial resolution (Woodcock & Strahler, 1987), accurate radiometric calibration (Chander, Markham, & Helder, 2009), high geometric precision (Lee, Storey, Choate, & Hayes, 2004; Masek, Honzak, Goward, Liu, & Pak, 2001), and long historical record (Markham, Storey, Williams, & Irons, 2004). The policy providing free access to Landsat data has made Landsat data even more popular (Woodcock et al., 2008) and has completely revolutionized the utilization of Landsat data (Wulder, Masek, Cohen, Loveland, & Woodcock, 2012). Take change detection as an example: previously, we detected land cover change by comparing two dates of clear Landsat images (Collins & Woodcock, 1996; Healey, Cohen, Yang, & Krankina, 2005; Masek et al., 2008), but now algorithms use tens (Huang, Goward, et al., 2010; Huang, Thomas, et al., 2010; Kennedy, Cohen, & Schroeder, 2007; Vogelmann, Tolk, & Zhu, 2009; Zhu, Woodcock, & Olofsson, 2012) or even hundreds (Zhu & Woodcock, 2014) of Landsat images at the same location. In this new data rich era, many preprocessing methods that require user input are no longer practical. One of the most immediate problems is cloud, cloud shadow, and snow detection in Landsat images.

Clouds, their shadows, and snow significantly influence optical sensors like Landsat (Dozier, 1989; Irish, Barker, Goward, & Arvidson, 2006; Zhu & Woodcock, 2012). The brightening effect of clouds and snow and the darkening effect of cloud shadows significantly influence the reflectance of different spectral bands. Screening of clouds, cloud shadows, and snow is especially crucial for remote sensing activities like change detection because undetected cloud, cloud shadow, or snow will likely result in identification of change where none occurred ("false positive errors"). Considering the relatively small areas of land cover change, this type of error significantly decreases change detection accuracy. Therefore, identification of clouds, cloud shadows, and snow is usually the first step in most remote sensing activities, and for certain applications like change detection, very accurate detection is required.

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The detection of clouds, cloud shadows, and snow is not always easy, especially if we want to detect them accurately. Clouds are notoriously difficult to detect in Landsat images, due to the limited Landsat spectral bands and the complexity of clouds themselves (Zhu & Woodcock, 2012). Many types of clouds exist, and each kind may have a different spectral signature based on cloud properties like cloud optical thickness, particle effective radius, thermodynamic phase, and cloud height (Platnick et al., 2003). Moreover the spectral signature of optically thin clouds can be very similar to the signature of the Earth surfaces underneath, making them more difficult to separate from clear observations. Cloud shadow detection can be difficult as well due to the spectral similarity of cloud shadows to dark surfaces. Thin cloud shadows are even more difficult to detect, as their spectral signature can be almost the same as clear pixels due to the penetration of solar radiation. Snow detection is usually considered relatively easier as the Normalized Difference Snow Index (NDSI) is very helpful for snow detection (Salomonson & Appel, 2004). However, the NDSI values of snow pixels can also change significantly depending on the grain size, the thickness of snowpack, and the amount of impurities (Warren & Wiscombe, 1980; Wiscombe & Warren, 1980). Moreover, most of snow-covered surfaces are actually a mixture of snow and other land cover types. In forested areas, snow is mixed with trees, and the NDSI values of these pixels are much lower than pure snow pixels (Klein, Hall, & Riggs, 1998; Xin et al., 2012). Additionally, snow and clouds can be very difficult to separate in some circumstances. Certain clouds, such as ice clouds, can have very similar spectral signatures to snow. Sometimes, it is almost impossible to separate clouds from snow based only on the spectral information.

To detect clouds, cloud shadows, and snow, one common approach is to identify them manually based on hand-drawn polygons. This works fine for processing a few Landsat images, but if we want to use a large number of Landsat images, more automated algorithms are needed. Recently, many new automated algorithms have been developed based on a single Landsat image (Huang, Goward, et al., 2010; Huang, Thomas, et al., 2010; Irish et al., 2006; Masek et al., 2006; Oreopoulos, Wilson, & Várnai, 2011; Roy et al., 2010; Scaramuzza, Bouchard, & Dwyer, 2012; Zhu & Woodcock, 2012). The development of these automated algorithms has made it possible for various kinds of remote sensing activities that use many Landsat images. However, for certain kinds of applications such as change detection, the single-date masking algorithms are still not accurate enough. Some of the single-date algorithms are capable of providing masks with high accuracy, but, given the relatively small areas of land cover change in most environments, any errors in the masking process will pose major problems for change detection. To remove clouds as much as possible, one solution for single-date algorithms is to use a lower threshold in detecting clouds (Zhu & Woodcock, 2012). However, this will also overestimate clouds and their shadows, and many clear pixels will be classified as cloud or cloud shadow, making change detection algorithms difficult for these pixels because of insufficient data.

To better detect clouds, cloud shadows, and snow, new algorithms based on multitemporal images have been developed for a number of satellite sensors, including Landsat (Goodwin, Collett, Denham, Flood, & Tindall, 2013; Hagolle, Huc, Pascual, & Dedieu, 2010; Jin et al., 2013; Wang, Ono, Muramatsu, & Fujiwara, 1999), Systeme Probatoire d'Observation de la Terre (SPOT) (Tseng, Tseng, & Chien, 2008), Spinning Enhanced Visible and Infrared Imager (SEVIRI) (Derrien & Le Gléau, 2010), and Moderate Resolution Imaging Spectroradiometer (MODIS) (Liu & Liu, 2013; Lyapustin, Wang, & Frey, 2008). The basic idea of these algorithms is that clouds, cloud shadows, and snow will cause sudden changes to the reflectance, and by comparing a reference image without clouds to the observed image, clouds, cloud shadows, and snow will be easily detected. These algorithms are reported to have higher accuracies in detecting clouds and their shadows. Goodwin et al. (2013) found that their multitemporal algorithm will produce better results in detecting cloud shadow compared to the Function of mask (Fmask) algorithm (Zhu & Woodcock, 2012). Despite the reported better results in these multitemporal algorithms, there are also disadvantages. The biggest disadvantage is that they may cause problems for applications like change detection because land cover change will also result in sudden changes to satellite observations. Most of these multitemporal cloud, cloud shadow, and snow detection algorithms rely on the assumption that between the time of the reference image and the observed image there is not any land cover change and differences in reflectance only result from clouds, cloud shadows, and snow. This may be true for some sensors with high temporal frequency such as MODIS or SEVIRI if the reference image is very close in time with the observed image. For sensors like Landsat, this assumption is often invalid, especially for places where land cover change is common. There have been several approaches proposed for limiting the effect of land cover change on multitemporal cloud and cloud shadow identification. For example, some of the algorithms use the Band 7/Band 1 ratio (Zhu et al., 2012) or the Band 3/Band 1 relationship (Hagolle et al., 2010) to distinguish some kinds of frequent changes (e.g. agriculture) from clouds. Lyapustin et al. (2008) propose to use an internally derived surface change mask to prevent the possibility of identifying surface change as clouds. On the other hand, Goodwin et al. (2013) use a geometry-based approach to distinguish land cover change from cloud shadows. However, it is difficult to exclude all kinds of land cover change with these empirically derived spectral tests or include all possible changes in a surface change mask, particularly given the wide variety of kinds of land cover change. This kind of commission error — where land cover change is removed from images as part of the cloud/cloud shadow screening process — is particularly serious when the ultimate goal of the analysis is to monitor land cover change. Moreover, as both clouds and snow usually make the visible bands brighter, it is difficult to separate snow from clouds based on simple image differencing. Most multitemporal algorithms assume that there is no snow in the image and the pixels that are brighter than the reference values are only due to clouds (Goodwin et al., 2013; Hagolle et al., 2010; Jin et al., 2013; Wang et al., 1999).

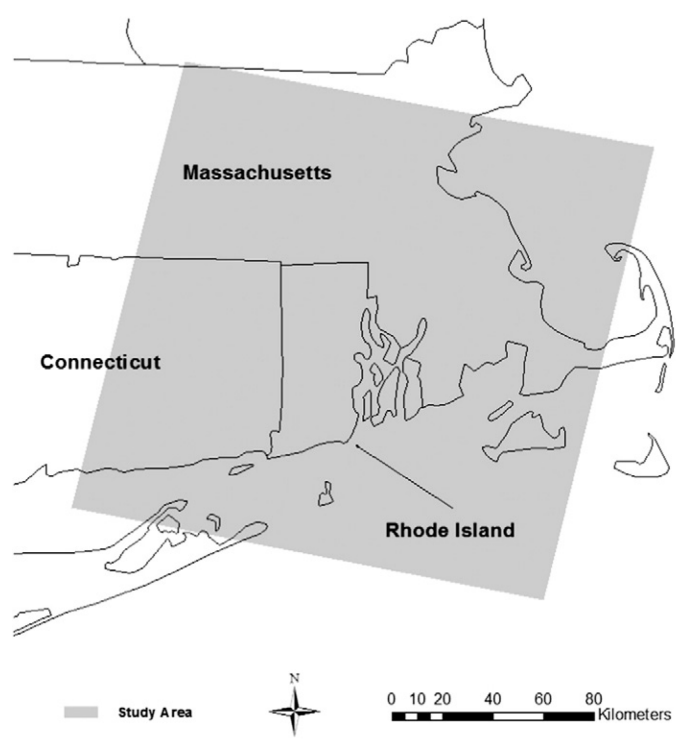

Fig. 1. Study area (Fig. 2 in Zhu & Woodcock, 2014).