A MULTISTAGE APPROACH FOR DETECTING AND CORRECTING SHADOWS IN QUICKBIRD IMAGERY

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ABSTRACT

High spatial resolution satellite imagery provides excellent opportunities for detecting fine spatial details on the ground. However, shadows that exist in high resolution images also create problems for land cover classification and environmental application. In various image classification studies, shadows have been either left unclassified or expediently assigned as a class. The class of shadow is not informational and as a result, the real land cover under shadows remains unknown. Furthermore, when using high resolution images to address environmental issues, we most likely need to assess the condition of land cover in addition to identifying land cover types. But radiance values of shadow pixels are contaminated and thus cannot be directly applied to quantitative environmental assessment. A multistage approach for detecting and correcting shadows is proposed in this study. QuickBird imagery of the Falcon Heights – Roseville area in Minnesota was used as an example to examine the results of the proposed methods. We first measured the spectral radiance and reflectance of different types of shadows. These spectral radiometric properties were examined and used as the basis for reclassifying shadows to different information classes and for obtaining shadow-free radiance values. A two-step ISODATA clustering algorithm was employed to detect shadowed areas. The detected shadow areas were corrected by the K-nearest neighbor algorithm and the linear correlation correction method for predicting values of shadow pixels. The classification accuracy and visual appearances were compared to evaluate the effectiveness of spectral radiometric restoration.

KEYWORDS: Land use and land cover, Classification, Shadows, High-resolution, QuickBird, Urban

INTRODUCTION

Urban land use and land cover have significant effects on local environment and global climate. There is an urgent need for developing strategic conservation planning for more environmentally sustainable cities based on the scientific understanding of landscape patterns. Detailed and accurate land use and land cover information is essential to document the current state of urban environment, to evaluate what and where changes have been made on the landscape, to examine the cause of these changes, and to predict the impact on ecological processes and climate change.

It has been widely recognized for decades that satellite observations of the Earth’s surface can be used to document land use and land cover. But until recently, satellite imagery has been limited in quantifying urban landscape patterns because of its low resolution in relation to the high spatial heterogeneity of urban land surfaces. The recent availability of high spatial resolution satellite imagery (e.g., QuickBird and IKONOS) provides opportunities to better resolve the spatial details of urban landscapes at fine scales. High resolution sensors are able to detect smaller objects and distinguish closely spaced objects; the small pixel size of high resolution imagery makes it possible to estimate urban land cover at the meter and sub-meter levels. With high resolution data, nearly every patch of urban land cover can be accounted for.
High spatial resolution images are appealing to land use and land cover classification in urban areas. However, the analysis of these images also requires sophisticated digital image processing techniques to deal with new challenges such as the problem of shadows. Extensive shadows regularly exist in high resolution images largely due to the narrow field of view of satellite sensors as well as the low solar elevation at the time of image acquisition. For instance, the instantaneous geometric field of view of QuickBird imagery is 61 cm at nadir for the panchromatic band and 2.44 m at nadir for the four multispectral bands. Shadows in remotely sensed imagery occur when objects totally or partially occlude the direct light from a source of illumination (Yao and Zhang, 2006). In urban areas, the problem of shadows becomes more complex because of the dramatic changes in surface elevation over a short distance (Dare, 2005). As a result, a significant proportion of high spatial resolution imagery in urban areas can be affected by shadows; this creates great difficulty in directly applying imagery data to document urban land use and land cover.

Shadows in high resolution imagery often lead to the reduction or total loss of spectral radiometric information, on which the interpretation of land cover and the evaluation of ground condition depend (Dare, 2005). Shadowed areas have been traditionally left unclassified or simply classified as shadows (Shackelford and Davis, 2003). The class of shadow is not informational and consequently, the real land cover under shadows remains unknown and a significant portion of land cover is lost in the classification. Reduction of spectral radiometric information could potentially lead to misclassification or inaccurate derivation of biophysical variables from shadow pixel values (Leblon et al., 1996). Total loss of such information means that shadowed areas of the image cannot be interpreted. In both cases, shadows pose an enormous challenge for applying high resolution satellite imagery to urban land use and land cover classification and environmental impact analysis. Without resolving shadows in satellite images, any further analysis of urban environment and climate becomes uncertain.

Resolving the shadow problem is two-fold: shadow detection and shadow removal. The former refers to the process of identifying pixels that are contaminated by shadows in remotely sensed imagery, whereas the latter is to restore the spectral radiometric information of those pixels to obtain a shadow-free image. Resolving shadows also includes two stages: shadow detection and removal in remotely sensed imagery and subsequently in land use and land cover classification map. That is to say, shadows are first identified in remotely sensed images and the spectral radiometric response was restored for shadowed areas before classification. Although a number of studies have investigated shadow detection and removal in high resolution remote sensing imagery (Rau et al., 2002; Sarabandi et al., 2004; Dare, 2005; Li et al., 2005; Tsai, 2006; Chung et al., 2009), only a few studies have assessed the impact of shadows on urban land use and land cover classification. Zhou et al. (2009) found that the shadow problem in land cover classification of aerial imagery data could be reasonably eliminated with object-oriented classification methods after thresholding shadow from non-shadow. However, the threshold value was still determined from the pixel-based histogram of brightness and the isolated shadow pixels were often misclassified as non-shadows.

This study aimed to examine shadows in high resolution QuickBird images of urban-suburban areas as well as the derived land use and land cover classification with pixel-based classification methods. We also reversed the order of two-stage shadow resolving process, i.e., shadow detection and removal in land use and land cover classification first, and followed by in remotely sensed imagery without thresholding shadow from non-shadow before image classification. The specific objectives included detecting shadows in QuickBird images with pixel-based classification, separating different types of shadows based on the ground feature upon which shadows were cast, reclassifying shadowed areas into informational land cover types, and restoring spectral radiometric information for the pixels that are contaminated by shadows.

**METHODS**

**Study Area**

The study area is a suburban residential neighborhood (northwest corner: 45°0′ N, 93°12′ W; southeast corner: 44°58′ N, 93°9′ W), located in Falcon Heights and Roseville, Minnesota, USA. Land use and land cover of the study area is dominated by high-density residential development, but also includes commercial and institutional land development such as industrial buildings, parking lots, highways, trees, and grass. Agricultural research fields of the University of Minnesota are also located in the study area but were masked because the land use is not typical of those in urban-suburban environments.

**Image Acquisition**

One QuickBird multispectral image of the study area was acquired on 18 August 2003 under clear sky conditions.
conditions. The images, with 11-bit radiometric resolution, have three visible bands (0.45–0.52, 0.52–0.60, and 0.63–0.69 µm) and one near infrared band (0.76–0.90 µm). The spatial resolution of the image is 2.8 m, taken at a sun elevation angle of 54.5° and an off-nadir view angle of 12.1°. The image was geometrically rectified and radiometrically corrected as described by Wu et al. (2005).

**Shadow Reflectance Measurement**

Spectral reflectances were measured for shadowed surfaces with a 16-band multispectral radiometer (CROPSCAN MSR-16R, 0.46–1.72 µm) to examine the spectral characteristics of shadows and verify the digital analysis of satellite imagery. The band widths of the spectroradiometer vary from 6.8 nm to 12 nm in the visible and from 11 nm to 13 nm in the near infrared. Both irradiance and radiance were measured simultaneously to derive surface reflectance. The four multispectral bands of QuickBird data were simulated with the appropriate CROPSCAN bands as weighted averages (Wu et al., 2005). The view angle of the spectroradiometer was constant by looking vertically downward with a 28° field of view (FOV). Measurements were made at 1 m above shadowed surfaces, which resulted in a projected view area with 0.5 m diameter.

Measurements were taken on 26 September 2006 for both shadows on grass (SOG) and shadows on impervious surfaces (SOI). Thirty seven shadowed plots were selected in the study area, in which 19 were SOG plots and 18 were SOI plots. Each type of shadow (i.e., SOG and SOI) was further divided into shadows cast by buildings (7 for SOG and 8 for SOI) and shadows cast by trees (12 for SOG and 10 for SOI), respectively. The irradiance conditions (i.e., direct or diffuse radiation) were also recorded to indicate different parts of shadow (i.e., umbra or penumbra). Three random sampling areas were selected within each shadowed plot. Measurements were then averaged for each plot to estimate multispectral reflectance values for each type of shadow. All measurements were taken within one hour of the solar noon to minimize the effect of diurnal changes in solar elevation angle.

**Shadow Detection and Removal in the Land Use and Land Cover Classification Map**

A multi-stage image classification scheme was developed. To reduce the spectral confusion between water and shadow, water in the QuickBird image was masked with the Ramsey County open water outlines, which were derived from 2003 aerial orthophotography utilizing stereo processing techniques. Unsupervised ISODATA clustering was initially used to map major land use and land cover types including impervious surfaces, water, bare soil, crops, trees, and grass. However, one of the spectral classes was inevitably shadow. ISODATA clustering was applied again to the shadow class only to separate shadows into two types: SOG and SOI, regardless of being cast by buildings or by trees. Lastly, SOG and SOI pixels were reclassified to information classes, i.e., grass and impervious surfaces, respectively.

**Shadow Detection and Removal in the QuickBird Image**

For the evaluation of biophysical conditions, it is necessary to restore the spectral radiometric information for shadowed areas in the original QuickBird imagery. Shadow pixels in the satellite image were first identified by overlaying it with the reclassified shadow map containing two classes: SOG and SOI. To restore spectral radiometric information of the detected shadowed areas in the QuickBird imagery, the K-nearest neighbor algorithm was applied to resample digital numbers for the pixels that are contaminated by shadows. The neighborhood of the shadowed pixels was confined to the corresponding information classes, i.e., either grass or impervious surfaces. For comparison, the linear correlation correction method (Sarabandi et al., 2004) was also employed to predict values of shadow pixels. The shadow detection and removal were conducted separately for each of the four spectral bands of the QuickBird image.

**Accuracy Assessment**

Ramsey County color aerial orthophotography (collected on April 9, 2006, spatial resolution, 0.15 m) was used as the reference image to assess the accuracy of shadow detection and removal in the classification map. Thirty random points were selected for SOI and SOG, respectively. The producer’s and user’s accuracies of each shadow class were computed as well as Kappa statistics. The performance of the shadow detection and removal in the QuickBird image was inspected by visual analysis. Shadow-resolved images with the K-nearest neighbor algorithm and the linear correlation correction method were compared visually with each other and with the original image to evaluate the effectiveness of shadow correction.
RESULTS AND DISCUSSION

Shadow Characteristics

Different types of shadow (i.e., SOG and SOI) had distinct spectral characteristics. The NDVI values of shadowed areas largely depended on the spectral characteristics of the object (either grass or impervious surfaces) upon which shadows were cast (Fig. 1). SOG had much higher NDVI values than SOI. The levels of NDVI for both SOG and SOI were comparable to those for sunlit grass and impervious surfaces, respectively.

The measurements also indicated that the spectral characteristics of shadows might be affected by two other factors although the effects were not as significant as below-shadow ground conditions. First, the spectral characteristics of shadows changed with the objects that cast shadows, i.e., building or trees, although the NDVI of SOI was less affected than that of SOG (Fig. 1a). Second, the NDVI values changed with how the shadow reflectance was derived in terms of irradiance, i.e., direct radiation or diffuse radiation (Fig. 1b). Technically, Shadow reflectance should be the ratio between diffuse radiance and diffuse irradiance. However, both direct and diffuse irradiance are often used in determining surface reflectance from satellite images. The implication of this is that different parts of shadows (i.e., the umbra and penumbra) need to be treated differently when deriving surface reflectance since these shadow parts will be visible in high-resolution satellite images (Dare, 2005).

Shadow Detection and Removal in the Classification Map and QuickBird Image

The ISODATA image clustering showed that shadow accounted for about 7% of total land cover in the study area, among which 37% were SOI and 63% were SOG. Shadows in the satellite image were not uniform as indicated by the ground measurements and the type of shadow was mainly determined by the land cover upon which shadows were cast. The success of separation between SOI and SOG in satellite images can be attributed to the high radiometric resolution of QuickBird imagery data. The large dynamic range (11 bits) makes the detection of shadows significantly easier than would be the case with 8 bits. Figure 2 shows a sample street block of the study area where shadows were detected and removed in the land use and land cover classification. Isolated shadow pixels, which are common in residential areas, were successfully detected and reclassified to information classes.

Shadow pixels corresponding to the shadow areas in the land use and land cover classification map were extracted in the original QuickBird image (Fig. 3a); the spectral radiometric information of these pixels was restored with the K-nearest neighbor algorithm (Fig. 3b) and the linear correlation correction method (Fig. 3c). Figure 3 illustrates the results of shadow removal in the original QuickBird image covering the same area as shown in the classification map (Fig. 2). Overall, both shadow removal methods generated visually appealing images; but imagery produced with the linear correction method apparently had a slightly smoother transition from shadowed areas to non-shadowed areas.
Figure 2. A sample street block showing shadow areas were detected and separated in the land use and land cover classification map with the two-stage ISODATA clustering (a). Areas in gray are shadows on grass (SOG) while areas in black are shadows on impervious surfaces (SOI). SOG and SOI were reclassified to grass (green) and impervious surfaces (white), respectively (b). Dark green and brown colors represent areas covered by trees and bare soil, respectively.

Accuracy of Shadow Detection and Removal
Shadows were detected and separated with reasonable accuracy in the classification map: SOG was detected with a high producer’s accuracy (90%) while SOI was detected with a high user’s accuracy (94%) (Table 1). After accounting for chance agreement, however, SOI was identified more accurately than SOG, probably due to the low spatial variation of SOI spectral characteristics (Fig. 1a). When compared with the original QuickBird image, it appears that most shadowed areas were either removed or significantly reduced, although some isolated shadow pixels were still missed in the classification even with the pixel-based method. The visual contrast of the shadow-resolved image with the K-nearest neighbor algorithm remained unchanged while the overall contrast level was slightly modified with the linear correlation correction method (Fig. 3).

It should be cautioned, however, that independent assessment of the accuracy of shadow detection and in particular shadow removal, beyond visual analysis, is difficult to achieve. Shadows that existed on the day of acquisition will not exist again unless imaging conditions are identical. Most likely, the reference image for validating the performance of shadow detection and removal such as the aerial photography used in this study was acquired under different sun-view illumination geometry. The ground surveyed data, even collected on the same

Figure 3. QuickBird false color images of a sample street block (a) showing shadow areas were detected and removed with the K-nearest neighbor algorithm (b) and with the linear correlation correction method (c).
Table 1. Accuracy assessment of shadow detection. a

<table>
<thead>
<tr>
<th>Class</th>
<th>Producer’s Accuracy</th>
<th>User’s Accuracy</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOG</td>
<td>90.0</td>
<td>73.0</td>
<td>0.75</td>
</tr>
<tr>
<td>SOI</td>
<td>78.4</td>
<td>93.6</td>
<td>0.93</td>
</tr>
</tbody>
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a SOG and SOI refer to shadows on grass and shadows on impervious surfaces, respectively.

date when the satellite image was acquired cannot be used to verify estimated pixel values for shadowed areas because the ground was covered by shadows at the time of data collection. If possible, the ground data should be collected immediately before or after image acquisition; otherwise ground features and shadows could well have changed.

CONCLUSIONS

Accurate and detailed land cover information of urban areas derived from remote sensing images is essential for urban land planning, management, and landscape analysis. A pixel-based multi-stage method was developed to detect and remove shadows in high resolution QuickBird satellite imagery and the classification map. Shadow detection and removal were achieved by taking advantage of the high spatial and high radiometric resolution of QuickBird data. The results indicated that shadows on grass and shadows on impervious surfaces could be detected and separated based on their distinct spectral characteristics. By reclassifying shadows to corresponding information classes, a significant portion of land cover could be recovered in the classification process. Both the K-nearest neighbor algorithm and the linear correlation correction method were promising in restoring the spectral radiometric information for pixels that are contaminated by shadows. Besides visual analysis, quantitative validation is needed in the future in order to evaluate the effectiveness of these methods for estimating shadow-free pixel data.

REFERENCES


