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Nathan J. Moore
Michigan State University

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Review of Shadow Detection and De-shadowing Methods in Remote Sensing

AmirReza SHAHTAHMASSEBI[1], YANG Ning[1], WANG Ke[1], Nathan MOORE[2], SHEN Zhangquan[1]

(1. *Institute of Agriculture Remote Sensing and Information Technology*, *College of Environment and Natural Resource*, *Zhejiang University*, *Hangzhou* 310058, *China*; 2. *Department of Geography*, *Michigan State University*, *East Lansing*, *MI*, 48823, *USA*)

Abstract: Shadow is one of the major problems in remotely sensed imagery which hampers the accuracy of information extraction and change detection. In these images, shadow is generally produced by different objects, namely, cloud, mountain and urban materials. The shadow correction process consists of two steps: detection and de-shadowing. This paper reviews a range of techniques for both steps, focusing on urban regions (urban shadows), mountainous areas (topographic shadow), cloud shadows and composite shadows. Several issues including the problems and the advantages of those algorithms are discussed. In recent years, thresholding and recovery techniques have become important for shadow detection and de-shadowing, respectively. Research on shadow correction is still an important topic, particularly for urban regions (in high spatial resolution data) and mountainous forest (in high and medium spatial resolution data). Moreover, new algorithms are needed for shadow correction, especially given the advent of new satellite images.

Keywords: shadow; detection; de-shadowing; urban; forest

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1 Introduction

The atmosphere, land, and water of the Earth are amazingly complex and do not lend themselves well to being recorded by remote sensing devices that have constraints such as spatial, spectral, temporal and radiometric resolution (Jensen, 2007). Therefore, Earth′s components can introduce a range of errors such as geometric errors, atmospheric effects, and topographic effects into the remote sensor data. Such errors can attenuate quality of remote sensor data recorded and in turn may have an impact on the accuracy of remote sensing research such as change detection and land cover mapping. Hence, employing image preprocessing operations is a necessary and crucial step in order to produce corrected image or at least reduce impacts of these errors.

One of the most common types of error encountered in remotely sensed data is shadow. This problem is a major source of confusion and misclassification in extracting land cover information from remote sensing data (Saha *et al.*, 2005). In addition, the presence of shadow can also lead to misleading results if change detection is applied to a ground surface because of changes in the shadows, depending on the time and season (Liu and Yamazaki, 2012).

So far, different shadow correction methods have been developed in order to produce shadow-free imagery or at least imagery with relaxed impacts due to shadow (Nakajima *et al.*, 2002; Arellano, 2003; Riano *et al.*, 2003; Saha *et al.*, 2005). A shadow correction algorithm is relied a two-step process: detecting the location of shadow and de-shadowing. However, only a few pa-

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Corresponding author: WANG Ke. E-mail: kwang@zju.edu.cn

pers have described this topic in detail (Riano *et al.*, 2003; Mather, 2004; Dare, 2005; Jensen, 2007; Ren *et al.*, 2009; Shahtahmassebi *et al.*, 2011). In particular, the investigations on the sequence of shadow correction (detection and de-shadowing) with respect to topographic shadow, urban shadow, cloud shadow, and composite shadow are missing. A synthesis of these studies is needed but thus far has fallen outside the scope of any single paper.

Motivated by this fact, this paper reviews the dominant shadow correction methods for both steps (detection and de-shadowing). Some advanced topics like the impacts of shadow on microwave imagery (Mather, 2004) are not discussed in this paper because they are specific to a selected research sub-field and limited by the data available.

2 What Is Shadow?

Shadow occurs when an object totally or partially occludes light directly from the light source (Arevalo *et al.*, 2008). Shadows can be divided into two classes: cast and self (Arevalo *et al*., 2005) (Fig. 1). A cast shadow is projected by the object in the direction of the light source; a self shadow is the part of the object which is not illuminated by direct light. The part of a cast shadow where direct light is completely blocked by its object is called umbra, while the part where direct light is partially blocked is called penumbra (Arevalo *et al*., 2008). Self and cast shadows produce different brightness values. Self shadows usually have a higher brightness than cast shadows since they receive more secondary lighting from surrounding illuminated objects (Dare, 2005). Cast shadows can, however, cause a significant reduction in spectral variation thereby causing correlation failure (Bishop *et al*., 2003).

The causes of shadow in remotely sensed imagery can be grouped into three categories: 1) Shadow by urban materials such as building and trees. This is a special problem in high spatial resolution imagery. 2) Shadow by mountain (topographic shadow). This can be a major difficulty in medium spatial resolution imagery and high spatial resolution imagery as well. 3) Cloud shadows. This problem can occur in high, medium, and coarse spatial resolution imagery.

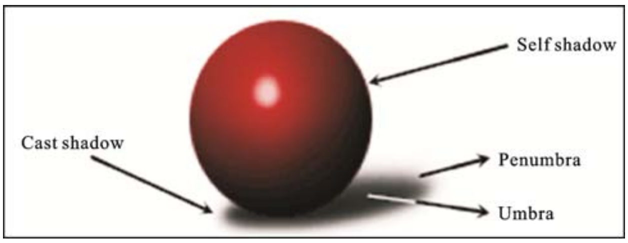

Fig. 1 Shadow types (Arevalo *et al*., 2005)

It is noteworthy that cloud shadow and topographic shadow are not spectrally distinguishable in optical imagery (Martinuzzi *et al*., 2007). However, their differences can be determined by geographic position. The direction of shadow occurrence relative to the cloud is the same for the entire scene as it depends on the sun illumination angle, a constant for any given scene (Martinuzzi *et al*., 2007).

In remote sensing, many research endeavours have been oriented towards the removing shadow from satellite imagery such as IKONOS and QuickBird (Nakajima *et al*., 2002; Sarabandi *et al*., 2004; Chen *et al*., 2007; Arevalo *et al*., 2008), Landsat ETM (Arora and Mathur, 2001; Riano *et al*., 2003; Saha *et al*., 2005; Yang *et al*., 2007; Richter *et al*., 2009), and National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) (Simpson and Stitt, 1998; Arellano, 2003). However, we can derive benefit from shadow. For instance, the characteristics of stand structure of the forest can be modeled by estimating shadow lengths and crown diameters of individual trees using high-resolution sensors like IKONOS data (Asner and Warner, 2003). In another example from Turkey, tree stem length was estimated from tree crown area and tree shadow area by using QuickBird imagery (Ozdemir, 2008). A low sun-angle image gives long shadows, and for this reason might be preferred by geological users because these shadows may bring out subtle variations in topography (Mather, 2004).

3 Shadow Detection Methods

3.1 Background

A lot of research has been conducted on the detection of shadow regions in remotely sensed imagery. Table 1 summarizes the major techniques. The type of method implemented can profoundly affect the qualitative and quantitative estimation of the shadow regions. In general, shadow detection algorithms are organized into two categories: thresholding and modelling (Liu and Yama-

Table 1 Summary of shadow detection methods

Technique	Advantage	Disadvantage	Characteristic	Reference
Thresholding	Simple, quick and easy	It can not well identify shadow regions from other dark objects	Based on spectral value, band ratio	Earthquake zeon (Miura and Midorikawa, 2006); forestry (Shahtahmassenbi *et al.*, 2011); glacier detection (Heiskanen *et al.*, 2002)
Modeling	Determining location of shadow precisely	Geometry of scene and light sources unknown, too restrictive	Use information of sensor, light source direction and geometry of observed objects	Urban (Nakajima *et al.*, 2002; Zhan *et al.*, 2005; Arevalo *et al.*, 2008)
Invariant color model	Being sensitive to shadow and able to discriminate between shadow and other dark objects in image	Instability for certain color values which leads to the misclassification of non-shadow pixels as shadow	Calculate ratio Hue-Saturation-Value (HSV) or ratio of Red, Green and Blue bands, color space $C_1C_2C_3$	Segmenting shadow (Tsai, 2006); urban (Sarabandi *et al.*, 2004; Arevalo *et al.*, 2008)
Shade relief	Simple, easy, and available in most remote sensing software	It does not calculate shadow that is cast by topographic features onto surrounding surface	Shaded relief technique based on solar elevation, solar zenith and Digital Elevation Model	ERDAS IMAGINE (9.1)

zaki, 2012). The first class includes the methods that elect a threshold value of the digital number (DN) (e.g., based on the histogram) to determine shadow areas from non-shadow regions. Most documented shadow detection techniques are based on the first class because they are not very complicated. The second group is based on a mathematical concept, which uses prior information, in order to simulate shadow regions.

Apart from these methods, there are other less-commonly used algorithms for detecting shadow regions, for example, the automatic cloud/shadow detection method (Hegarat-Mascle and Andre, 2009), the Self-Adaptive Feature method (Liu *et al.*, 2011), the detection of shadow based on pulse coupled neural networks (Huang *et al.*, 2011), object-based shadow extraction (Liu and Yamazaki, 2012), and visual interpretation (Ortega-Huerta *et al.*, 2012). However, we do not explore these methods here because they are often only appropriate for very specific uses and because it was not practical to analyze the precise contribution of each paper due to their specific nature. Further information can be found in Prati *et al.* (2003) and Al-Najdawi *et al.* (2012).

3.2 Thresholding

Thresholding is a range of techniques (e.g., Histograming, Vegetation Indices) to discriminate between shadow regions and non shadow areas (Nagao *et al.*, 1979; Cheng and Thiel, 1995; Rosin and Ellis, 1995; Shettigara and Sumerling, 1998). Thresholding can be performed by selecting only pixel values of shadowy regions. Speed and simplicity are the main advantages of thresholding techniques. One disadvantage of thresholding techniques is the difficulty in selecting suitable thresholds in order to distinguish shadow from similar objects due to the pixel similarity between them, for instance, water bodies and shadowy areas. Also, it might be difficult to discriminate between cloud shadow and topographic shadow (Martinuzzi *et al.*, 2007).

Miura and Midorkawa (2006) applied a thresholding technique on near infrared band of IKONOS data to eliminate shadow areas in an earthquake zone. Song and Civco (2002) used the brightness value in Landsat TM bands 1 (blue) and 4 (near infrared) to detect clouds and shadows in Madagascar. In another study, Dozier (1989) used a thresholding technique to discriminate snow from other materials in shadow. Shettigara and Sumerling (1998) thresholded SPOT (System for Earth Observation) images to extract shadows of buildings and trees, but due to the low resolution, there was no distinct peak in the histogram denoting shadow pixels. Heiskanen *et al.* (2002) successfully delineated glacier borders in cast shadows in the Svartisen ice cap in Norway by applying threshold values to the ETM+ thermal infrared band. Hendriks and Pellikka (2004) experimented with a glacier masking procedure combining a thresholded Normalised Difference Snow Index (NDSI) image and the thermal band of ETM+. Cheng and Thiel (1995) used an adaptive threshold method in their measurement of building heights from shadows in SPOT images. Building on these, Chen *et al.* (2007) developed the Spectral Shape Index (SSI) to distinguish shadow from water body. Most recently, Martinuzzi *et al.* (2007) used the brightness values in band 4 to differentiate cloud areas from non shadow areas. However, some topographic shadow in certain urban areas and land-water transition zones was included in cloud shadow regions.

Moreover, Lu (2006) detected clouds/hazes and their cast shadows on IKONOS images by thresholding technique which was based on the maximum and minimum filters and second-moment texture measures. However, this algorithm may not be appropriate for medium or coarse spatial resolution images because of the mixed spectral features from different land covers and clouds/hazes or shadow, and the lack of spatial information. In addition, this study highlighted that detecting haze or light shadow from other land covers is a challenging task because they have a mixture between hazes or light shadow with other land covers, thus they are often confused with bare soils or crown-cast shadow.

3.3 Modeling

Using model-based methods is another way to predict shadow, especially in urban areas. These methods include the sensors/camera localization, the light source direction and the geometry of observed objects, from which a priori knowledge of shadow areas is derived (Arevalo *et al.*, 2008). However, in most applications the geometry of scene and/or the light sources are unknown. Another disadvantage is in complex scenes with a great diversity of geometric structures, as is usually the case of QuickBird imagery, where these models are too restrictive to provide a good approximation.

Airborne Laser Scanner (ALS) data can also be used to simulated and detect shadow regions (Nakajima *et al.*, 2002, Zhan *et al.*, 2005). In this way, high quality and homogenous Digital Surface Models (DSM) can be directly derived from ALS data. Then the location of shadow is simulated by using sun angle and azimuth, which are taken from high spatial resolution data (e.g., IKONOS imagery) and height from DSM. Though valuable, this sort of data is rare, requires aircraft use, and is frequently prohibitively expensive.

3.4 Invariant color model

Shadow can also be detected by invariant color models. Tsai (2006) presented a method which uses the spectral ratio image in hue, intensity and saturation (HIS) space to segment shadow, but dark blue objects and dark objects in images were incorrectly segmented. Susuki *et al.* (2000) presented a method that applies separation of spatial frequency components and probabilistic shadow segmentation in the Red-Green-Blue (RGB) space and compensations of intensity and saturation values to improve the visibility of features in shadow region while retaining non-shadow region and the natural tint of shadow region. The parameters of the above methods only fit for limited illumination conditions and cannot be applied to complex images that include shadow cast by various features in complex environments (Tsai, 2006). Among many color spaces that are invariant to shadow such as Hue-Saturation-Value (HSV) or ratio of Red (R), Green (G) and Blue (B) bands, color space (C_1, C_2, C_3) can be used as the best non-linear transformation for purposes of shadow detection (Sarabandi *et al.*, 2004). These indices are defined as follows:

$$C_1 = \arctan\left(G/\max(R,B)\right) \tag{1}$$

$$C_2 = \arctan\left(R/\max(G,B)\right) \tag{2}$$

$$C_3 = \arctan\left(B/\max(R,G)\right) \tag{3}$$

where R, G, and B correspond to the red, green and blue values of each pixel in the image, respectively. Moreover, this technique is sensitive to shadow and is able to discriminate between shadow and other dark objects in the image. However, one of the problems when using the C_3 component is its instability for certain color values which leads to the misclassification of non-shadow pixels as shadow (false positives) (Arevalo *et al.*, 2008). This occurs for both pixels with low values of saturation and for pixels with extreme (i.e., low and high) intensity values (Gevers and Smeulders, 1999; Salvador *et al.*, 2001).

3.5 Shaded relief

Shadow can also be detected by the shaded relief algorithm. This is based on solar elevation, solar zenith and a Digital Elevation Model (DEM). According to the above parameters, areas that would be in sunlight are highlighted and areas that would be in shadow are shaded. It is important to note that the relief algorithm identifies shadowed areas, i.e., those that are not in direct sun (Fig. 2). However, this algorithm does not calculate the shadow that is cast by topographic features onto the surrounding surface (ERDAS IMAGINE 9.1).

In summary, thresholding is the most common approach for detecting shadow regions. This method is useful in many shadow detection applications, since it is

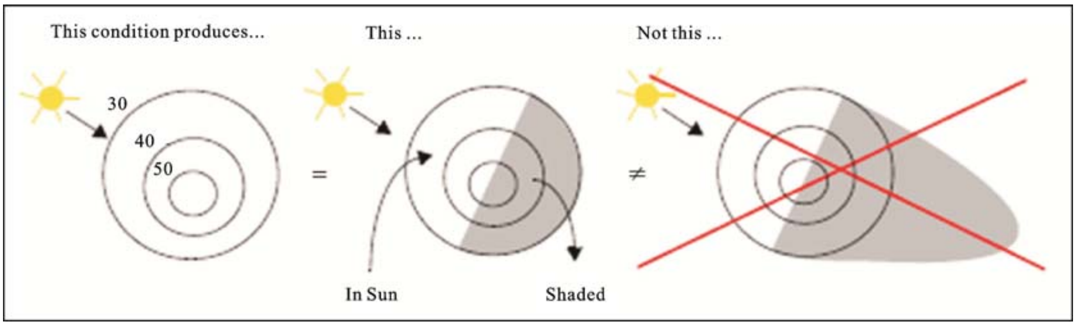

Fig. 2 Shade relief program in ERDAS imaging software. The contour values (30, 40 and 50) on image represent elevation. (ERDAS IMAGINE 9.1)

simple, quick and available in most commercial and non-commercial remote sensing software.

4 De-shadowing Methods

4.1 Background

After shadow detection, the next step is removing shadow or reducing impacts of shadow. Many algorithms have been developed to attain this objective. Table 2 provides brief description of these techniques. Shadow correction algorithms can be divided into two main groups: objects and techniques. From objects aspect, these algorithms fall into four classes—correcting topographic shadow, correcting shadow of urban components, correcting cloud shadows and correcting composite shadow. In terms of techniques, shadow correction algorithms are grouped into different categories based on corresponding objects. In the following subsection, we present details of these techniques.

It is noteworthy that more recent studies have been focused on recovery of information in shadow instead of eliminating shadowy regions or relaxing the effects of shadow (Nakajima *et al.*, 2002; Massalabi *et al.*, 2004; Zhan *et al.*, 2005; Liu and Yamazaki, 2012; Wan *et al.*, 2012). There are two major reasons to support this novel approach. First, although the reflectance recorded in the shadow regions is weak, there is still useful information in these areas which makes shadow restoration possible (Chen *et al.*, 2007; Wang *et al.*, 2008). Second, it may use surrounding information of shadowy areas (spatial information) in order to fill shadowy regions (Rossi *et al.*, 1994; Addink and Stein, 1999; Kouchi and Yamazaki, 2007; Shahtahmassebi *et al.*, 2011; Nole *et al.*, 2012).

4.2 De-shadowing technique in mountainous regions

In mountainous regions, shadows frequently occur in terrain areas with steep slopes when the sun elevation angles are low. Shadow areas show less reflectance than sunny areas which causes variation in the reflectance response, particularly when similar land covers appear with the different digital number (DN) (Riano *et al.*, 2003; Yang *et al.*, 2007). Fahsi *et al.* (2000) demonstrated that the strong topographic variations in mountainous terrain may cause pixels of the same forest cover type to be spectrally heterogeneous and pixels of different types to have similar spectral characteristics. As a result, the accuracy of forest maps produced from an automatic mapping procedure over steep mountainous terrain is often low (Dorren *et al.*, 2003). For this purpose, several methodologies have been proposed for removing or at least reducing the effects of mountainous shadows from remotely sensed data (Yang *et al.*, 2007; Gao and Zhang, 2009; Ren *et al.*, 2009), due to a strong influence of topography on the signal recorded by space borne optical sensors (Richter *et al.*, 2009).

4.2.1 Band ratio, vegetation indices and multisource classification

Band ratio and vegetation indices are the most common and simple approaches for decreasing impacts of topographic shadow (Riano *et al.*, 2003; Mather, 2004; Yesilnacar and Suzen, 2006; Jensen, 2007; Lu and Weng, 2007). For example, the NDVI strongly reduces the impact of varying illumination conditions and shadowing effects caused by variations in solar and viewing angle (Sotomayor, 2002). However, these techniques have some drawbacks. First, the band ratio is nonlinear and can be influenced by additive noise effects such as the atmospheric path radiance (Mather, 2004; Jensen, 2007). Second, spectral resolution will be lost when the band ratio is used (Riano *et al.*, 2003). Furthermore, some vegetation indices based on the constants such as Enhanced Vegetation Index (EVI) are more sensitive to the

Table 2 Summary of de-shadowing techniques

	Technique	Advantage	Disadvantage	Characteristic	Reference
Category I. Forest	Visual interpretation	Easy, simple, and quick	Costly, time consuming	Visual analysis	Ren *et al.*, 2009
	Band ratio and vegetation indices	Strongly reducing impacts of shadow	Non-linear Be influenced by additive noise Spectral resolution will be lost	Calculating band ratio	Riano *et al.*, 2003; Mather, 2004; Yesilnacar and Suzen, 2006; Jensen, 2007; Lu and Weng, 2007
	Multisource classification	Nullify topographic component	Resolution and accuracy of DEM will influence performance of topographic correction	Combining DEM with vegetation indices	Giles *et al.*, 1994; Dorren *et al.*, 2003; Saha *et al.*, 2005
	Topographic correction models	Normalize area of sunlit canopy	Do not explain relationship between terrain, shadow and shadowing Lacking comprehensive physical analysis	Mathematical models	Ekstrand, 1996; Tokola *et al.*, 2001; Bishop *et al.*, 2003
	Recovery techniques	Restored information in topographic shadow	Meet difficulties in complex landscapes with mixed pixel problems	Mathematical models	Shahtahmassebi *et al.*, 2011
Category II. Urban	Recovery information in shadow	Restore information in shadow without removing shadow regions	Background problem and time consuming	Data mining techniques	Nakajima *et al.*, 2002; Zhan *et al.*, 2005; Chen *et al.*, 2007
	Histogram matching	Recover DN values of shadow-covered pixel	Be sensitive to window size	Image processing techniques	Sarabandi *et al.*, 2004; Dare, 2005
	Multisource data fusion	Use information of two images	Limitation of image acquisition time Image registration error	Fusion techniques	Dare, 2005; Zhou *et al.*, 2009
Category III. Cloud	Microwave data	Do not have cloud contamination problem	Emitted energy is very low Large area should be imaged Be poor resolution		Arellano, 2003
	Hybrid algorithm	Fast, exclusively on spectral calculation Avoid time consuming geometric cloud/shadow pattern considerations	Useful geometric information is neglected	Based on spectral information	Richter and Muller, 2005
	Multisource fusion and multi-date imager	Fill shadow regions	Can not use for small cloudy regions Co-registration, sensor viewing and solar geometry	Wavelet technique Fusion	Carvalho, 2001; Arellano, 2003; Roy *et al.*, 2008
	Unmixing	Use information of shadow regions Be available on remote sensing software	Endmember collection Neglect diffuse skylight	Based on concept of unmixing process	Richter and Muller, 2005

topographic effects than band ratio indices (NDVI) (Matsushita *et al.*, 2007). This is because their constants (e.g., soil adjustment factor in the EVI) make these indices much more sensitive to the direct effects of topography.

Applying multisource classification with the help of ancillary data such as Digital Elevation Models (DEM) and NDVI is another way to reduce the impacts of shadow (Giles *et al.*, 1994; Dorren *et al.*, 2003; Saha *et al.*, 2005). The use of NDVI imagery as an additional layer has been recommended, since the band ratio derivatives may help in nullifying the topographic component to some extent (Holben and Justice, 1981; Apan, 1997). Eiumnoh and Shrestha (2000) exploited the advantages of incorporating both NDVI and DEM in the classification process and showed an improvement in the classification accuracy on the order of 10% to 20%. However, using DEM as an additional band for shadow correction also poses some difficulties. First, the resolution and accuracy of DEM would influence the performance of topographic correction (Conese *et al.*, 1993; Law and Nichol, 2004; LeciaGeosystems, 2008). Second, the additional input bands do not always guarantee better classification results (Blesius and Weirich, 2005).

4.2.2 *Topographic models*

Many researchers have attempted to improve land cover classification in mountainous regions by using topographic correction models such as cosine correction, C correction, and Minnaert correction (Ekstrand, 1996; Tokola *et al.*, 2001; Bishop *et al.*, 2003). Colby (1991) developed a backward radiance correction model which utilizes the Minnaert constant based on the non-Lambertian assumptions. The method can be used to minimize differences in values of brightness for similar surface materials caused by topographic conditions, shadows or seasonal changes in sun illumination factors. The Sun-canopy-sensor (SCS) correction is the appropriate method in forested terrain since it normalizes the area of sunlit canopy rather than the underlying terrain (Gu and Gillespie, 1998). However, they still do not fully explain the relationship among terrain, crown structure, shadowing and mutual shadowing within a forest and tree canopies (Soenen *et al.*, 2007). Topographic models may also not be suitable for classification of vegetation cover in rugged terrain areas, because tree crowns are usually in certain shapes and can not be considered as a plane. Other disadvantages include a lack of comprehensive physical analysis, subjectivity in operation and separation of atmospheric correction (Yang *et al.*, 2007).

4.2.3 *Recovery information in topographic shadow*

Another possible approach to reduce the effects of topographic shadow is restoring information in shadow areas based on surrounding information. In this technique, Shahtahamssebi *et al.* (2011) restored the information in topographic shadow by using two filling methods in order to improve the accuracy of a forest map over mountainous regions (Fig. 3). The results suggest that filling algorithms were simple and cost-

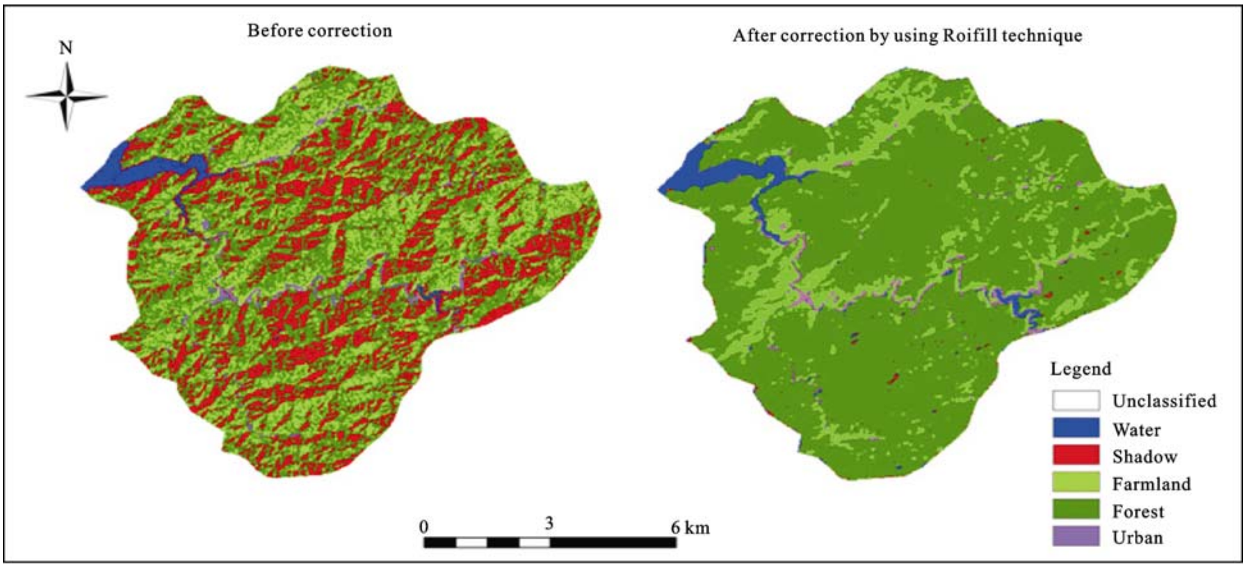

Fig. 3 Forest cover map before and after shadow correction (Bada Town land cover and forest map derived from Landsat ETM + September 2000). Roifill is one of the filling algorithm (Shahtahmassebi *et al.*, 2011)

efficient for reducing effects of topographic shadow. However, these techniques may meet difficulties in complex landscapes with the 'mixed pixel' problem, especially on forest borders (Shahtahmassebi *et al.*, 2011). Moreover, this technique is based on conventional interpolation techniques which consider uniform variability throughout the whole image. However, spatial structure occurs in remotely sensed images and spectral information is not uniformly distributed across the landscape (Zhang *et al.*, 2011).

4.3 De-shadowing technique in urban areas

High spatial resolution images such as QuickBird have opened a new window of using remotely sensed imagery in urban regions because of the possibility of extracting detailed information. However, the improvement in spatial resolution of satellite imagery affects shadows such that it causes the partial or total loss of radiometric information in the affected areas (Arevalo *et al.*, 2005). Therefore shadow regions decrease the quality of these data in terms of visual interpretation and classification. For example, there are many shadow areas in urban areas, and it becomes difficult to extract information in these areas from high-resolution satellite imagery like IKONOS due to the high object density and the relatively high proportion of the shadow-covered areas (Nakajima *et al.*, 2002).

Recently image restoration has become an active area of remote sensing research for de-shadowing in urban areas in high spatial resolution imagery (Fig. 4). The core hypothesis of this technique is that there is still useful information in shadow regions though the signals recorded in these areas are quite weak (Sarabandi *et al.*, 2004; Chen *et al.*, 2007; Liu and Yamazaki, 2012). Therefore, it is likely to improve signals in the shadow regions instead removing the signals. As sunlight is the primary energy source of passive remote sensing, it is assumed R_s (Reflectance of atmospheric elements (skylight)) and R_{sr} (Reflectance of a ground object caused by scattered sunlight) are both in proportion to R_{dr} (Reflectance of a ground object caused by direct sunlight) (Chen *et al.*, 2007). Accordingly there should be a linear relationship between radiance in the shadow area and in the non-shadow area, and the relationship is actually the relationship of illumination condition between shadow area and non-shadow area. Different equations can be used to recover information in shadow. For example, several studies have adopted the amount conversion of statistics for this purpose as described in Equation (4) (Nakajima *et al.*, 2002; Zhan *et al.*, 2005; Chen *et al.*, 2007) (Fig. 4-third line):

$$y = {}^{S_y}\!\!/_{S_x}\left(x - x_{\mathrm{m}}\right) + y_{\mathrm{m}} \tag{4}$$

where x is the grey value of shadow area, y is the grey value of output, and S_x and S_y are the standard deviation of shadow area and non-shadow area, respectively. x_{m} and y_{m} are the mean values of shadow area and non-shadow area, respectively. Some researchers have used gamma correction techniques (Nakajima *et al.*, 2002) (Fig. 4-second line), object-based approach (Zhan *et al.*, 2005), linear-correlation and histogram matching (Sarabandi *et al.*, 2004). Although the recovery techniques make certain improvements in recovering information, they also have shortcomings. For instance, the gamma correction approach uses a single gamma parameter for all pixels, thus ignoring the existence of different backgrounds of shadow areas. It is also time-consuming to manually determine the category of a shadow area (Zhan *et al.*, 2005).

Histogram matching is one of the classical methods used to bring the brightness distributions of two given images as close as possible to each other (Sarabadni *et al.*, 2004; Dare, 2005). This method is used to recover the DN values of the shadow-covered pixels by matching the histogram of the shadow regions to the histogram of the non-shadow areas of the same class. However, this operation is sensitive to the window size in which the histograms are matched. Detailed descriptions of histogram matching can be found in Shu and Freeman (1990), and Rau *et al.* (2002).

Multisource data fusion and multi-temporal imagery are other techniques for reducing the effects of shadow in high-resolution imagery (Dare, 2005). Multisource data fusion works by replacing shadow pixels in one image with non-shadow pixels of the same region on the ground from another image acquired at a different time. In terms of multi-temporal imagery, multiple images are acquired at different time over a specific region (Tseng *et al.*, 2008). Zhou *et al.* (2009) compared three methods for land cover classification of shaded areas from high spatial resolution imagery in an urban environment. The result showed that multisource data fusion provides a significantly better means for shadow classification than

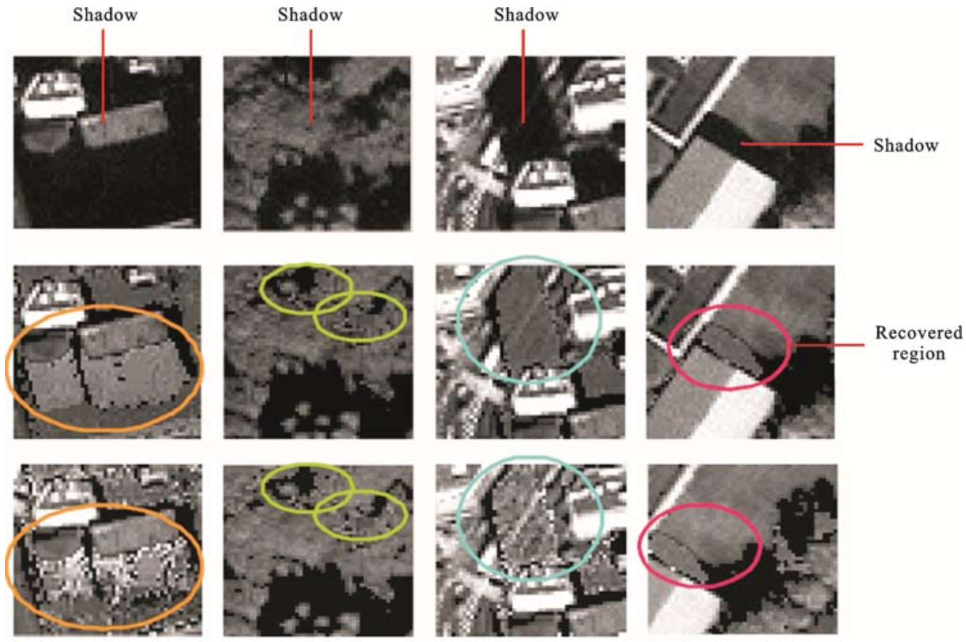

Fig. 4 Two examples of recovery information in shadow. Images in first line are original IKONOS images, which are building, tree, road and ground from the left to right; the second line shows images after using gamma correction; the third line indicates the result after using the amount conversion of statistics shadowing based on Equation (4) (Nakajima *et al.*, 2002)

the other two methods. Gotez *et al*. (2003) demonstrated that multi-temporal imagery could be useful for reducing impacts of shadowing within the forest canopy from adjacent trees.

However, there are a number of problems with applying multisource imagery fusion to high-resolution satellite imagery (Dare, 2005). First, it is unlikely that non-shadowed data can be extracted from another high-resolution satellite image since the limitations on image acquisition time (described above) will lead to the same regions on the ground being in shadow. Second, the images must be accurately registered to each other to ensure the correct pixels are being used in the fusion procedure. In a high density urban environment accurate image registration poses significant problems. Also regarding multi-temporal imagery, this process would be logistically difficult to accomplish in many areas, and cost-prohibitive for most applications using IKONOS (Goetz *et al*., 2003).

4.4 De-shadowing cloud shadow

The average percentage of cloud cover in equatorial regions is on the order of 75% and in some regions like northwestern Europe—during the least cloudy months—cloud coverage remains around 40% (Arellano, 2003). In optical remote sensing, cloud shadows caused by spectral irradiance reaching the ground in cloud-shadow areas is both reduced in intensity and altered in its spectral properties (Choi and Milton, 1999; Lu, 2007). As a result, clouds and their shadows decrease the quality of remotely sensed data. Simpson and Stitt (1998) found that cloud shadow can produce both negative and low-positive values of NDVI, especially in highly vegetated areas where cloud shadow attenuates. Because of this natural variability in NDVI, simple thresholding schemes can not accurately classify pixels contaminated by cloud shadow in an arbitrary scene.

The first solution might be to use radar data because radar operates in the microwave range of the electromagnetic spectrum and has no cloud contamination problem (Arellano, 2003). However, radar does not always provide promising results. In fact, the emitted radiation in the microwave range is very low while in the visible range the maximum energy is emitted. As a result, in order to obtain imagery in the microwave region and measure these signals, which are weak, large areas are imaged; consequently, this results in relatively poor spatial resolution (Arellano, 2003).

Richter and Muller (2005) conducted the hybrid algorithm by using visible channel and shortwave infrared bands to de-shadow cloud shadow satellite and airborne imagery. The advantage of the presented method is its fast processing performance, because it relies exclusively on spectral calculations and avoids time-consuming geometric cloud/shadow pattern considerations. This algorithm consists of five major components: 1) calculation of the covariance matrix and zero-reflectance matched filter vector; 2) derivation of the unscaled and scaled shadow function; 3) histogram thresholding of the unscaled shadow function to define the core shadow areas; 4) region growing to include the surroundings of the core shadow areas for a smooth shadow/clear transition; and 5) de-shadowing of the pixels in the final shadow mask. The drawback is that useful geometric information is neglected.

For many other areas, cloud cover is a confounding factor and precludes the use of single image updates of land cover per year, and thus per pixel processing methods using multisource data fusion or multi-date imagery are required for such areas (Wang *et al*., 1999; Hansen and Loveland, 2012). Roy *et al*. (2008) developed a semi-physical fusion approach that used Moderate Resolution Imaging Spectro radiometer (MODIS) and Landsat ETM + data to decrease impacts of cloud shadow (Jin *et al*., 2013). Using robust nonlinear wavelet regression is another way to reduce impacts of clouds and their shadows (Carvalho, 2001). This approach predicts the reference values for clouded areas better that all other approaches do, and performs almost as well, equivalent to linear prediction in shadow areas. In another study, wavelet image fusion was applied to detect clouds and their shadow and subsequently fill out the missing information in a multi-temporal set of ASTER images (Arellano, 2003). However, the author warned that this method could not perform well for smaller clouds compared to bigger clouds because the borders of small clouds were not detected during cloud detection. In other words, the success of this technique depends on the detection of clouds and their shadows. As stated in the previous subsection, the major problems of the multi-temporal technique and data fusion are also co- registration, computing sensor viewing and solar geometry (Roy *et al*., 2008).

Another technique employs unmixing of atmospherically corrected data using the concept of spectral endmembers (Richter and Muller, 2005) (Fig. 5). Shadow is defined as a zero-reflectance endmember, and the sum of all endmember weights is constrained to 1. After unmixing, the de-shadowing operation divides the reflectance by 1 minus the sum of the non-shadow endmember weights. Problems with this approach include the dependence of the results on the choice of endmembers and the neglecting of the diffuse skylight.

4.5 De-shadowing composite shadow

The previous section discussed about a certain type of shadow and corresponding de-shadowing techniques. However, it is interesting to consider the relationship between different shadow types and composite situation because sometimes all the shadow type might be simultaneously appeared within an image scene in the certain situation. For example, Lu (2007) found that cloud shadow and tree crown shadow could appear together in the forest region within the IKONOS image. This situation poses substantial new challenges for correcting impacts of different shadow simultaneously or sequentially.

So far most of the approaches for de-shadowing have been developed for correcting impacts of one type of shadow. However, relatively little research has been conducted on the de-shadowing composite shadow. This can be partially explained by three factors. Firstly, each shadow condition has its own characteristics and correction techniques as discussed in the previous sections. In addition, different shadow types have different effects on ground-measured visible and near infrared shadow reflectance (Leblon *et al*., 1996). Secondly, de-shadowing algorithms have been generally specified for one type of sensor. For example, the gamma technique is more appropriate for high spatial resolution imagery than medium spatial resolution data. Third, there is no universal rule to determine the sequence of de-shadowing.

Although there is a lack of reference concerning a standard procedure for correcting impacts of composite shadow, the following points might be useful to do this task.

4.5.1 Sequence

If the image scene has been contaminated by different types of shadows, the question for this situation becomes which type of shadow is important and should be corrected first. As already mentioned, there is no sufficient citation to support a sequence of de-shadowing in this aspect.

Nevertheless, it might be possible to determine this sequence through understanding importance of each type of shadow separately. The result of a literature

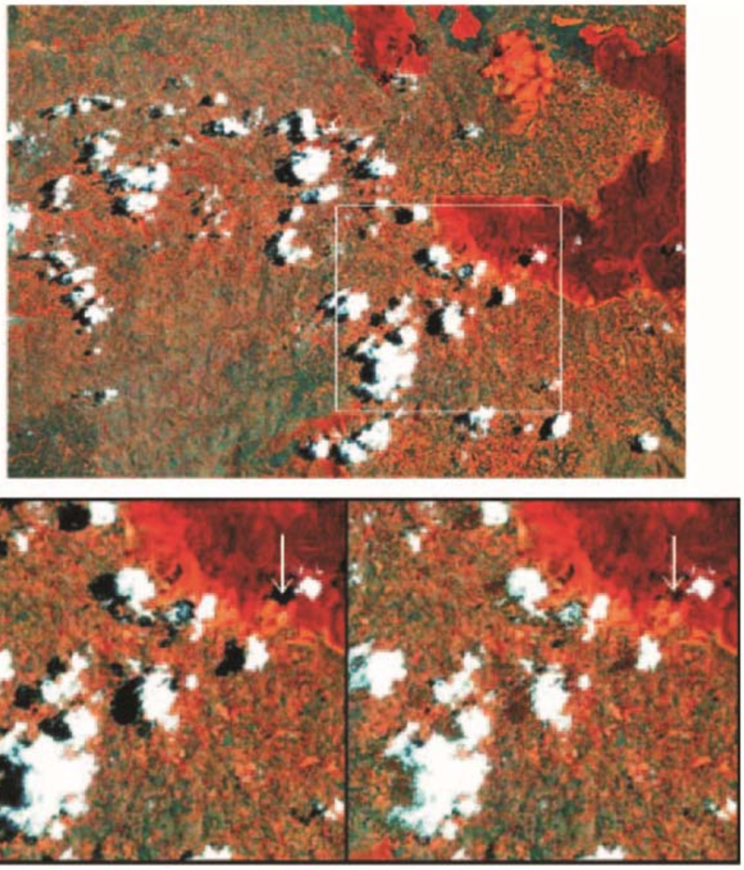

Fig. 5 Landsat ETM + before (left) and after (right) de-shadowing (Richter and Muller, 2005)

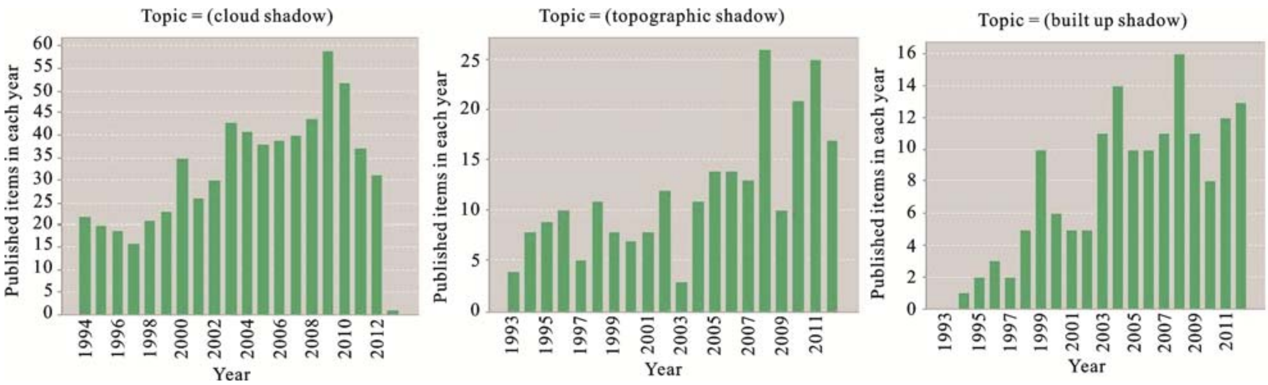

Fig. 6 Yearly publications from 1993 to 2012 and from 1994 to 2013 indexed by web of knowledge. The search was conducted on November 29, 2012 in order to determine sequence of de-shadowing in composite condition

search via web of knowledge, the largest abstract and citation database of Science Citation Index (SCI) journal publications, indicates that more weight has been given to the cloud shadow correction and topographic shadow correction, respectively (Fig. 6). The last priority is correcting small ground features shadow like urban shadow and crown tree shadow.

It should be made clear that topography shadow and clouds shadow causes serious interferences in remotely sensed and some target occlusion (Statella and Da Silva, 2008). These authors also found that clouds can also reduce the useful area of the image as much for the occlusion as for their projected shadows on the ground. By contrast, the problem of the ground features shadows is only significant for a particular part of the image such as urban environment or forest (Zhou *et al*., 2009). Accordingly, if all types of shadows have existed in the image scene, it would be better to carry out the following sequence respectively: 1) de-shadowing cloud shadow, 2) de-shadowing topographic shadow, and 3) de-shadowing ground features shadows.

4.5.2 Sensor

In the composite situation, the de-shadowing process may also depend on the spatial resolution of sensor. Shadow correction approaches for medium and coarse resolution data are generally limited to the cloud shadow and topographic shadow correction. In high spatial resolution data, however, ground features shadows are added to the scene, for example, tree shadow and built-up shadow. Beside this, the region under shadow is more heterogeneous in these images compared to the medium and coarse spatial resolution data. Therefore, the remote sensing community should develop a technique/techniques not only to detect and correct cloud and topographic shadow in high spatial resolution imagery but also to do similar jobs for ground features′ shadows.

4.5.3 Technique

Supposing that all kinds of shadow simultaneously occur within an image scene, it is clear that the range of possible techniques that can be used for shadow correction is extremely limited. In this spirit then, the basis for correcting the impacts of a composite shadow should be focused on cost-effective techniques (it can be used for all types of shadows and sensors) and on decreasing impacts of shadow either simultaneously or sequentially.

Vegetation Indices and multiple techniques (multi-source and multi-temporal) approaches may more generally be appropriate for this situation, partly because they may use for all type of shadows and for all sensors, and partly because they can simultaneously carry out. In other words, we do not need follow a sequential procedure. The strength of the Vegetation Indices such as NDVI is in its ratioing concept, which reduces many forms of noise (e.g., cloud shadows, illumination differences and certain topographic variations) present in multiple bands (Ahmad, 2012).

Recently, with the wide availability of the different types of satellite data, there is a possibility of using multiple techniques (multisource and multi-temporal) for de-shadowing impacts of composite shadow. These techniques can reduce the uncertainty associated with data acquired by different sensors or by same sensor with temporal variation (Nizalapur, 2008). Zhou *et al*. (2009) compared three methods for land cover classification of shaded areas from high spatial resolution imagery in an urban environment. They found that multisource data fusion achieved the best accuracy. A number of studies indicated that wavelet merging techniques yielded a better improvement of spectral and spatial information contents (Lu, 2006). It should be noted that these studies have be focused on one type of shadow. Nevertheless, their algorithms would be a useful example for reducing effects of a composite shadow.

5 Software

In this sense, remote sensing software packages have provided some choices in order to detect and remove shadowy regions. Variety of remote sensing software (commercial and non-commercial) can be used for shadow detection by histogram thresholding. In addition, commercial software such as ERDAS IMAGINE and IDRISI Andes offer the shade relief technique to simulate shadow areas. However, shade relief technique does not simulate cast shadow regions.

It is noteworthy that VIPER TOOL 1.5 has provided a relatively complete package for detecting and removing shadow. The primary advantage of this package is that it can explore the best relationship between image bands and cosine of the incidence angle for modeling and removing topographic shade. The VIPER TOOL 1.5 is free of charge and must be added to ENVI.

Another software is Atmospheric and Topographic Correction for satellite imagery (ATCOR). In this software, cast shadow can be calculated based on solar zenith and azimuth angle employing a ray tracing program. This software is add-on ERDAS IMAGINE 9.1.

Last but not least, at an advanced level, programming is an independent and a practical way for shadow correction. For example, cloud shadow pixels in image date 1 can be replaced by corresponding pixels from image date 2 by writing some simple code in the ENVI equation menu (Lu, 2007).

6 Discussion and Recommendation

Shadow correction consists of a sequence of two processing steps: shadow-detection and de-shadowing. The crucial factors for successfully implementing shadow correction are the object of shadow (e.g., topographic shadow), the spatial resolution of the sensor and the type of shadow. Also identifying a suitable shadow detection technique and de-shadowing method has considerable significance for precise shadow correction procedure in order to produce shadow-free imagery or to at least reduce impacts of shadow.

Those shadow detection methods based on a determination of thresholds for identifying shadow from non-shadow areas have a common problem: it is difficult to discriminate true shadow pixels from non-shadow regions such as water due to the pixels′ similarity phenomena. Although shadow detection based on non-linear techniques is very sensitive to shadow area, they cause the mixed pixel problem between shadow and non-shadow areas similar to thresholding techniques. Shadow detection techniques based on the shaded relief technique can avoid such problems but require highly accurate DEMs and it does not detect cast shadow as well.

In terms of de-shadowing techniques, these approaches may vary with the objects of shadow and sensor types. For example, the impacts of shadow due to urban material in high resolution imagery may be relaxed by using recovery techniques (Liu and Yamazaki, 2012). For medium spatial resolution data, however, these techniques may not provide promising results for reducing impacts of topographic shadow. One common technique for removing shadow regardless of shadow object is band ratio which can be used for coarse, medium and high spatial resolution data (Yesilnacar and Suzen, 2006; Lu and Weng, 2007). However, this technique is nonlinear and might be influenced by additive noise effects such as atmospheric path radiance (Mather, 2004; Jensen, 2007). Also, topographic effects such as shadow may produce more error on some vegetation indices based on the constant value (e.g., EVI) (Matsushita *et al*., 2007). Advanced de-shadowing techniques such as topographic models (for removing topographic shadow), and recovery approaches (for retrieving information in shadow in urban regions) and wavelet transformation (for cloud shadow removing) appear to be choices, but still some difficulties exist over them. For example, using recovery techniques in high spatial resolution image is manual and time consuming. Moreover, although topographic correction models are efficient, they are very complex.

The merits and demerits of shadow correction techniques discussed in this paper could be considered as a guideline to improve previous techniques or develop new methods. Our general recommendations of improving previous techniques are:

(1) Shadow correction algorithms (detecting and de-shadowing) are generally required to be robust, fast, accurate and automatic.

(2) These algorithms should reduce impacts of mixed pixel problem between shadow regions and similar objects to the shadow (e.g., water body, forest and buildings) that appear dark on images, thus, improving accuracy of land cover mapping.

(3) In developing and improving shadow correction techniques, one should also bear in mind the needs of purifying information in shadow as much as possible instead removing or losing this information.

(4) Several studies demonstrated that shadows are an accentuated problem in medium spatial resolution imagery (Asner and Warner, 2003; Saha *et al.*, 2005; Gitas and Devereux, 2006; Shahtahmassebi *et al.*, 2011) and high spatial resolution imagery (Nakajima *et al.*, 2002; Zhan *et al.*, 2005; Chen *et al.*, 2007; Lu, 2007).In addition, the amount of such data is growing sharply. As a result, it is necessary for future research to develop guidelines on correcting shadow regions on these images, especially topographic shadow and shadow in urban regions.

The following specific recommendations may help to develop new shadow correction algorithms:

(1) Shadow regions can be considered as abnormal/noisy areas within the remotely sensed image. As a result, the integration of target/outlier detection techniques (e.g., clustering) might be an appropriate way to detect location of shadowy regions instead simple thresholding techniques.

(2) Although many studies are focused on improving shadow detection techniques, few methods have developed for detecting cast shadow (Giles, 2001; Dare, 2005; Lu, 2007). Therefore, future research should be focused on discerning differences between cast and self shadow on remote sensing data, thus detecting accurately shadowy regions.

(3) Technically speaking, shadow regions can be considered as missing areas within a remotely sensed image. Although conventional interpolation techniques such as bilinear interpolation would be suitable to fill shadowy pixels in images, these techniques might be inappropriate for this attain. The reason is that these techniques consider uniform variability throughout the whole image

while spatial structure occurs in remotely sensed images and spectral information is not uniformly across the landscape (Zhang *et al*., 2011). Therefore, it should be evaluated the use of other approaches, particularly based on geostatistical techniques, which take into account spatial autocorrelation (Tobler, 1970; Rossi *et al.*, 1994; Addink and Stein, 1999; Zhang *et al*., 2007; Pringle *et al*., 2009; Zhang *et al*., 2009; Zhang *et al.*, 2011; Nole *et al*., 2012; Zhu *et al.*, 2012), in order to retrieve missing values in shadow areas.

(4) The comparative performance of various algorithms in different regions (e.g., rugged terrain, hills, plant canopy) must be examined quantitatively, otherwise those interested in correcting shadow in a specific regions may not obtain optimal results because of lack of information about tried and evaluated steps of shadow correction. Remote sensing communities need to know which techniques to apply in which situations. In addition, most remote sensing software programs are composed of atmospheric correction, geometric correction, and radiometric correction tools but such software do not offer any special tool or menu for shadow correction procedure (detection and de-shadowing). To this end, we suggest following a sample decision tree algorithm to be evaluated and then added to the remote sensing software for deciding which technique should be used in a given situation (Fig. 7). It should be noted that the structure of this algorithm (shadow correction parts) is important, not any specific method in it, because one may select another technique.

(5) Many studies are focused on correcting impacts of one type of shadow. However, all types of shadow might appear in the image at the same over certain situation (e.g., forest, urban). Therefore, more research is needed to develop advance techniques for correcting impacts of composite shadow.

7 Conclusions

Image pre-processing has different steps, among which shadow correction is one of the crucial steps. In a way, the accuracy of land cover classification and change detection relies on this step. The objective of shadow correction (shadow detection and de-shadowing) in land cover remote sensing represents a significant challenge and it has led to some the most innovative algorithms in

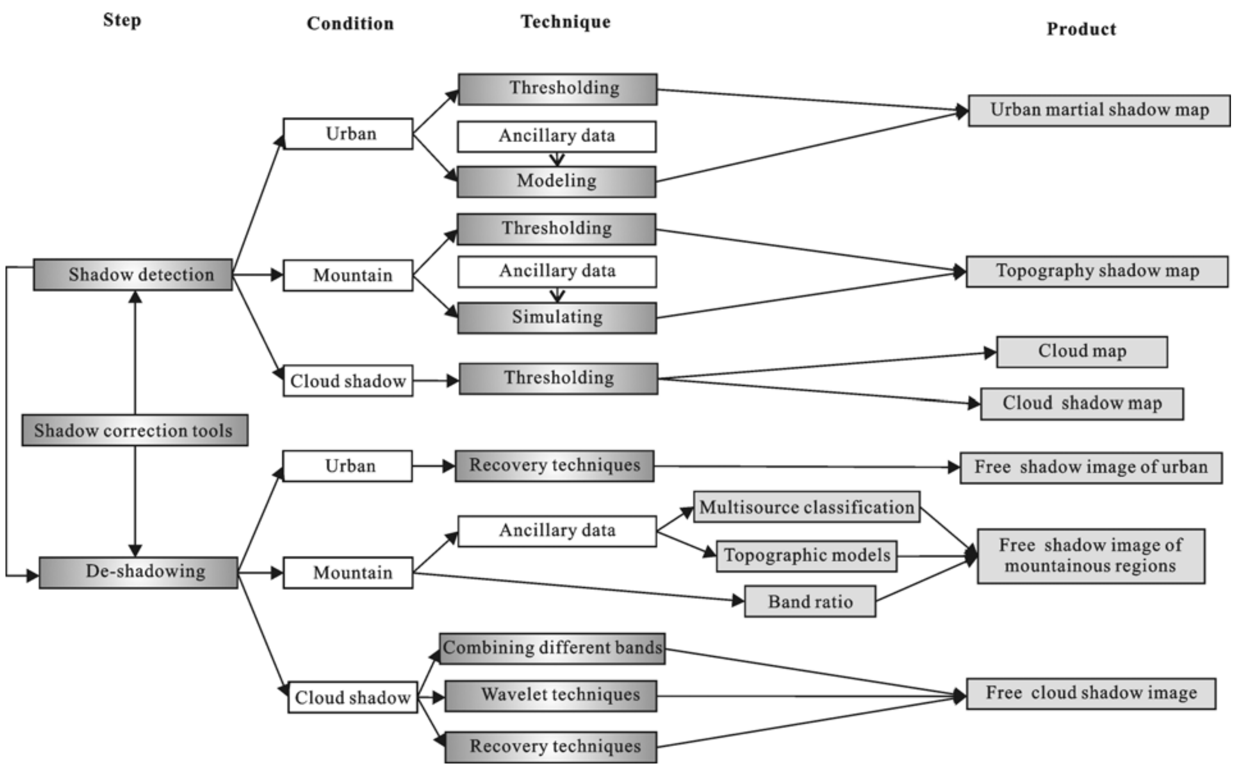

Fig. 7 A sample shadow correction decision tree for adding to remote sensing software. Ancillary data includes DEM, temperature image, Lidar data, *etc*.

image pre-processing and related fields in recent years, particularly predicting information in shadow regions (recovery). The ability to correct shadow regions depends on an accurate and effective strategy of both detecting shadow and de-shadowing, both of which are fundamentally important to our conception and understanding of producing a shadow-free image.

The commonly used shadow detection techniques and de-shadowing methods in the shadow correction procedure are thresholding and recovery information in shadow, respectively. There is a need for classification of various algorithms that have been employed in shadow correction research to allow greater understanding of their disadvantages and advantages. Also, by increasing the amount of remotely sensed data, particularly new data, there is a need to develop new shadow correction algorithms. In addition, a standard shadow correction tool should be added to remote sensing software.

Moreover, future research is likely to be focused on using target detection techniques and geostatistics in order to detect shadow regions and predict information in corresponding regions, respectively. In addition, future research needs to develop appropriate algorithms for de-shadowing effects of composite shadow.

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