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Fully constrained linear spectral unmixing based global shadow compensation for
high resolution satellite imagery of urban areas

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Abstract

Shadows commonly exist in high resolution satellite imagery, particularly in urban areas, which is a combined effect of low sun elevation, off-nadir viewing angle, and high-rise buildings. The presence of shadows can negatively affect image processing, including land cover classification, mapping, and object recognition due to the reduction or even total loss of spectral information in shadows. The compensation of spectral information in shadows is thus one of the most important preprocessing steps for the interpretation and exploitation of high resolution satellite imagery in urban areas. In this study, we propose a new approach for global shadow compensation through the utilization of fully constrained linear spectral unmixing. The basic assumption of the proposed method is that the construction of the spectral scatter plot in shadows is analogous to that in non-shadow areas within a two-dimension spectral mixing space. In order to ensure the continuity of land covers, a smooth operator is further used to refine the restored shadow pixels on the edge of non-shadow and shadow areas. The proposed method is validated using the WorldView-2 multispectral imagery collected from downtown Toronto, Ontario, Canada. In comparison with the existing linear-correlation correction method, the proposed method produced the compensated shadows with higher quality.

Keywords: Global shadow compensation, object-based shadow detection, linear spectral unmixing, spectral mixing space, spectral scatter plot, WorldView-2.

47

48 **1 Introduction**

49 High spatial resolution satellite imagery, such as IKONOS, QuickBird, GeoEye, and
50 WorldView, exhibits enough detailed features to distinguish small objects of land cover in urban
51 areas. Unfortunately, the combined effect of low sun elevation, off-nadir viewing angle, and
52 high-rise buildings results in the ubiquity of shadows in high resolution satellite imagery of
53 urban areas. The reduction or even total loss of spectral information under shadow areas
54 obstructs the image interpretation. It is thus of great importance to restore shadow information
55 before any image processing step (e.g., classification, mapping, and object recognition) is
56 applied.

57 In the workflow of shadow compensation, shadow detection is usually conducted first
58 (Shahtahmassebi et al., 2013), because the quality of shadow detection can directly influence the
59 outcome of shadow restoration (Li et al., 2014). Two strategies have been reported in the
60 literature to detect shadows; pixel-based and region-based strategies (Zhou et al., 2009). The
61 former regards individual pixels as the basic unit to determine whether it is a shadow pixel,
62 whereas the latter views a piece of shadow as a continuous region. Given the small size of pixel
63 cells in high spatial resolution imagery, shadow pixels tend to aggregate together as a patch or a
64 cluster. In this case, the pixel-based shadow detection may induce “salt and pepper” noise in a
65 continuous piece of shadow, further resulting in the discontinuity of land covers in restored
66 shadow areas. On the other hand, the region-based strategy has been more preferred and
67 frequently used by recent studies (Dare, 2005; Lorenzi et al., 2012; Massalabi et al., 2004). Most
68 of the region-based shadow detection methods are implemented through the refinement of pixel-
69 based detection using a local morphological filtering operator (Dare, 2005; Lorenzi et al., 2012),

while very few studies detect shadow regions by integrating imagery segmentation and classification within the framework of object-based image analysis (Massalabi et al., 2004). Unlike pixel-based refining methods, object-based shadow detection is able to make full use of spectral, textural, and contextual features to separate non-shadow and shadow areas (Massalabi et al., 2004).

Shadow restoration is the core component of shadow compensation. There are two types of shadow restoration strategies in terms of the processing extent, namely local and global strategies. The local strategy restores spectral information of a shadow pixel or region based on the neighbouring non-shadow land covers (Massalabi et al., 2004), whereas the global strategy handles all the shadows in the imagery in their entirety (Chen et al., 2007; Dare, 2005; Lorenzi et al., 2012; Sarabandi et al., 2004). In most cases, the local strategy can produce a better shadow-restored result because every shadow pixel or region is restored separately. Nevertheless, it is very time consuming to apply the local strategy for a large urban scene. In contrast, the global strategy is more easily implemented, although not all the shadow pixels or regions are well restored. A common basic assumption for both the local and global strategy is that the spectra of land covers in shadow areas are highly related to those in non-shadow areas and the relations between them can be detected through a computation method (e.g., gamma correction (Massalabi et al., 2004; Sarabandi et al., 2004), histogram matching (Dare, 2005; Li et al., 2005; Lorenzi et al., 2012; Sarabandi et al., 2004; Tsai, 2006), and linear-correlation correction (Chen et al., 2007; Sarabandi et al., 2004; Yamazaki et al., 2009; Zhou et al., 2009)). Following this approach, this study assumes that the construction of the spectral scatter plot in shadow areas is analogous to that in non-shadow areas within a two-dimension spectral mixing space.

In this paper, we propose a fully constrained linear spectral unmixing based global shadow compensation approach for high spatial resolution satellite imagery of urban areas based on the above assumption. The remainder of this paper is organized as follows. In the second section, the study area and dataset is described. Details of the proposed shadow compensation approach are given in the third section. The fourth and fifth sections demonstrate the experimental results and discussion, respectively. The main conclusions are drawn in the last section.

2 Study area and dataset

Located in Toronto, Ontario, Canada, the study area is a typical urban land, characterized by a complex mosaic of different land cover types, including street trees, grass, and many high-rise buildings. WorldView-2 original multispectral imagery of the central Toronto urban area was adopted for the experiment. It contains eight spectral bands with 2 m resolution (coastal, blue, green, yellow, red, red edge, near infrared 1 (NIR 1), and near infrared 2 (NIR 2)). Detailed wavelength information of each spectral band is listed in Table 1. In this study, a 2×2 km subset of the original dataset of 1000×1000 pixels was selected (Fig. 1).

The satellite imagery was acquired at 16:42 on June 2nd, 2011 and the solar zenith angle was approximately 22.4 degrees while the satellite zenith angle was approximately 9.0 degrees. It is also worth noting that this experimental area is the downtown Toronto where many buildings are over 20 m height. Thus, the combination of the low sun elevation, off-nadir viewing angle, and high-rise buildings resulted in the abundance of large shadow areas, which makes it suitable to test the proposed shadow compensation approach.

Table 1. Wavelength range of each spectral band in the WorldView-2 multispectral imagery.

Spectral band	Coastal	Blue	Green	Yellow	Red	Red edge	NIR 1	NIR 2
Wavelength (nm)	400-450	450-510	510-580	585-625	630-690	705-745	770-895	860-900

Fig. 1. Location of the study area in downtown Toronto, Ontario, Canada and WorldView-2 multispectral imagery used for experiment and analysis (Band NIR 1, red, and green as R, G, and B). This subset is under WGS84 UTM coordinate system.

3 Methods

The processing steps of the proposed global shadow compensation method are provided in the flowchart (Fig. 2). The non-shadow and shadow areas were first separated from the multispectral imagery through the utilization of supervised object-based shadow detection. The endmembers were thereafter identified and optimized using the automated endmember searching method in the non-shadow and shadow areas, respectively. Employing the fully constrained linear spectral unmixing, the fractions of land covers in the shadow area were unmixed by the

129 optimized endmembers from the shadow area. Using unmixed fractions, the spectra of land
 130 covers in the shadow area were further restored on the basis of endmembers optimized from the
 131 non-shadow area. Then, the edge of non-shadow and shadow areas was smoothed to refine the
 132 shadow-restored imagery. Finally, a commonly-used linear shadow correction method was also
 133 adopted and compared with the proposed global shadow compensation approach to examine the
 134 performance.

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 137 Fig. 2. The processing flowchart of the proposed global shadow compensation method.

138 139 3.1 Object-based shadow detection

It is widely accepted that shadow detection should precede shadow restoration because the quality of shadow detection can directly affect the accuracy of the ultimate shadow-restored imagery. In contrast to the unsupervised histogram threshold method that has been popularized in grayscale or single band of multispectral imagery (Chen et al., 2007; Dare, 2005; Zhou et al., 2009), this study adopted object-based shadow detection using a state-of-the-art supervised classifier, the support vector machine (SVM) (Arbel and Hel-Or, 2011; Lorenzi et al., 2012). Particularly, the BerkeleyImageSeg software package (BIS; <http://www.imageseg.com>) was implemented to partition the WorldView-2 multispectral imagery into segments of appropriate size for object-based shadow detection. The program utilized the region merging algorithm proposed by (Benz et al., 2004) based on three parameters of threshold, shape (0.1-0.9), and compactness (0.1-0.9). A higher threshold often leads to segments of larger size, whereas higher shape and compactness indicate more round and smooth segments, respectively. After a series of trial-and-error parameter selection, this study chose to use 40, 0.5, and 0.5 as threshold, shape, and compactness for image segmentation. A set of training samples including 50 non-shadow polygons and 50 shadow polygons is manually selected for classification using the radial basis function (RBF) SVM.

3.2 Fully constrained linear spectral unmixing based shadow restoration

3.2.1 Construction of the spectral scatter plots and automated endmember searching

As defined by Small (2003), spectral mixing space is a self-consistent basis for providing the description of urban surface material characteristics. All the pixels in the entire imagery are dotted, and form a spectral scatter plot within a specific spectral mixing space (Small, 2003). Moreover, the construction of spectral scatter plots can vary a lot in different spectral mixing

spaces. Due to the similarity and continuity of land covers between the non-shadow and shadow areas, the construction of the spectral scatter plot in the shadow area should be very analogous to that in the non-shadow area. We hypothesized that the spectral scatter plots of the non-shadow and shadow areas should demonstrate the same construction or shape but differ in size. Thus, the proposed shadow compensation was implemented by restoring the size of the spectral scatter plot in the shadow area to the size of the spectral scatter plot in the non-shadow area, while also retaining its shape.

Compared with the vegetation-impervious-soil model proposed by Ridd (1995), the vegetation-high albedo-low albedo model is more suitable for linear spectral mixing of high resolution urban imagery (Small, 2003; Yang et al., 2014). While impervious surfaces in urban areas become separated as bright and dark surface materials with decreasing spatial resolution, soil can also be categorized into high albedo surface (Yang et al., 2014). Therefore, vegetation, high albedo, and low albedo become widely used as endmembers for linear spectral unmixing of high resolution urban imagery (Small, 2003; Yang et al., 2014).

The quality of linear spectral unmixing is largely determined by the endmember selection. Due to the endmember variability, multiple endmember spectral mixture analysis (MESMA) has attracted growing attention in spectral analysis (Somers et al., 2011; Zare and Ho, 2014). However, Rogge et al. (2006), Veraverbeke et al. (2012), and Yang et al. (2014) indicated that applying MESMA takes longer and may not always provide better results. Specifically, Yang et al. (2014) proved that a triangle should be the optimal construction of the spectral scatter plot for linear spectral unmixing in a two-dimension spectral mixing space, and the vertices of this triangle should be the optimal three endmembers. From this perspective, it is of great necessity and significance to construct an appropriate two-dimension spectral mixing space where the

shape of the spectral scatter plot is a triangle and three vertices represent the vegetation, high albedo, and low albedo endmembers, respectively.

Apparently, the endmember of low albedo is located close to the coordinate origin in any spectral mixing space due to the lowest digital number (DN) values in all the spectral bands. In addition, the NIR 1 and NIR 2 bands in the WorldView-2 dataset are considered to be the appropriate spectral bands for vegetation representation and the other bands are able to characterize high albedo land covers. In order to select the appropriate two-dimension spectral mixing space, we combined one spectral band from the coastal, blue, green, yellow, red, and red edge bands, with the other one from the NIR 1 and NIR 2 bands for constructing 12 alternatives. These spectral mixing spaces in the non-shadow and shadow areas are separately presented in Fig. 3.

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Fig. 3. Different spectral mixing spaces constructed with various bands (Coastal, Blue, Green, Yellow, Red, Red edge, NIR 1, NIR 2) in the non-shadow (left) and shadow (right) areas.

It was shown by Small (2003) and Yang et al. (2014) that the straight edges between the vertices of a triangle can result in a valid and meaningful linear spectral unmixing. In contrast to the NIR 2 band, the spectral scatter plots on the basis of the NIR 1 band construct better triangles with straight and distinct edges in both the non-shadow or shadow areas (Fig. 3). Moreover, the spectral mixing space constructed by the red and NIR 1 bands is believed to have the capability

to produce the best quality of linear spectral unmixing among the six spaces on the basis of NIR 1 band (Fig. 3). Within this spectral mixing space, the highest similarity of the triangles between the non-shadow and shadow areas further ensures that it is the best spectral mixing space to identify the optimal endmembers in both the non-shadow & shadow areas, and to unmix the spectra of pixels in the shadow area. However, the linear spectral unmixing in this two-dimension spectral mixing space is not able to provide endmember fractions for more than two spectral bands. To obtain a multispectral shadow-restored imagery, the same procedure is also implemented within another two-dimension spectral mixing space constructed by the green and NIR 1 bands because the green band is another component of the standard false color composite in addition to the red and NIR bands. Meanwhile, the spectral scatter plots also indicate good triangles for the non-shadow and shadow areas within the green-NIR 1 spectral mixing space (Fig. 3).

In the spectral mixing space constructed by the red and NIR 1 bands (non-shadow & shadow shown in Fig. 3), the vertices of the scatter plot triangle represent the vegetation, high albedo, and low albedo endmembers. It is worth noting that very dark pixels exist in the shadow area but also scatter in the non-shadow area because the shadow area was detected based on spectral properties of segmented land cover objects rather than those of individual pixels. Hence, the endmember of low albedo is the vertex which locates the closest to the coordinate origin (O) for no matter the non-shadow or shadow area. Besides that, the vertex of the triangle close to the axis of NIR 1 band represents the vegetation endmember while the other vertex close to the axis of red band represents the high albedo endmember. In order to search for these three vertices, an endmember spatial measure index (ESM_n) was newly proposed by Yang et al. (2014) from the perspective of avoiding endmember collinearity and multi-collinearity (Van Der Meer and De

Jong, 2000; Van der Meer and Jia, 2012). As concluded by Yang et al. (2014), the higher value of ESM_n indicates a better endmember combination for linear spectral unmixing. Specifically, ESM_n can be denoted as ESM_2 in the two-dimension spectral mixing space constructed by the red and NIR 1 bands, which is directly proportional to the determinant (Det) of two endmember vectors,

$$ESM_2 \propto Det(\overrightarrow{EM_V} - \overrightarrow{EM_L} \quad \overrightarrow{EM_H} - \overrightarrow{EM_L}) \quad (1)$$

, where $\overrightarrow{EM_V}$, $\overrightarrow{EM_H}$, and $\overrightarrow{EM_L}$ represent the endmember vectors of vegetation, high albedo, and low albedo, respectively.

We can notice from Eq. (1) that the value of ESM_2 is proportional to the area of the triangle constructed by these three vertices (endmembers). The best endmember combination is in effect corresponding to the largest area of the triangle among all the triangles constructed by any three vertices. Considering one of the triangle vertices (low albedo endmember) is fixed to the pixel nearest the coordinate origin, we need to search the other two vertices (vegetation and low albedo endmembers) from the remaining pixels in order that three vertices constructs a triangle with the largest area. Nevertheless, it will be too time consuming if calculating the ESM_2 for every pair of two pixels, particularly in the case of a huge experimental area. Thus, this study developed a rapid algorithm to automatically search for three endmembers which construct the largest area of triangle. For a cluster of pixels scattered in a two-dimension space, it is not difficult to prove that three pixels that construct the largest triangle area must locate at the convex hull of all the pixels. So we firstly extracted the convex hull for the spectral scatter plot by implementing Graham's scan (Graham, 1972), which is a time-efficient method of computing the convex hull of a finite set of points in the plane. Besides that the endmember of low albedo is determined as the pixel closet to the coordinate origin, the vegetation and low albedo

endmembers were then selected from the remaining pixels at the convex hull. Compared to the calculation for every pair of two pixels, the rapid endmember searching can remarkably decrease the time complexity from $O(n^2)$ to $O(n \log n)$.

Due to the various sizes of the scatter plot triangles (Fig. 3), this study optimized two sets of endmember combinations (vegetation, high albedo, and low albedo) for the non-shadow and shadow areas, respectively. As such, two sets of endmember combinations were also automatically identified within the green-NIR 1 spectral mixing space.

3.2.2 Fully constrained linear spectral unmixing

As an important branch of soft classification, linear spectral unmixing has been frequently adopted in many remote sensing applications, especially for medium/low resolution imagery. In recent years, several studies have started to unmix fine-scale imagery (e.g., IKONOS and WorldView-2) (Nichol and Wong, 2007; Nichol et al., 2010; Small, 2003; Yang et al., 2014). As mentioned previously, the linear spectral unmixing was adopted to obtain the fractions of vegetation, high albedo, and low albedo for any pixel in the shadow area. Mathematically, linear spectral unmixing in the red-NIR 1 spectral mixing space is a process of solving the linear equations below:

$$\begin{cases} DN_{RED}(s) = f_V DN_{VRED}(s) + f_H DN_{HRED}(s) + f_L DN_{LRED}(s) \\ DN_{NIR1}(s) = f_V DN_{VNIR1}(s) + f_H DN_{HNIR1}(s) + f_L DN_{LNIR1}(s) \end{cases} \quad (2)$$

, where $DN_{RED}(s)$ and $DN_{NIR1}(s)$ are the DN values of the unmixed shadow pixel in the red and NIR 1 bands; f_V , f_H , and f_L are the fractions of vegetation, high albedo, and low albedo, respectively; $DN_{VRED}(s)$ and $DN_{VNIR1}(s)$ denote the DN values for each endmember optimized from the shadow area (X : V , H , L , i.e., vegetation, high albedo, and low albedo). Additionally,

the sum of vegetation, high albedo, and low albedo fractions should be equal to one for any given unmixed pixel:

$$f_v + f_H + f_L = 1 \quad (3)$$

To simplify the solution procedure, we translated the scatter plot triangle so that the pixel of low albedo endmember exactly located the coordinate origin. Meanwhile, the optimized vegetation and high albedo endmembers will move towards the coordinate origin corresponding to the offset of the low albedo endmember. The linear translation will not affect the fraction of each endmember (i.e., f_v , f_H , f_L) as the shape of the scatter plot triangle does not change in this process. Given that the post-translated spectrum of low albedo endmember is assigned as (0, 0), Eq. (2) can thus be rewritten as:

$$\begin{cases} DN'_{RED}(s) = f_v DN'_{vRED}(s) + f_H DN'_{HRED}(s) \\ DN'_{NIR1}(s) = f_v DN'_{vNIR1}(s) + f_H DN'_{HNIR1}(s) \end{cases} \quad (4)$$

, where $DN'_{RED}(s)$ and $DN'_{NIR1}(s)$ represent the post-translated DN values of the unmixed shadow pixel in the red and NIR 1 bands, whereas $DN'_{xRED}(s)$ and $DN'_{xNIR1}(s)$ represent the post-translated DN values for each endmember from the shadow area (X : V , H , i.e., vegetation and high albedo). It can also be noticed that Eq. (4) must produce a unique solution when the vegetation and high albedo endmembers are optimized by the largest value of ESM_2 due to no collinearity of $\overrightarrow{EM_v(s)} - \overrightarrow{EM_L(s)}$ and $\overrightarrow{EM_H(s)} - \overrightarrow{EM_L(s)}$. With the calculated f_v and f_H , the fraction of low albedo (f_L) can be easily derived using Eq. (3).

Furthermore, fully constrained linear spectral unmixing also requires that any endmember fraction should not be over the range of zero to one. The schematic triangle of the post-translated scatter plot in the red-NIR 1 spectral mixing space is shown as Fig. 4. Assuming $EM_v(s)$ and

$EM_H(s)$ are the selected pair of pixels from the shadow area as vegetation and high albedo endmembers with the highest value of ESM_2 , it is apparent to notice that the pixels within the triangle $EM_V(s) EM_H(s) EM_L(s)$ have the meaningful fraction of vegetation, high albedo, and low albedo (0-1). Nevertheless, it is not always true that all the pixels are dotted into this triangle even using the optimized endmembers. For any pixel outside of the triangle, this study solved Eq. (4) by searching the point on the boundary of this triangle with the minimum Euclidean distance to the outlier. In particular, the outlier pixels were divided into two zones (Fig. 4). For the pixel in Zone 1, the solution is the closest vertex (i.e., $EM_V(s)$ or $EM_H(s)$), indicating that it is a pure vegetation or high albedo pixel. Besides that, the solution for the pixel in Zone 2 is the closest point on any side of the triangle. This is a necessary step to validate the unmixed fraction of each endmember is ranging from zero to one. Similar to endmember searching, the fully constrained linear spectral unmixing was implemented within both the red-NIR 1 and green-NIR 1 spectral mixing spaces.

Fig. 4. An illustration of schematic scatter plot triangle in the two-dimension spectral mixing space constructed with the red and NIR 1 bands. $EM_V(s)$, $EM_H(s)$, and $EM_L(s)$ represent vegetation, high albedo, and low albedo endmembers optimized from the shadow area.

3.2.3 Shadow restoration

It is observed from the red-NIR 1 spectral mixing space (Fig. 3) that the similarity of scatter plot triangles between the non-shadow and shadow areas provides a great opportunity for spectral restoration in the shadow area by utilizing the spectral information in the non-shadow area. A feasible way is thus to stretch the scatter plot triangle in the shadow area towards the triangle size in the non-shadow area. For any pixel in the shadow area, the fractions of vegetation (f_V), high albedo (f_H) and low albedo (f_L) remain the same and the restored DN values can be denoted:

$$\begin{cases} \hat{DN}_{RED} = f_V DN_{VRED}(n) + f_H DN_{HRED}(n) + f_L DN_{LRED}(n) \\ \hat{DN}_{NIR1} = f_V DN_{VNIR1}(n) + f_H DN_{HNIR1}(n) + f_L DN_{LNIR1}(n) \end{cases} \quad (5)$$

, where $\hat{DN}_{RED}$ and $\hat{DN}_{NIR1}$ are the shadow-restored DN values in the red and NIR 1 bands; $DN_{XRED}(n)$ and $DN_{XNIR1}(n)$ are the DN values for each endmember optimized from the non-shadow area (X : V , H , L , i.e., vegetation, high albedo, and low albedo).

In addition, the shadow-restored DN value for the green band ($\hat{DN}_{GREEN}$) was calculated through the expansion of the scatter plot triangle in the green-NIR 1 spectral mixing space.

$$\hat{DN}_{GREEN} = f'_V DN_{VGREEN}(n) + f'_H DN_{HGREEN}(n) + f'_L DN_{LGREEN}(n) \quad (6)$$

, where f'_V , f'_H , and f'_L represent the fractions of vegetation, high albedo, and low albedo in this two-dimension spectral mixing space; $DN_{XGREEN}(n)$ represents the DN value for each endmember optimized from the non-shadow area in the green band ($X: V, H, L$, i.e., vegetation, high albedo, and low albedo).

3.2.4 Edge refinement

Since object-based shadow detection can always result in the spatial discontinuity of land covers on the edge of non-shadow and shadow areas, we smoothed the shadow edge through the utilization of mean filter in a 3×3 moving window (Eq. (7)). The shadow edge was detected from the shadow imagery using the Laplacian operator in a 3×3 moving window (Eq. (8)).

$$\begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \quad (7)$$

$$\begin{pmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{pmatrix} \quad (8)$$

For further comparison, the conventional linear-correlation correction method was utilized for shadow restoration to evaluate the performance of the proposed method. Compared with other shadow restoration techniques (e.g., gamma correction and histogram matching), the linear-correlation correction method was proven more effective (Dare, 2005; Sarabandi et al., 2004). It assumes the signals recoded in the shadow area are still able to provide enough useful information for shadow restoration despite being relatively weak. Specifically, a linear relationship between DN values of the shadow area and those of the non-shadow area for each spectral band (i.e., the green, red, and NIR 1 bands) can be expressed as (Chen et al., 2007; Sarabandi et al., 2004; Yamazaki et al., 2009; Zhou et al., 2009):

$$\hat{DN} = \frac{\sigma(n)}{\sigma(s)}(DN - \mu(s)) + \mu(n) \quad (9)$$

, where $\hat{DN}$ and DN represent the shadow-restored and original DN values of any shadow pixel; $\mu(n)$ and $\mu(s)$ are the mean DN values for the non-shadow and shadow areas while $\sigma(n)$ and $\sigma(s)$ are the standard deviation of the non-shadow and shadow areas. In order to eliminate the impact caused by shadow detection, both of them were implemented based on the same object-based detected shadow imagery.

4 Comparison of methods

In this section, the proposed global shadow compensation approach based on the fully constrained linear spectral unmixing is implemented to produce the shadow-restored imagery, and further visually compared with the mentioned linear-correlation correction method, in terms of the entire imagery and four subsets.

The shadow area detected by object-based image classification is shown in Fig. 6. The proportion of shadow area occupies about 15 percent of the entire imagery, which provides enough samples to verify the performance of the proposed compensation method. It is also worth noting that object-based shadow detection successfully extracts patches of shadow area rather than scattered shadow pixels. Since most of the shadows exist as the form of patches in high resolution imagery, the object-based detected shadow area ensures the homogeneity of land covers within each shadow patch.

The vegetation, high albedo, and low albedo endmembers are automatically optimized by the proposed rapid endmember searching method in two spectral mixing spaces (i.e., Red + NIR 1 bands and Green + NIR 1 bands). Moreover, two sets of endmembers (Table 2) are identified

in the non-shadow and shadow areas, respectively. Since all the endmembers of low albedo locate at the coordinate origin (O), we don't have to translate the scatter plot triangle in this experiment. Due to the common spectral basis (i.e., NIR 1 band), the vegetation endmembers selected from these two spectral mixing spaces are identical for both the non-shadow (1033, 75, and 278 as NIR 1, Red, and Green bands) and shadow areas (547, 61, and 192 as NIR 1, Red, and Green bands). However, the high albedo endmembers optimized within these two spaces are very different from each other. In the shadow area, the fraction of vegetation, high albedo, and low albedo endmembers are derived by the described fully constrained linear spectral unmixing method. For the Red + NIR 1 and Green + NIR 1 spectral mixing spaces, a subset of vegetation, high albedo, and low albedo fraction maps are depicted, respectively (Fig. 5). Thereafter, the shaded spectra of the NIR 1, red, and green bands are recovered using Eq. (5) and (6), as shown in Fig. 6 with a band combination of standard false color composite.

Table 2. Vegetation, high albedo, and low albedo endmembers optimized from two spectral mixing spaces (Red + NIR 1 and Green + NIR 1) for the non-shadow and shadow areas.

Endmember	Non-shadow area		Shadow area	
	Red + NIR 1	Green + NIR 1	Red + NIR 1	Green + NIR 1
Vegetation	(75, 1033)	(278, 1033)	(61, 547)	(192, 547)
High albedo	(2047, 2047)	(2047, 1298)	(478, 471)	(771, 443)
Low albedo	(0, 0)	(0, 0)	(0, 0)	(0, 0)

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(A)

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(B)

(C)

Fig. 5. An illustration of original multispectral imagery (A) and fraction maps (B-G) for a subset area where shadows are dominant, including vegetation (B and C), high albedo (D and E), and low albedo (F and G). The fraction maps (0-1) are derived within the Red + NIR 1 (B, D, and F) and Green + NIR 1 (C, E, and G) spectral mixing spaces, respectively.

The conventional linear-correlation correction method is also implemented for shadow restoration as a comparative experiment. Similarly, the spectra of the NIR 1, red, and green bands are recovered according to Eq. (9), respectively. For each spectral band, the mean and standard deviation (SD) in the non-shadow and shadow areas are summarized in Table 3. The shadow-restored imagery is depicted using a standard false color band combination (Fig. 6), as well.

Table 3. Mean and SD of NIR 1, red, and green bands for the non-shadow and shadow areas.

Spectral band	Non-shadow area		Shadow area	
	Mean	Std. dev.	Mean	Std. dev.
NIR 1 band	311.80	151.49	73.10	43.22
Red band	227.02	126.08	70.17	31.08
Green band	408.63	181.30	179.79	46.00

Fig. 6. Shadow compensation results of the entire experimental area (under WGS84 UTM coordinate system). Upper left: original multispectral imagery; upper right: shadows (White); lower left: fully constrained linear spectral unmixing based shadow-restored imagery; lower right: linear-correlation correction based shadow-restored imagery. Green frames (A, B, C, and D) are four subset areas from the entire imagery.

To compare differences in details, four small subsets of 100×100 pixels are randomly chosen from the entire imagery (Green frame A, B, C, and D in Fig. 6) and zoomed in for visual interpretation (Fig. 7). The shadow patches in the selected four subsets are labelled alphabetically, most of which are pure shadow (i.e., single land cover) while a few of them are compound shadow (i.e., multiple land covers), such as Fig. 7Ab, Bc, Bd, Bf, Cb, Cc, De, and Dh. In contrast with the pure shadow patches, the compound shadow patches contain vegetation and sealed surface (e.g., roads, rooftops, and parking lots), thus more important for urban land cover classification. Overall, the proposed method produces the better shadow-restored imagery than the conventional method in the above compound shadow patches. In the cases of Fig. 7Ab and

Cc, for instance, the vegetation information is better compensated and strengthened in the fully constrained linear spectral unmixing based shadow-restored imagery. We also found that the conventional linear-correlation correction method often overcompensates some pixels of sealed surfaces. For example, the pixels on the edge of shadow patch shown as Fig. 7Ab are not so evident and distinguishable from the others inside but these edge pixels are overcompensated to the white. Moreover, the pixels surrounding vegetation in the cases shown as Fig. 7Bd and De are very bright which is not reasonable. The proposed method overcomes this drawback and compensates the shadow patches to a reasonable brightness. In addition to the compound shadow, the shadow-restored imagery using the proposed method outperforms the other in terms of the pure shadow because the restored spectral information is more similar to the adjacent non-shadow land covers (Fig. 7Db, Dc, Dd, Df, Dg, and Di). Since the rationale of the proposed method is to expand the scatter plot triangle of shadow area to the similar one of non-shadow area, the shadow-restored imagery using the proposed method is able to retain the characteristics of spectral mixing space better. Further, it is worth noting that the edges of shadow patches are considerably distinct so that they are not continuous to the adjacent non-shadow land covers (Fig. 7Cb, Cc, and Cg). This is the underlying flaw for the object-based shadow detection. In this study, the proposed method refined the shadow-restored by smoothing the edge of non-shadow and shadow areas which guarantees the continuity on the edge.

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B

C

D

Fig. 7. An illustration of shadow compensation results in four subset areas A, B, C and D. From left to right: original imagery; shadow area (White); fully constrained linear spectral unmixing based shadow-restored imagery; linear-correlation correction based shadow-restored imagery.

5 Discussion

In terms of shadow compensation, the above visual inspection demonstrated the advantages of the proposed method over the conventional method. It is also implied that the success of the proposed global shadow compensation approach is mainly dependent upon two prerequisites. One is the accuracy of linear spectral unmixing, and the other one is the similarity of the constructions of spectral scatter plots between the non-shadow and shadow areas.

The endmember fractions are used to characterize the spectral features of land covers in the shadow area, so inaccurate fractions can negatively impact the restoration of shaded surface

468 materials. Moreover, endmember searching is one of the most crucial steps to accurately unmix
469 endmember fractions. Most of the existing endmember searching methods were built upon
470 representative selection within each independent class, such as EAR (Dennison and Roberts,
471 2003), MASA (Dennison et al., 2004), and CoB (Roberts et al., 2003). However, this popular
472 strategy is more appropriate to select training samples for supervised classifiers rather than to
473 select endmembers for linear spectral unmixing. More broadly, linear spectral unmixing is a kind
474 of image classification and endmember searching is also considered as generalized training
475 sample selection. Nonetheless, endmember searching has its typical and unique characteristics
476 because linear spectral unmixing is implemented within a spectral mixing space. Different from
477 the general selections of training samples, endmembers should be identified by investigating the
478 construction of spectral scatter plot, not focusing on only one class. Specifically, Yang et al.
479 (2014) elaborated that a triangle with straight edges is the optimal construction of a spectral
480 scatter plot for linear spectral mixing in a two-dimension spectral mixing space. Valid and
481 correct unmixed fractions could be derived when assigning three vertices of the triangle as
482 endmembers. Therefore, it is of great significance for linear spectral mixing to construct the
483 appropriate spectral mixing space so that the construction of the spectral scatter plot resembles
484 the optimal triangle, while the vertices represent the target endmembers. For example, we chose
485 three endmembers of vegetation, high albedo, and low albedo and further compared 12 two-
486 dimension spectral mixing spaces (Fig. 3) in which the vertices of the scatter plot triangles
487 represented these endmembers. In comparison with the other feature spaces, we implemented
488 endmember searching and linear spectral unmixing in the red-NIR 1 and green-NIR 1 spectral
489 mixing spaces because the more triangle-analogous spectral scatter plots indicated more accurate
490 unmixed fractions. In addition, we would like to clarify that linear spectral unmixing also differs

from the common classifiers (e.g., maximum likelihood classifier, support vector machine, random forest) in internal mechanisms. While these classifiers are implemented based on statistical clustering, linear spectral unmixing is not. In other words, we cannot process linear spectral unmixing as a solution for a mathematic problem. It has been already proved that linear spectral unmixing is theoretically able to implement as long as the number of endmembers is not greater than the number of spectral bands. Nevertheless, this prerequisite only ensures at least one mathematic solution, but not the validity and accuracy. From this point of view, the analysis of spectral scatter plot can provide the underlying foundation for endmember searching and linear spectral mixing in a given spectral mixing space. Whenever unmixing multispectral or hyperspectral imagery, it should be the highest priority to construct an appropriate spectral mixing space (e.g., band math, transformation) for the endmembers of interest in order to guarantee they locate at the vertices of a good scatter plot triangle.

The similarity of the constructions of spectral scatter plots between the non-shadow and shadow areas is the basic hypothesis of the proposed shadow restoration method, which represents an improvement on the assumption used by the conventional linear-correlation correction method. In essence, the linear-correlation correction method adopts the similarity in one-dimension spaces whereas the proposed method adopts the similarity in two-dimension spaces. Obviously, two-dimension spaces characterize this similarity in more details than one-dimension spaces, and thus can retain the construction of spectral scatter plot. On the other hand, the linear-correlation correction is not a restoration process in the strict sense, although it is widely known and utilized for shadow compensation. As the standard deviation of non-shadow area ($\sigma(n)$) is always greater than that of shadow area ($\sigma(s)$), it is obvious to derive from Eq. (9) that,

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$$\frac{\hat{DN} - \mu(n)}{DN - \mu(s)} = \frac{\sigma(n)}{\sigma(s)} > 1 \quad (10)$$

When the DN value of a shadow pixel (DN) is greater than the mean value of the entire shadow area ($\mu(s)$), Eq. (10) would be:

$$\hat{DN} - \mu(n) > DN - \mu(s) \quad (11)$$

Since the mean DN value of non-shadow area ($\mu(n)$) is greater than that of shadow area ($\mu(s)$), the restored DN value of this pixel ($\hat{DN}$) must be greater than the original DN value (DN).

However, when DN is less than $\mu(s)$, Eq. (10) would become:

$$\hat{DN} - \mu(n) < DN - \mu(s) \quad (12)$$

We cannot conclude that $\hat{DN}$ is greater than DN , thus we are not able to regard this process as restoration in the strict sense. In some cases, the restored DN value is even less than the original DN value. During the experiment, it was noticed that a few shaded pixels become negative when implementing the conventional linear-correlation correction method. By contrast, the proposed method restored the shadow pixels so that all the restored DN values were not less than the original DN values in any spectral band. Despite that, the proposed method is not effective for the restoration of pixels with a zero value (black shadows). Since 0-pixels fail to provide any useful spectral information, we cannot calculate the endmember fractions and restore the spectral information in those shadows. Although this problem can cause an incomplete shadow restoration, the 0-pixels rarely exist in shadow areas over the actual imagery.

6 Conclusions

In this study, a novel global shadow compensation approach using fully constrained linear spectral unmixing was proposed for high resolution satellite imagery of urban areas. Compared to the conventional linear-correlation correction method, the proposed method benefited the shadow-restored imagery in three aspects: 1) the compound shadow containing vegetation and sealed surface was better restored and recovered without overcompensated pixels; 2) the characteristics of spectral mixing space were better retained so that the spectral properties of restored shadow patches were quite similar to the adjacent land covers; and 3) the edge of non-shadow and shadow areas was smoothed in order to ensure the continuity of land covers.

Although the proposed approach successfully improved shadow compensation for the utilized WorldView-2 imagery, the existence of 0-pixels and the accuracy of shadow detection could still limit its potential applications. In addition, the accuracy of object-based shadow detection also strongly impacts the performance of the proposed compensation approach. The misclassification of shadows and very dark rooftops can result in overcompensation of brightness in the entire imagery. Therefore, further work will be conducted to eliminate the 0-pixels with the assistance of local operators and to reduce the misclassification of shadows and very dark rooftops in future work.

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