Shadow Analysis in High-Resolution Satellite Imagery of Urban Areas

Paul M. Dare

Abstract
High-resolution satellite imagery (HRSI) offers great possibilities for urban mapping. Unfortunately, shadows cast by buildings in high-density urban environments obscure much of the information in the image leading to potentially corrupted classification results or blunders in interpretation. Although significant research has been carried out on the subject of shadowing in remote sensing, very few studies have focused on the particular problems associated with high-resolution satellite imaging of urban areas. This paper reviews past and current research and proposes a solution to the problem of automatic detection and removal of shadow features. Tests show that although detection and removal of shadow features can lead to improved image quality, results can be image-dependent.

Introduction
Shadows have played an important role in remote sensing for almost as long as the science has been in existence. From the earliest days of aerial photography, the effects of shadowing have been utilised to highlight ground features in applications such as archaeology and aerial reconnaissance. However, more often than not, shadows are considered a nuisance obscuring important object space detail. Unlike airborne imaging where shadows can be minimised by flying at certain times during the day, low Earth orbit satellite-based sensors are limited to acquiring images at fixed times of the day. If the solar elevation is low at the time, then the presence of shadows will be unavoidable.

The principal problem caused by shadows is either a reduction or total loss of information in an image. Reduction of information could potentially lead to the corruption of biophysical parameters derived from pixels values, such as vegetation indices (Leblon et al., 1996). Total loss of information means that areas of the image cannot be interpreted, and value-added products, such as digital terrain models, cannot be created.

The problem of shadowing is particularly significant in high-resolution (approximately 1 m) satellite imaging (HRSI). The equatorial crossing time of 1030 of the Ikonos satellite was chosen to ensure stable imaging conditions (the atmosphere is generally clearer in the morning than later in the day). This, however, means that the solar elevation will never be high, irrespective of latitude and season. The effects of shadowing can be reduced slightly by increasing the look angle of the sensor (basically looking at a region on the ground where the local solar time is slightly later), but this in turn increases the occlusion of features in the image. Figure 1 shows an image of Melbourne, Australia, acquired at 0958 on the 23 March (mid-autumn). The solar elevation angle was approximately 38°, and consequently, long shadows are visible.

The effects of shadowing are compounded in regions where there are dramatic changes in surface elevation, namely in urban areas. The tall buildings depicted in Figure 1 are casting shadows that are obscuring many other surface features. Even the smaller buildings are casting shadows that are obscuring details on the surrounding streets. It is somewhat ironic that the features that high-resolution satellite sensors have been designed to image are those features which are most affected by shadowing. In comparison, large-scale features, which are more appropriately imaged by lower resolution sensors such as regional vegetation patterns, consist of fewer dramatic changes in elevation, and hence, are less likely to be affected by their own shadows.

The objective of this paper is to present a methodology for detecting and removing shadows from HRSI of urban areas. However, before this is tackled, the physical principles behind shadowing are investigated, and a literature review of previous shadow analysis research is presented. Methodologies and results are then presented for the two themes of this paper: shadow detection and shadow removal.

Definition of Shadows
When considering the shadow cast by a typical high-rise building, there are actually two shadows present: the cast shadow (the one cast on the ground) and the self shadow (the part of the object that is not illuminated, i.e., the façade of the building). It is likely that the cast shadow and the self shadow have different brightness values. The brightness of all the shadows in an image depends on the reflectivity of the object upon which they are cast as well as the illumination from secondary light sources. Self shadows usually have a higher brightness than cast shadows since they receive more secondary lighting from surrounding illuminated objects. Although the work presented in this paper does not discriminate between cast shadows and self shadows, almost all of the shadows in the images used in this study are cast shadows due to the sensor look angle at the time of acquisition.

With high-resolution satellite remote sensing (i.e., images with a ground resolution of 1 m or better) it cannot be assumed that the light source is a point source at infinity...
Figure 1. Shadows cast by buildings in Melbourne’s central business district (Ikonos panchromatic channel).

Figure 2. Estimation of the size of the penumbra for a typical building.

For the Ikonos image shown in Figure 1, $e = 38^\circ$ and $\varepsilon = 0.266^\circ$, giving a value of $w$ of $0.0245H$. Thus, the width of the penumbra cast by the top of a building 50 m high is 1.23 m, a distance which corresponds to over one pixel in Ikonos images and almost exactly two pixels in Quickbird images. The implication of this is that the penumbra will be visible in high-resolution satellite images, and hence there will not be a definite boundary between shadowed and non-shadowed regions.

Previous Research

Shadow Detection and Removal

Previous research into shadow detection and removal in low to medium resolution imagery has almost exclusively focussed on the problem of cloud shadows rather than ground feature shadows. Wang et al. (1999) describe an automated technique for the detection and removal of cloud shadows from Landsat TM imagery based on changes in reflectance (to detect the clouds) and changes in frequency components of the image (to detect the corresponding shadows). Regions, where data has been lost, is replaced with corresponding data from images acquired at a different time. Simpson and Stitt (1998) propose a procedure for cloud shadow removal from AVHRR data using both radiometric and geometric image analysis. Leblon et al. (1996) describe in detail the effects of shadowing on electromagnetic reflectance from different surfaces. Measurements were made using ground-based radiometers duplicating the spectral sensitivity of the SPOT HRV and Landsat TM sensors. An example of ground feature shadows (as opposed to cloud shadows) imaged by medium resolution sensors (Landsat TM) is provided by Giles (2001). The effect of terrain-cast shadows in mountainous areas on image classification is described, and an automatic shadow detection algorithm, based on the geometric properties of the terrain, is evaluated against manual interpretation.

Lui and Moore (1993) investigated cloud shadow removal from a moderate resolution airborne sensor, the Daedalus Airborne Thematic Mapper. The technique for removal of cloud features relies on thermal infrared information which is used to replace the intensity component of an RGB false colour composite image. Since thermal infrared data is not acquired by high-resolution sensors, this method cannot be applied to the study presented in this paper. Another procedure for removing shadows using geostatistical interpolation (kriging) has been described by Rossi et al. (1994).

Although research into shadow detection and removal from high resolution imagery has been less thoroughly researched, there have been attempts over the years to tackle some of the problems. Rau et al. (2002) mention shadow removal as part of a wider study into the generation of “true” orthoimages in an urban context. Shadows are detected using a geometric model based on the same fundamental principals described by Giles (2001). Removal of the shadows is by image enhancement, the parameters of which are determined by local histogram matching. Shu and Freeman (1990) describe a procedure for detecting and removing cloud shadow from aerial photographs. As with other researchers, they separate the problem into two sub-problems: shadow detection and shadow removal. The removal procedure uses a grey scale transformation to enhance the image, but more importantly, it tackles the problem of partially shadowed areas, an issue mentioned by few other researchers.

In addition to the work cited above, important work into shadow detection and removal has been carried out by many other researchers. The problem of shadowing in...
moderate resolution imagery (in particular Landsat TM and MSS) caused by changes in terrain has been discussed by Richter (1998), Itten and Meyer (1993), Kawata et al. (1988) and Hall-Koneyves (1987).

Shadow Exploitation
In high-resolution images, shadows have more frequently been used to aid reconstruction of the three-dimensional geometry lost in the imaging process. A classic example is given by Irvin and McKeown (1989), who used shadows in aerial photographs to recover the shape and heights of buildings. Liow and Pavlidis (1990) also used detection of shadows (using edge detection and region growing segmentation) to recover the shape of buildings in aerial photographs. More recently, Shettigara and Sumerling (1998) described a method of determining the heights of extended features (buildings once again), imaged by the SPOT satellite sensor, from the shadows they cast. Prior to this, Hartl and Cheng (1995) and Cheng and Thiel (1995) describe an alternative method to achieve the same aim, namely building height determination from shadow measurement in SPOT images.

One final application which takes advantage of shadows is automatic tie point identification, as described by Brivio et al. (1992). Shadows cast by mountainous terrain were automatically matched with artificial shadows generated from a DEM, thus allowing automatic tie point identification. A review of the current status of research into shadowing in remotely sensed imagery, as well as analysis of work carried out over the past couple of decades, has shown that research has kept pace with the developments in imaging technology. Early research focussed on the removal of shadows caused by clouds and terrain from low to moderate resolution imagery (AVHRR and Landsat MSS). In parallel to this, research into the exploitation of shadows for three-dimensional modelling took place using high-resolution aerial photographs. Currently, high resolution satellite imagery is readily available, but shadows pose an enormous problem for image interpretation in urban regions. The remainder of this paper investigates the possibilities of detecting shadows in high-resolution images of urban areas and reducing their impact to improve image interpretation.

Shadow Detection
Shadow Detection Techniques for High-Resolution Satellite Imagery
High-resolution, satellite-based imaging sensors (Quickbird and Ikonos) provide one band of panchromatic data and four bands of multispectral data at a quarter of the resolution of the panchromatic data. The choice of which bands to use for shadow detection (panchromatic, multispectral, or a combination of both) depends on the type of detection algorithm employed. Spatial detection will obviously require higher spatial resolution, whereas spectral detection (such as classification) will require greater spectral resolution.

Four different (but potentially inter-related) algorithms for separating shadow pixels from non-shadow pixels are classification, segmentation, thresholding, and geometric modelling. Each of these procedures is described in more detail below.

Thresholding
Thresholding is simply the method of binarizing an image by setting all pixels whose values are greater than some threshold level to “high”, and the remaining pixels to “low”. The classic problem associated with thresholding, and one that has generated significant research over the years, is selecting the most suitable threshold level to best separate desired features from undesired features. Since the shadows in high resolution satellite images occupy the lower end of the histogram, with few other features having such low grey levels, thresholding is a potentially ideal method of shadow detection: by choosing the correct threshold level, it should be straightforward to separate shadow from non-shadow, without too many pixels being misclassified.

Not surprisingly, thresholding as a method of shadow detection has been used by many previous researchers. Nagao et al. (1979) used bimodal histogram splitting as a method of shadow detection in high-resolution aerial photographs. Shettigara and Sumerling (1998) thresholded SPOT images to extract shadows of buildings and trees, but due to the low resolution of the data, there was no distinct peak in the histogram denoting shadow pixels. An alternative method was therefore used to determine the threshold level based on the correlation of the accuracy of tree height measurements with a range of threshold values. Cheng and Thiel (1995) used an adaptive threshold method in their measurement of building heights from shadows in SPOT images.

Classification
Image classification is most commonly used with multispectral data, rather than panchromatic data, to extract image features. However, the lower resolution of the Ikonos multispectral data (4 m compared to 1 m for the panchromatic data) means that the spatial precision of shadow boundaries detected by classification of the multispectral image would be poorer than shadow boundaries extracted from the panchromatic image.

During the course of this study, classification was tested with both pansharpened multispectral data and single band panchromatic imagery. Both images were classified using an unsupervised classification algorithm in order to give two final classes: shadow and non-shadow. The tests showed that results for both the panchromatic data and the pansharpened data were almost identical. This would be surprising (multispectral data would be expected to give a much better result than single band panchromatic data) were it not for the radiometric properties of the feature being detected.

Region Growing Segmentation
Segmentation is simply the process in which an image is split into a contiguous spatial array of discrete regions (Gonzalez and Woods, 1992). Unlike with classification, in region growing segmentation pixels are assigned to regions based on their spatial and spectral distance from those regions to which they could potentially be assigned. The classic problem with region growing segmentation is that the result is dependent on the starting points (or, seed points) from which regions are grown. In shadow detection, this problem is much less of an issue since shadows generally represent the lowest pixel values in the image, and thus the points with the lowest grey values in the image can be used as seed points from which regions can be grown.

However, before this can be done, the criteria by which pixels are assigned to a segment must be defined. The common approach is to use the spectral distance between the pixel in question and the mean grey value of the neighbouring region: pixels which are radiometrically too distant from the region will not be added. The final question then is what distance should be used to ensure maximum likelihood of agglomerating all the shadow pixels with fewest non-shadow pixels added. Just as with the question of seed point choice, this is a typical problem of image segmentation. The solution to choosing the optimum parameter for pixel agglomeration comes once again from an examination of the histogram of the shadowed image.
Three Dimensional Modelling
Each of the shadow detection methods described above use the radiometric properties of the image to detect shadows. An alternative technique is to use knowledge of the imaging geometry and solar illumination at the time of image acquisition. This method has been used by Rau et al. (2002) in urban areas, and Giles (2001) in mountainous areas. It relies on a knowledge of the three-dimensional structure casting the shadows, which in an urban context would be a 3D city model and the corresponding underlying terrain model. Assuming a sufficiently accurate city model is available, simple geometry, as described by Richter (1998) can be used to determine in ground coordinates, which points will be in shade and which will be directly illuminated. This information can then be re-projected back into the image to separate shadow pixels from non-shadow pixels.

The problem of this method is in the acquisition or creation of a suitably accurate city model. If a model cannot be acquired from a source such as a topographic database, then either significant manual processing is required to create one from high resolution imagery or automatic processing must be used. However, the difficulties of automatically creating accurate 3D city models from aerial or satellite imagery are well documented (Gülch, 2000; Fraser et al., 2002). High-resolution satellite imagery poses more difficulties due to the limited availability of stereo data and the high cost of precision data.

Proposed Methodology for Shadow Detection in High-Resolution Satellite Imagery
Based on experiments with the various shadow detection techniques described above, a methodology has been developed for extracting shadows from single band high resolution panchromatic satellite images. There is no assertion being made here that this is the only methodology to follow, or even that it is the best possible methodology. It is being proposed as a technique which has proved to be successful in the context of the images with which it was tested. The algorithm separates shadow from non-shadow by thresholding at a predetermined level and post-processing the segmented regions. The simplicity of the algorithm reflects the simplicity of the task: only two regions need to be extracted, and one of those regions occupies a well-defined portion of the brightness values. Each of the processing steps of the proposed algorithm is described in more detail below.

Density Slicing
The large dynamic range of high resolution satellite imagery (11 bits, giving some 2048 grey levels) does not only offer the opportunity to extract useful spatial information from shadowed regions, but also makes the detection of shadows significantly easier than would be the case with 8 bits (255 grey levels). Many current software packages, as well as popular image formats, are designed to process 8 bit data. Indeed, there are significant benefits in working with 8 bits as compared to 11, and thus it is fortunate that pixels representing shadows typically fall somewhere in the range of grey levels between 0 and 255. A simple density slicing of the 11 bit imagery where all values between 255 and 2047 (the upper limit of 11 bit data) are set to 255, and values below 255 retain their original values, allows not only the imagery to be reduced to 8 bits leading to more efficient processing, but also removes the vast majority of the non-shadow structure from the imagery (see Figure 3). Figure 3 also highlights the large amount of information present in shadowed regions, which is often lost in 16-bit to 8-bit conversions.

Thresholding
Tests showed thresholding to be the ideal method of shadow detection in high resolution satellite images due to the spectral content of the images. However, the difficulty with thresholding lies in selecting the most appropriate threshold level. Bimodal histogram splitting provides the most robust method of threshold level selection for this particular study since the image has only two features of interest: shadow and non-shadow. Figure 4 shows the histogram for the image displayed in Figure 3.

It is clear from the bimodal nature of Figure 4 that there are two predominant features in Figure 3. It was found by experiment that taking the mean of the two peaks gave consistently accurate threshold levels from separating the shadow from the non-shadow regions.
Region Encoding
After thresholding, the shadow and non-shadow regions were encoded such that all discrete regions were given a unique identity. Attributes of each region (such as size and location in image space) could then be calculated and recorded. This processing step was necessary for the filtering of regions that has to be performed to remove potential blunders.

Region Filtering
Extracted regions have to be filtered in order to separate shadow from falsely detected, non-shadow regions. A particular difficulty encountered when thresholding high resolution satellite imagery is that water and shadows have almost identical radiometric responses: three of the methodologies described above (thresholding, classification, region growing segmentation) misclassify water as shadow. Therefore, it was necessary to filter the regions to separate shadow from water. A simple, but reliable, method of distinguishing between these two features is to examine the variance of groups of pixels. Due to the fact that many features are actually visible within the shadowed regions mainly because of secondary illumination, the variances of shadowed regions are higher than the variances of water regions (Figure 5). Thus, variance can be used as a distinguishing attribute of shadow and water regions (Table 1).

Figure 5 shows two segments extracted from the Ikonos image; the extra detail in the shadow region and hence higher variance, compared to the water, is clear. Table 1 shows the attributes for a range of shadowed regions selected from across the test images compared to the one water region. In all cases, the variances are higher, irrespective of other attributes, such as size or mean value. Thus, variance can be used as a distinguishing factor in the comparison of shadowed regions and water surfaces in high resolution satellite imagery. Selection of the “variance threshold” can be made from an examination of the images.

As a final filtering step, small regions (less than 25 pixels in size) were removed from the image. This was necessary to avoid creating a “noisy” image in the shadow enhancement procedure described below.

Results of Shadow Detection
The shadow detection algorithm described above was applied to two different high resolution satellite images (Ikonos and Quickbird) of the Melbourne Central Business District (CBD). Figure 6 shows each test image and the corresponding shadow masks generated by the shadow detection algorithm. Note that the study areas are slightly different; this was due to the differing imaging conditions at the time of acquisition of each image.

Although the regions of interest of the two example images are very similar (high density urban), the results of the shadow detection algorithm are quite different. This is due to imaging conditions at the time of acquisition and post-processing. The Ikonos image (Figure 6a) was acquired at a nominal resolution of 0.84 m, and re-sampled by the data supplier to a pixel size of 1 m. Post-acquisition radiometric processing has left a comparatively dark image; the mean grey level of the shadow regions is approximately 76. Examination of the histogram gave the optimum threshold level as 135. After thresholding at this level and filtering the resulting binary image, the final number of shadow regions detected was 124. By comparison, the Quickbird image (Figure 6c) was supplied with a pixel size of 0.7 m. Post-acquisition, radiometric processing left a considerably brighter image, with a mean shadow grey level of approximately 174. The optimum threshold level for separating shadow and non-shadow in this data set was 215. The shadow detection algorithm yielded 104 distinct shadow regions in the image.

The lower resolution of the Ikonos image has led to the shadow features being imaged at a smaller scale giving them a very different appearance when extracted, as compared to the Quickbird shadows (compare Figures 6b and 6d). Even so, comparison of the detected shadow regions with the original images shows that shadow detection and extraction has been successful. Further analysis is possible by overlaying the boundaries of the shadow regions onto the original images.

Even with close analysis of Figure 7a, it is very difficult to detect errors in the shadow boundaries. However, in Figure 7b, at least one blunder can be easily seen in the centre right of the image. Independent validation of the performance of the shadow detection algorithm, beyond visual analysis, is difficult to achieve, since unlike most other remote sensing applications, the image data cannot be verified with ground surveyed data: the shadows that existed on the day of acquisition will not exist again until imaging conditions are identical, by which time other ground features could well have changed.

<table>
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<td>26209</td>
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Table 1. Comparison of Attributes of Shadow and Water Segments

Photogrammetric Engineering & Remote Sensing

Shadow Removal
Techniques for Shadow Removal from High-Resolution Imagery
For the majority of remote sensing applications, it would be preferable that high-resolution satellite imagery could be acquired when lighting conditions were at their optimum
and shadows minimized. Unfortunately this is not always possible, and thus, alternative techniques have to be developed to cope with the problems caused by shadows. Three techniques are presented below for “removing” shadows from high-resolution imagery.

**Masking**

The most straightforward method for removing shadows from imagery after they have been detected is to simply mask them out, i.e., set all shadow pixels to black. The result is an image with no shadows, but even less information than the original image. For manual interpretation, this approach to shadow removal is not favoured, since in many cases the shadows are actually useful for recognising buildings. In automatic image interpretation, for example classification, the removal of a complete class will reduce the likelihood of pixels being misclassified as this class. However, if the shadow class is well-defined, misclassification may well be unlikely to occur, and hence, pre-classification masking is unnecessary.
there are a number of clear problems with applying this technique to high-resolution satellite imagery. 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, assuming non-shadowed data is available (from another source, such as aerial photography), the question must then be asked: if aerial photography is available to fuse with the satellite imagery, why is the satellite imagery required at all? Third, assuming there is good reason to fuse aerial photography and high-resolution satellite imagery for shadow removal, the problem of radiometric differences between the two sensors must be addressed: high-resolution satellite imagery has four bands (near infrared, red, green, blue) while aerial photography is either greyscale, color or color-infrared. Thus, there is no guarantee that patching in data from aerial photography to eliminate shadows in high-resolution imagery is going to aid image interpretation, such as classification. Finally, there is the problem of image registration: the images must be accurately registered to each other to ensure the correct pixels are being used in the fusion procedure. In a region where there is little topographic variation, this is not a problem. However, in a high-density urban environment accurate image registration poses significant problems. The only real solution is to perform rigorous photogrammetric processing on all the data sets to be registered, a procedure which would necessarily require a high-resolution 3D city model.

As a result of these issues, it would not be a useful exercise to evaluate multisource data fusion as an option for shadow suppression in high-resolution imagery in urban environments.

Radiometric Enhancement

Radiometric enhancement as a method of reducing the severity of shadows in high-resolution imagery has been previously discussed by Shu and Freeman (1990) and Rau et al. (2002). The technique described, based on histogram matching, is similar to image balancing in orthomosaic generation: the histograms of neighbouring regions are adjusted to match each other in order to minimize the radiometric differences across the boundary of the regions. Shu and Freeman (1990) proposed three methods to carry out this task: an algebraic greyscale transformation, histogram equalization, and a mean and variance transformation; they found the third method to be most successful. Since the radiometry of an image can vary spatially quite considerably, histogram matching is best carried out on a local rather than global level. It is beneficial to match the histogram of the shadow with the histogram of the region immediately surrounding the shadow. However, unless individual buildings and their corresponding shadows are spatially isolated from each other, matching on a region by region basis can be very difficult to achieve in practice: the many neighbouring shadows from multiple buildings become agglomerated into a single shadow region. In such cases there is no other option but to use the statistics for the entire shadow region.

Results of Shadow Removal

Radiometric enhancement of shadow regions was carried out for the Ikonos and Quickbird images shown in Figures 6a and 6c. The shadow regions shown in Figure 6b and 6d were used as masks for the radiometric enhancement. The parameters of the radiometric enhancement (a mean and variance transformation) were determined by comparing the histograms of the shadowed and non-shadowed regions. The results are shown in Figure 8.
Comparison between Figure 6 and Figure 8 show that radiometric enhancement has led to much greater detail becoming visible in the images. However, from the figures it is clear that radiometric enhancement of shadowed regions is image dependent, with Figure 8b (Quickbird) showing much more visually pleasing results than Figure 8a (Ikonos). In the Ikonos results, not only has less detail been revealed, but also artificial artefacts (bright boundaries at the edges of the shadow regions) have been introduced. There are two possible reasons for these effects. First, radiometric post-processing of the images means the Quickbird image is simply brighter than the Ikonos image, leading to more detail being present in the shadows. Consequently, the radiometric enhancement of the Quickbird shadows results in more details becoming visible than is achieved with the Ikonos shadows. Second, problems with radiometric enhancement occur at the boundary between shadow and non-shadow due to the existence of the penumbra (semi-shadow region). Thresholding of the Ikonos imagery has evidently extracted these regions as shadow, whereas with the Quickbird data these regions have not been extracted. Furthermore, these artefacts are more evident in the Ikonos image since there are far more shadow boundaries due to the more fragmented nature of the shadow regions.

Two possible solutions to the problem caused by the penumbrae are to either change the threshold level so that the penumbrae are not extracted, or to process the binary shadow regions to remove the pixels corresponding to the penumbrae. Unfortunately, neither of these solutions is particularly appropriate. Changing the threshold level is difficult to justify since this level was determined automatically from the histogram of the original image. Processing the binary shadow image is difficult since the penumbra pixels are hard to isolate. The shadow cast by the top of a 50 m building will create a penumbra of approximately 1 m (1 pixel in the Ikonos image). However, the bottom of the building will not create any penumbra at all. Therefore, to remove pixels from the binary image it is necessary to know the height of the feature to which those pixels correspond.

Despite this potential problem, the binary shadow image was processed by eroding the edges of all the regions by one pixel to remove possible penumbra pixels, and the radiometrically enhanced image was recalculated. The result is shown in Figure 9.

The result is an image with fewer bright boundaries around the shadows, but more dark boundaries. Comparing Figure 9 with Figure 8a, it is difficult to say which image
shows better radiometric enhancement. A final solution to the penumbra problem is suggested by Shu and Freeman (1990), who tackled the issue by defining three distinct regions (shadow, semi-shadow, and non-shadow) and adjusting the brightness of each one independently of the others. Due to the complex structure of high-resolution imagery of urban areas, this method is unlikely to produce useful results here.

Conclusions
This paper has presented the problems of shadowing in high-resolution satellite imagery and methods to detect and remove those shadows. It was found that many algorithms for successful shadow detection exist with the simplest algorithms such as bimodal histogram splitting providing the best chances for separating shadow from non-shadow regions in the imagery. The process of removing shadows from the image by radiometrically enhancing shadow regions has proved to be a much more difficult challenge to overcome. Few researchers have tackled the issue of shadow removal in urban areas, but now with high-resolution satellite imagery being widely available it is a problem that must be resolved. At present, radiometric enhancement of shadow regions is the only viable method of shadow removal. However, this study has shown that results can be variable, depending on image acquisition parameters such as spatial resolution and radiometric post-processing. Despite the problems, automatic shadow detection and enhancement can greatly improve the interpretability of some images (such as the Quickbird example in this paper).

Future work will continue to focus on improved methodologies for the detection and removal of shadows. Three-dimensional city modelling should prove to be a valuable technique for shadow detection, assuming that a precise model is available. Work is currently underway to develop superior automatic techniques for extracting three-dimensional models from high-resolution satellite imagery. In addition, more advanced shadow discrimination algorithms based on textural as well as radiometric classification may yield better results than bimodal histogram splitting alone.

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References