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Application of geographically weighted regression to fill gaps in SLC-off Landsat ETM+ satellite imagery

Chuanrong Zhang\textsuperscript{a*}, Weidong Li\textsuperscript{a}, and Daniel Civco\textsuperscript{b}

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Landsat 7 enhanced thematic mapper plus (ETM+) satellite imagery is an important data source for many applications. However, the scan line corrector (SLC) failed on 31 May 2003. As a result of the SLC failure, about 22\% of the image data is missing in each scene; this is especially pronounced away from nadir. In this article, a local regression method called geographically weighted regression (GWR) is introduced for filling the gaps of the Landsat ETM+ imagery, and it is compared with kriging/cokriging for this purpose. The case studies show that the GWR approach is an effective technique to fill gaps in Landsat ETM+ imagery, although the image restoration is still not perfect. GWR performed marginally better than the complex cokriging method, which too has proven to be an effective method, but is computationally intensive. Although there are visible seam lines at the edges of the filled wide gaps in some bands, the validation results – including RMSE values, error distribution maps, and classification results for the case studies – demonstrate that the DN values estimated by GWR are in fact closer to those of the original image than the corresponding values estimated by kriging/cokriging.

1. Introduction

Landsat enhanced thematic mapper plus (ETM+) satellite imagery is an important data source for many applications. For example, Landsat ETM+ satellite imagery has been used for land-use/cover mapping and change detection (e.g. Civco et al. 2002; Lo and Choi 2004; Mundia and Aniya 2005), large-area impervious surfaces mapping (e.g. Yang et al. 2003; Hurd and Civco 2004), burn severity assessment (van Wagendonk, Root, and Key 2004), and prediction of biophysical variables such as biomass, percentage woody canopy cover, and leaf area index (Cohen et al. 2003). However, the scan line corrector (SLC), a small mirror in the optical path of the ETM+ instrument, failed on 31 May 2003. As a result of the SLC failure, individual image scans overlap in some parts of images acquired thereafter, while leaving large physical gaps in others. On average, about 22\% of the image data are missing in each scene. This problem has produced obvious negative impacts on image usability.

Efforts have been made to develop methods and tools to fill the data gaps in the ETM+ imagery. For example, a joint USGS/NASA (United States Geological Survey/National Aeronautics and Space Administration) research team developed a local linear histogram-matching (LLHM) method to resolve the missing-data problem (USGS 2004). This histogram-based compositing algorithm works well if the merged images and selected input
scenes satisfy predetermined criteria such as there being minimal cloud, snow cover or fires, low temporal variability, and minimal date separation (Scaramuzza, Micijevic, and Chander 2004; USGS 2004). However, the LLHM method can yield poor results if the scenes being combined exhibit radical differences in target radiance due, for example, to the presence of clouds, snow, or sun glint (USGS 2004). To overcome the limitations of the LLHM method for some images within these special situations, Zhang, Li, and Travis (2007) introduced the kriging/cokriging geostatistical method for filling the data gaps in SLC-off Landsat ETM+ imagery. The method yielded unbiased estimates with minimum errors. Pringle, Schmidt, and Muir (2009) further demonstrated that the cokriging geostatistical interpolation method is generally a good one for estimating the data in the gaps in the SLC-off Landsat ETM+ imagery. However, the kriging/cokriging methods are computationally intensive, thus not practical for processing a very large set of images. Maxwell (2004); Maxwell, Schmidt, and Storey (2007) introduced an object-based segmentation method to fill the missing pixels in SLC-off images, which was further evaluated for land-cover classification by Bédard et al. (2008). However, the method failed to estimate small or narrow objects in the images and also did not work well if the gap-filled scenes included heterogeneous landscapes. Boloorani, Erasmi, and Kappas (2008) developed a multi-source method called projection transformation for filling simulated gap areas in Landsat ETM+ imagery. Their results showed that the gap lines were still visible in areas with sharp radiometric differences. This technique may not work well for applications that require per-pixel accuracy and also for areas with temporally dynamic features such as agricultural fields and urban areas. Recently, several methods based on pixel similarity have been proposed for filling gaps in Landsat ETM+ SLC-off imagery (Chen et al. 2011; Zhu, Liu, and Chen 2012; Zeng, Shen, and Zhang 2013). However, similarity is not equal to correlation. Dissimilar pixels that are close together may be strongly correlated, while very similar pixels that are separated by greater distances may have weak correlations. For example, an elevation on a hill slope has stronger correlations with its nearest dissimilar elevations lying below and above it than with other distant elevations with similar or the same values. In the case of this study, pixels that are similar at one time may become very different at another time in the same study area. This causes problems for similarity-based methods. These similarity-based methods share some common limitations such as possible violation of the spatial correlation law, subjectively predetermined parameters, and slow computing speed. Although case studies have been used to verify that these methods can work well under some situations (Chen et al. 2011; Zhu, Liu, and Chen 2012; Zeng, Shen, and Zhang 2013), these similarity-based methods are not well-established methods and need further testing.

In general, many methods have been proposed to fill the gaps in Landsat ETM+ imagery. There seems to be no perfect method existing that satisfies all the various applications. Each of the aforementioned methods has its own advantages and disadvantages. In this article, a well-established and widely tested local regression method called geographically weighted regression (GWR) is introduced for filling the gaps in Landsat ETM+ imagery. GWR was specifically designed to deal with the spatial nonstationarity of regression coefficients between the target variable and explanatory variables (Brunsdon, Fotheringham, and Charlton 1996; Fotheringham, Charlton, and Brunsdon 1998; Yu, Peterson, and Reid 2009). GWR has been extensively used to model spatial distributions and relationships in a variety of fields, particularly in human geography in recent years (e.g. Tu and Xia 2008; Koutsias, Martínez-Fernández, and Allgöwer 2010). Studies showed that GWR could better account for spatial heterogeneity with less smoothing effect and might have higher accuracy than other modelling techniques such as regression kriging and cokriging (Wang, Zhang, and Li 2012; Wang et al. 2013; Wang, Zhang, and Li 2013).
has also been used to process remote-sensing-derived information. Foody (2003) was one of the first to apply GWR to remote-sensing-derived information to examine the relationship between the normalized difference vegetation index (NDVI) and rainfall. Later, GWR was used to examine the relationships between environmental variables derived from remotely sensed images (Wang, Ni, and Tenhunen 2005; Yu, Di, and Yang 2008; Kamarianakis et al. 2008; Propastin 2009; Salas et al. 2010; Comber et al. 2012; Xie, Zhang, and Berry 2013; Markogianni, Dimitriou, and Kalivas 2013). GWR studies for processing remote-sensing-derived information have been reported; however, there are few studies published addressing the application of GWR for directly processing remotely sensed data themselves. The objective of this study is to introduce the GWR approach for filling gaps in Landsat ETM+ SLC-off imagery with comparison to the other well-established spatial statistical methods—kriging/cokriging. Kriging/cokriging techniques have been used in many situations and were well documented in the remote-sensing literature (e.g. Rossi, Dungan, and Beck 1994; Curran and Atkinson 1998; Stein, Van Der Meer, and Gorte 1999; Addink 1999; Pardo-Igúzquiza, Chica-olmo, and Atkinson 2006; Zhang, Li, and Travis 2009). By using neighbouring pixel data from both the original gapped image and the reference image to estimate the local coefficients, it is expected that the GWR approach may serve as a useful alternative method for efficiently filling gaps in Landsat ETM+ SLC-off images. The development of efficient implementations of GWR in readily available GIS software facilitates the expedient processing of remote-sensing imagery and other geospatial data, and hence, the speed of filling gaps using GWR should be fast.

2. Methods

2.1. Geographically weighted regression

Traditional regression is a global model because its estimated parameters are derived from all observations in a study area; that is, it assumes the estimated parameters are constant across the study area. However, variations or spatial non-stationarity in relationships between the dependent and independent variables over space commonly exist in spatial data sets, and the assumption of stationarity or structural stability over space may be unrealistic (Fotheringham, Charlton, and Brunsdon 1998). So, when analysing spatial data, spatial nonstationarity should be taken into account.

GWR is an extension of traditional regression, in which variations in rates of change are allowed, which means that regression coefficients are specific to a location rather than being global estimates (Brunsdon, Fotheringham, and Charlton 1996; Fotheringham, Charlton, and Brunsdon 1998). That is, GWR allows the parameter estimates to be a function of location. The GWR method is expressed by

\[ y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{n} \beta_j(u_i, v_i) x_{ij} + \epsilon_i, \quad (1) \]

where \((u_i, v_i)\) is the spatial location of the \(i\)th observation, \(\beta_j(u_i, v_i)\) is the value of the \(j\)th parameter at location \(i\), \(y_i\) is the value of dependent variable \(y\) at location \(i\), \(x_{ij}\) are series of explanatory variables, and \(\epsilon_i\) represents the error terms, which are generally assumed to be independent and normally distributed with zero means and constant variance. The regression parameters in this equation are estimated for each location \((u_i, v_i)\). Therefore, the GWR model can measure spatial variations in relationships.
The parameters in the GWR model are calibrated using the weighted least squares method. In matrix form, the parameters of the GWR model for each location are estimated by

$$\hat{\beta}(u_i, v_i) = \left( X^T W(u_i, v_i) X \right)^{-1} X^T W(u_i, v_i) Y,$$

where \( W(u_i, v_i) \) is an \( (m \times m) \) spatial weighting diagonal matrix, \( X \) is an \( [m \times (n + 1)] \) independent data matrix, and \( Y \) is an \( (m \times 1) \) dependent data vector. ‘T’ stands for the transpose of a matrix.

To estimate parameters in the GWR model, it is important to decide the spatial weighting matrix. Because the weights in GWR vary according to the location of point \( i \) (the location of the \( i \)-th observation), the spatial weighting matrix has to be calculated for each point \( i \), and the weights depict the proximity of each data point to the location of \( i \) with points in closer proximity carrying more weight in the estimation of the parameters for location \( i \). Different methods can be used to calculate the weights. One way is to specify \( W_{ij} \) as a continuous function of \( d_{ij} \), the distance between \( i \) and \( j \). One choice for this function is a Gaussian kernel function:

$$w_{ij} = \exp \left[ -\frac{1}{2} \left( \frac{d_{ij}}{h} \right)^2 \right],$$

where \( w_{ij} \) is the weight of location \( j \) in the space in which data are observed for estimating the dependent variable at location \( i \) and \( h \) is referred to as the bandwidth. If \( i \) and \( j \) coincide, the weighting of data at that point will be unity, and the weighting of other data will decrease according to a Gaussian curve as the distance between \( i \) and \( j \) increases.

An alternative kernel choice uses the bi-square function:

$$w_{ij} = \left[ 1 - \left( \frac{d_{ij}}{h} \right)^2 \right]^2 d_{ij} < h,$$

$$w_{ij} = 0 \quad d_{ij} \geq h,$$

where the parameters are the same as in Equation (3). This function is a distance decay function, in which the weights of more distant points from an unsampled location \( i \) decrease and the weights will fall to zero for those observations that are far enough from the location \( i \) to be estimated (i.e. beyond the bandwidth).

These spatial kernels are fixed in terms of their shapes and magnitudes over space and belong to the fixed kernel choice for solving local regression analysis (Fotheringham, Brunsdon, and Charlton 2002). In this study, we applied the fixed kernel choice. It should be noted that there is another choice called the adaptive kernel choice for solving local regression analysis. In the adaptive kernel choice, the selections of the weighting function and optimal bandwidth \( h \) are different for different densities of sample data (Pineda Jaimes et al. 2010).
2.2. Kriging/cokriging methods

Although detailed information about kriging/cokriging methods for gap filling of SLC-off Landsat ETM+ satellite imagery can be found in Zhang, Li, and Travis (2007, 2009) and elsewhere in the literature, a brief introduction is provided here.

Variograms are used to characterize the spatial structure and measure the spatial variation in remotely sensed images as inputs for kriging/cokriging systems. The joint spatial dependence of two correlated variables is often modelled using a cross-semivariogram (in our case this refers to the two codependent images). Ordinary kriging is the most common and robust form of kriging. It accounts for local fluctuations in the mean by limiting the domain of stationarity of the mean to the local neighbourhood (Matheron 1963, 1971). Cokriging considers the spatial dependence of two or more sets of variables and their interdependence simultaneously (Goovaerts 1997). By incorporating related secondary information, cokriging considers the spatial cross-correlation between primary and secondary variables, thus improving the interpolation accuracy. To describe the experimental variograms and cross variograms for use in cokriging, a mathematical model of coregionalization (Journel 1989) has to be fitted to the experimental variograms and cross variograms.

2.3. Prediction accuracy evaluation indices

2.3.1. Root mean square error (RMSE)

The RMSE can be used to measure the overall accuracy of the gap-filled pixels and the global average deviation between the values of the gap-filled pixels and the true pixel values. The RMSE is calculated by

\[ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} [z(x_i, y_i) - z^*(x_i, y_i)]^2}, \]

where \( z \) represents DN values of the interpolated pixels, \( z^* \) represents DN values of the true pixels, and \( n \) is the number of the interpolated pixels.

2.3.2. Error distribution maps

The RMSE can be used to help evaluate the overall gap-filling performance; however, these global statistics cannot spatially assess the effectiveness of different methods as the performance of different methods may be location-dependent. To assess spatially the effectiveness of GWR or kriging/cokriging methods, the corresponding error (true digital number (DN) value minus estimated DN value) distribution maps of the test polygon areas for different bands were created in this study. Error distribution maps can graphically depict the spatial distribution of gap-filling errors.

2.3.3. Classification accuracy of interpolated images

To further confirm that the interpolated images are not only suitable for visual interpretation but also facilitate computer-aided processing, the original images and the gap-filled images were classified into thematic maps using the unsupervised ISODATA clustering method (Leica Geosystems 2003). The classification results from the original images and the gap-filled images were compared. Such results can help identify the difference between the original imagery and the gap-filled imagery in computer aided processing analysis.
3. Data and parameter preparation for case studies

The general case study area is located in western Connecticut (USA) and covered by Landsat World Reference System Path 14-Row 31. Because the whole scene is too large for visualization, several small areas were selected for processing and analysis. Furthermore, because the missing data areas across the scene vary in size from two pixels near the centre of the image to 14 pixels along the eastern and western edges, in order to test the effectiveness of the GWR method in these case studies, three small areas were selected, including one small area located close to the centre where there exist narrow gaps, one small area located in the middle of the image where medium-wide gaps occur, and one small area located close to the western edge where wide gaps occur. The study aims to test whether GWR could work well for heterogeneous landscapes containing small or narrow objects, which are difficult to estimate for most interpolation methods. Therefore, the selected areas for case studies all have complex landscapes including both small and narrow objects.

Four cases studies were conducted in this research – the first two case studies concerned the gap-filling of SLC-off Landsat ETM+ imagery and the latter two case studies were for validation. In the first two case studies, the gap imagery containing gaps was obtained on 16 April 2005 and the secondary imagery (used as an explanatory variable or secondary variable) was acquired on 24 April 2002. In the two validation case studies, the simulated imagery with gaps (discussed later) was acquired on 24 April 2002 and the secondary imagery was obtained on 10 May 2002. All of the data were downloaded from the USGS EarthExplorer website (http://earthexplorer.usgs.gov/).

The parameter estimates at any regression point in the GWR model are dependent not only on the imagery containing gaps and the secondary imagery data but also on the selected kernel function and bandwidth. There are two types of kernel construction methods – the fixed kernel method and the adaptive kernel method. The fixed kernel method uses a fixed distance to solve each local regression analysis, while the adaptive kernel method uses a smaller number of neighbours where feature distribution is dense and a larger number of neighbours where feature distribution is sparse. Because remote-sensing images contain dense sample data, the fixed Gaussian kernel choice was used to calculate weights for GWR analysis. The bandwidth can be thought as a smoothing parameter, with larger bandwidths causing greater smoothing. The trial and error method was applied to decide the bandwidth parameter in this study. It has been found that the length of 30 pixels (i.e. a distance of 900 m) is the ‘best’ bandwidth, which can produce parameters with good local variation, for all of the four case studies.

Variogram and cross variogram calculation for ordinary kriging and cokriging requires judgment and decisions on the part of the analyst (Isaaks and Srivastava 1989). An appropriate lag distance for experimental variogram and cross variogram was determined by generating and visually comparing several experimental variograms and cross variograms calculated with different lag distances. After comparing several lags, the lag distance selected for the case study was 30 m, which is consistent with the spatial resolution of the Landsat 7 ETM+ sensor. Visual inspection of preliminary experimental variograms showed this distance was long enough to capture the spatial character within the data, yet small enough to avoid unreliable values calculated for larger lags. This distance was the one that best described the radiometric differences in the immediate neighbourhood of the central pixel. Because the samples in the images used to compute the variograms and cross variograms were large, the experimental variograms and cross variograms had smooth, gradual, or rounded shapes and were gently sloping near the sill.
This made it easy to fit the experimental variograms and cross variograms with standard mathematical models. The Trial and error method was applied to decide the parameters (nugget, range, and partial sill and anisotropy values) of the variogram and cross variogram models. Each variogram or cross variogram was fitted with the same basic model as in intrinsic coregionalization (Journel and Huijbregts 1978). The coefficient matrices of these models were positive definite.

4. Results

In the first case study, the narrow gaps in the 2005 SLC-off Landsat ETM+ imagery were filled. Figure 1(a) shows the original image with narrow gaps, which cross a river (linear object). The image is displayed as a band 4 (NIR), 3 (Red), and 2 (Green) red–green–blue (RGB) false colour composite. Figure 1(b) shows the secondary image, which was used as the explanatory variable to fill in gaps with both GWR and cokriging methods. Figure 1(c) illustrates the filled image using the simple replacement method. The obvious striping artefacts in this simple-replacement-filled image indicate that the images being combined exhibit substantial differences in target radiance. The two images were acquired at a similar season. They show different radiance values for several reasons, such as different sun–scene geometry introduced by different image acquisition dates.

Figures 1(d)–(f) show the gap-filled images produced using ordinary kriging, cokriging, and GWR methods, respectively. From these images it can be seen that all of the three methods can effectively fill in the narrow gaps with few visible differences. There are no obvious artefacts in any of the three gap-filled images. The linear river object has

![Figure 1](image-url)
been filled well and is continuous in all of the filled images using the three gap-fill methods.

In the second case study, wide gaps in the 2005 SLC-off Landsat ETM+ imagery were filled. Figure 2(a) shows the original image with wide gaps. It can be seen that the landscape in this area is complex and includes both small and narrow objects. Figure 2(b) shows the secondary image that was used as the explanatory (or ancillary) variable for both GWR and cokriging methods. As shown in Figure 2(c), the gap-filled image using the simple replacement method has obvious gap artefacts, suggesting that there are substantial differences between the original image and the secondary image.

Figures 2(d)–(f) show the gap-filled images using ordinary kriging, cokriging, and GWR methods, respectively. It can be seen that, while ordinary kriging filled the image with narrow gaps well in the first case study, it did not fill the image with wide gaps well.
in this case study because the shapes of the linear objects were not preserved. In addition, small objects were missed in the filled image by ordinary kriging. However, both gap-filled images done with cokriging and GWR preserved the continuous shapes of linear objects well, and small objects within the gaps were also well captured. The image filled by cokriging showed more smoothing effect than the filled image produced by GWR. However, the seam lines at the edges of the filled gaps in the GWR-filled image are relatively more visible than those in the cokriging-filled image, especially for the stripe that forms the gap in the middle of the image. The reason should be that cokriging directly based its estimated values (in the gaps) on the neighbouring pixels (outside the gaps) in the gapped image, whereas GWR did not do so directly. Therefore, there are visible seam lines at the edges of the filled gaps in the GWR-filled image. However, the general filling quality by GWR is actually better than that by cokriging, as explained later in the validation case studies.

From this case study, it was also found that the qualities of the filled images for different bands are also different for both the cokriging and GWR methods. Figures 3(a)–(c) show

![Figure 3](image)

Figure 3. Results of wide-gaps filling using cokriging and GWR for bands 2, 3, and 4. (a), (b), and (c) show the results of applying cokriging to bands 2, 3 and 4, respectively; (d), (e), and (f) show the results of applying GWR to bands 2, 3, and 4, respectively.
the gap-filled images for bands 2, 3, and 4 using cokriging, and Figures 3(d)–(f) show the gap-filled images for bands 2, 3, and 4 using GWR. From these filled images, one can see that different bands show different filling qualities. Both methods worked best for band 4 and worst for band 3. The GWR-filled image of band 3 has more obvious seam line artefacts, whereas the cokriging-filled image of band 3 has more smoothing artefacts. Possible causes are (1) the substantial differences between the original image and the secondary image vary from band-to-band; (2) GWR tends to give prominence to the effect of the explanatory variables; and (3) cokriging can be based directly on neighbouring data while GWR cannot. Table 1 provides the correlation coefficients and mean differences between the DN values of the original image and the secondary image for the wide-gap filling case study. One can see that band 3 has the smallest correlation coefficient of 0.595 and the largest mean difference of 6.7. Band 4 has the highest correlation coefficient of 0.846, and a smaller mean difference of 3.54. This suggests that there are more substantial differences in band 3 and less difference in band 4 between the original image and the secondary image. These differences may have caused both cokriging and GWR, which use information from both the original imagery and the secondary imagery, to perform differently with different bands.

To verify the feasibility and reliability of the GWR method and to assess the accuracy of the method, in the third case study, simulated data containing gaps were manually created by forming (i.e. cutting) some medium-wide strips from an image. The manually cut data were similar to the data gaps in the SLC-off ETM+ image used in the first case study but were wider. Figure 4(a) shows the original image in this validation case study and Figure 4(b) shows the simulated image with the medium width strips. Another image (shown in Figure 4(c)), which was acquired on 10 May 2002, was used as the secondary image (i.e. the explanatory variable) for gap-filling using both GWR and cokriging methods.

As was done in the previous two case studies, ordinary kriging, cokriging, and GWR methods were applied for gap-filling in this validation case study. Figures 4(d)–(f) illustrate the gap-filled images. It can be seen that the quality of the gap-filled images produced by cokriging and GWR are better than the image gap-filled by ordinary kriging, which has some smoothing effect. The gap-filled image by ordinary kriging displayed more smoothing effect in this case study than in the first case study. Despite the fact that the landscapes are heterogeneous in this validation case study, both cokriging and GWR worked well in filling the medium-width gaps. Compared visually with the real data in the original image, the continuity of the majority of the scene in the interpolated regions by both cokriging and GWR methods is good and the spatial patterns are restored well. Because ordinary kriging performed poorly compared to cokriging, in the latter comparison, only the comparison results between cokriging and GWR are shown.

Since there are real data in this case study available for validation, the RMSE between the true DN values in the original image and the estimated DN values by both cokriging and GWR were calculated at the corresponding locations. Table 2 gives the RMSE for the

<table>
<thead>
<tr>
<th>Correlation coefficient</th>
<th>Mean difference</th>
</tr>
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<tbody>
<tr>
<td>Band 2</td>
<td>0.733</td>
</tr>
<tr>
<td>Band 3</td>
<td>0.595</td>
</tr>
<tr>
<td>Band 4</td>
<td>0.846</td>
</tr>
</tbody>
</table>
cokriging and GWR filling for bands 2, 3, and 4 for this validation case study. The RMSEs for the cokriging are generally larger than those for the GWR for bands 2, 3, and 4. The smaller RMSEs for the GWR filling indicate that the overall performance of GWR is better than that of cokriging. However, performance may be location dependent. To assess the spatial differences between GWR and cokriging performances, corresponding error distribution maps were created. These maps are useful in analysing the reliability of the DN value of each pixel in

![Figure 4](image)

**Figure 4.** Images used for the validation of the medium-wide gap filling. (a) is the original image, (b) is the simulated image, and (c) is the secondary image acquired on 10 May 2002. (d), (e), and (f) show the results of applying ordinary kriging, cokriging, and GWR to the simulated image, respectively.

<table>
<thead>
<tr>
<th>Band</th>
<th>Cokriging</th>
<th>GWR</th>
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<tbody>
<tr>
<td>2</td>
<td>3.05</td>
<td>1.98</td>
</tr>
<tr>
<td>3</td>
<td>4.68</td>
<td>3.11</td>
</tr>
<tr>
<td>4</td>
<td>2.21</td>
<td>2.53</td>
</tr>
</tbody>
</table>

Table 2. The root-mean-square-errors (RMSEs) for cokriging and GWR gap-filling for bands 2, 3, and 4 for medium-width gap filling.
the gap-filled imagery. They are also helpful in determining where more information is needed in real world applications to make decisions effectively using the gap-filled imagery. Figure 5 displays the highlighted error spatial distribution maps for band 2. Gray and black locations show areas of positive (i.e. underestimation) and negative (i.e. overestimation) errors, respectively. An expected pattern in these error distribution maps is that the errors are greatest in those places where there are the least consistent DN values, such as the in areas containing small objects.

To confirm further that the interpolated images can be used for classification, the original image and the gap-filled images produced by cokriging and GWR were classified into thematic maps using unsupervised ISODATA clustering (Figure 6). It can be seen that the classification maps from the original image and the gap-filled images produced by both GWR and cokriging are similar. This means that the gap-filled images produced by both GWR and cokriging are similar to the original image and they can be used for computer-aided processing. There are, however, slightly different performances between GWR and cokriging. Figure 7 shows the highlighted classification differences between the original image and the filled images produced by GWR and cokriging. One can see that there are fewer classification differences between the original image and the image filled using GWR. This suggests that the DN values estimated by GWR are closer to those of the original image.

To validate further the effectiveness of the GWR method in filling wide gaps in Landsat ETM+ satellite imagery, in the fourth case study, the same wide strips as in the second case study were manually cut (Figure 2) from the 24 April 2002 imagery. Figures 8(a) and (b) show the original image and the simulated image used in this validation case study. Another image, which was acquired on 10 May 2002 (from the same scene as used in the third case study), was used as the secondary image (explanatory variable) (see Figure 8(c)) for both the GWR and cokriging methods. The manually cut gaps were filled using ordinary kriging, cokriging, and GWR methods.
Figure 6. Classified maps based on the image in Figure 4(a). (a) is the classified original image; (b) and (c) show the classification results after the narrow gaps were filled by cokriging and GWR, respectively.

Figure 7. Highlighted classification differences between the original image and the images resulting from filling the images with medium-wide gaps: (a) shows the differences when the gaps were filled using cokriging and (b) shows the differences when the gaps were filled by GWR. Some classification differences also occurred outside the gaps due to some lack of correspondence in classification caused by the differences in filled gaps.
Similar to the results shown in Figure 2, ordinary kriging performed the worst and the filled image in this case contained obvious smoothing effects. This suggests that ordinary kriging is not a good method for filling imagery with wide gaps. Cokriging and GWR performed much better than ordinary kriging. The image filled by cokriging, however, is a little smoother than that filled by GWR. The latter shows some visible seam lines at the edges of the filled gaps.

(Figures 8(d)–(f), respectively). Similar to the results of the second case study, both GWR and cokriging performed slightly differently with different bands in this validation case study. Figure 9 shows bands 2, 3, and 4 of the original image and the corresponding gap-filled images produced by cokriging and GWR. It can be seen that the filling effect for band 4 was the worst for both cokriging and GWR. These performance differences may have been caused by the different correlations and similarities between the corresponding bands of the original and secondary images. Table 3 shows the correlation coefficients and mean differences between the original image and the secondary image for different bands. It can be seen
Figure 9. Images used for the validation of the wide gap filling for bands 2, 3, and 4. (a), (b), and (c) show bands 2, 3, and 4 of the original image, respectively; (d), (e), and (f) show the results of applying cokriging to bands 2, 3, and 4, respectively. (g), (h), and (i) show the results of applying GWR to the same bands.

Table 3. Correlation coefficients and mean differences between the original image and the secondary image for the case of wide-gap filling.

<table>
<thead>
<tr>
<th>Band</th>
<th>Correlation coefficient</th>
<th>Mean difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 2</td>
<td>0.663</td>
<td>-2.66</td>
</tr>
<tr>
<td>Band 3</td>
<td>0.751</td>
<td>2.56</td>
</tr>
<tr>
<td>Band 4</td>
<td>0.692</td>
<td>-9.86</td>
</tr>
</tbody>
</table>
that band 4 has the largest mean difference (–9.86). This may be one important reason why band 4 was filled the poorest among the three bands. Band 3 has the largest correlation coefficient of 0.751, and the smallest mean difference of 2.56. This may be why band 3 showed the best performance among the three bands.

As was done for the third case study, the RMSEs for the filled images produced by cokriging and GWE were also calculated for evaluation purposes in this case study. Table 4 shows the RMSEs for bands 2, 3, and 4. Similar to the validation results in the third case study, the generally smaller RMSEs of GWR-filled images suggest that GWR performed overall better than cokriging in filling the wide gaps. However, the GWR-filled images show somewhat visible seam lines at the edges of filled gaps. The RMSEs for the gap-filling using cokriging and GWR are larger than those in the third case study because the simulated image has much wider gaps in this case study than that in the third case study.

To see where the estimation errors are located, the distribution maps for the errors describing the difference between the filled image and the original image were also created. Figure 10 shows the error distribution maps for bands 2, 3, and 4 (note: to facilitate better comparison between GWR and cokriging, the same legend was used for the same band but different bands used different legends). As indicated by the global RMSE, the error distribution maps produced using GWR also show less overestimation or

<table>
<thead>
<tr>
<th>Band</th>
<th>Cokriging</th>
<th>GWR</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>7.19</td>
<td>6.79</td>
</tr>
<tr>
<td>3</td>
<td>12.68</td>
<td>4.18</td>
</tr>
<tr>
<td>4</td>
<td>12.73</td>
<td>13.61</td>
</tr>
</tbody>
</table>

Figure 10. Error distribution maps for the results of filling images with wide gaps (See Figure 9). (a), (b), and (c) show the error distribution for bands 2, 3, and 4 after cokriging; (d), (e), and (f) show the error distribution for bands 2, 3, and 4 after GWR was applied.
underestimation than that produced by cokriging for the same band. But because of the much wider gaps, more overestimation or underestimation errors appear in this case study than in the third case study.

The original image and the gap filled images were also classified into thematic images using unsupervised ISODATA clustering. Figure 11 shows the classification results, which suggest that the images filled using both cokriging and GWR are good overall and they can be used for computer-aided processing, such as unsupervised classification. As shown in the third case study, this case study also found that there are slight performance differences between cokriging and GWR. Figure 12 shows the highlighted classification differences between the original image and the filled images produced by cokriging and GWR. It can be seen that there are fewer classification differences between the original image and the image filled by GWR, which means that GWR performed better than cokriging. All three forms of validation (i.e. RMSEs, error distribution maps, and classification results) indicate that the DN values estimated by GWR are closer to those of the original image than those estimated by cokriging, even though, there are visible seam lines at the edges of the filled gaps in the GWR-filled image.

5. Discussion

The case studies show that the GWR approach can be an alternative and superior technique to filling gaps in Landsat ETM+ imagery. In general, the continuity and accuracy of the filled imagery produced by GWR are good, even when applied to images with wide gaps. GWR performed better than the complex cokriging method, which has been a widely accepted method, but is more computationally intensive. Although there are visible seam lines at the edges of the filled wide gaps for some bands, the validation results including RMSE, error distribution maps, and classification results in the case studies demonstrate that the DN values estimated by GWR are in fact closer to those of the original image than the corresponding values estimated by cokriging. Note that

Figure 11. Classified maps based on the images with wide gap filling. (a) is the classified original image; (b) and (c) show the classification results after the narrow gaps were filled by cokriging and GWR, respectively.
Cokriging can fill the gaps more smoothly, especially at the edge of the gaps because it directly bases its estimated values on the neighbouring pixels in the image that contains the gaps. GWR, however, is not based directly on the neighbouring pixel data, and consequently may produce some visible seam lines at the edges of the filled wide gaps. Thus, many users may still prefer to use cokriging because cokriging gives better visual results as compared to GWR because of the seam line smoothing.

While cokriging uses global parameters (the combined variogram and cross-variogram models) for estimation, GWR applies regression within a local window and uses a kernel function to obtain local regression coefficients in place of the usually used global coefficients. Thus, GWR has the advantage in modelling some changes (here varying landscapes) in the nature of the relation over space. It is particularly useful when the gaps to be filled cover a large area because of the much higher computational efficiency of GWR than cokriging. It also can provide some insight on the spatially varying relationships between the original imagery and the ancillary imagery across the large area of coverage.

Although there are still some subtle differences or errors as compared with the non-interpolated areas in the validation case studies, such differences are typically minor and within the acceptable error limits of variability of most image classification methods. Therefore, classification of such filled imagery should give results similar to that of imagery without gaps and should be applicable to regional or global scale studies. It is apparent that the approach has great promise for filling data gaps in Landsat ETM+ imagery, and perhaps other types of imagery containing noise or missing data.

Indeed, the LLHM (local linear histogram-matching) method, which was proposed previously by the USGS, also estimated parameters locally using a moving window (Scaramuzza, Micijevic, and Chander 2004; USGS 2004). It is computationally more efficient than GWR. This method, however, ignores the spatial autocorrelation (i.e. nearby

Figure 12. Highlighted classification differences between the original image and the images resulting from filling the images with wide gaps: (a) shows the differences when the gaps were filled using cokriging and (b) shows the differences when the gaps were filled by GWR. Some classification differences also occurred outside the gaps because of some lack of correspondence in classification caused by the differences in filled gaps.
data are more highly correlated than those further apart) of image data in calculating the gain and bias parameters used in the method. Thus, it is inevitably inferior to the GWR method, in which parameters are estimated using local neighbourhood data with spatial weights assigned using a distance-based kernel function.

It should be noted that this study is focused on introducing a gap-filling method for the DN values of pixels in Landsat ETM+ imagery. However, the DN values recorded by the sensor are not corrected for object-illumination effects (e.g. those caused by the slope and orientation of the terrain) and intervening atmospheric effects (e.g. those caused by atmospheric and solar conditions). Thus, the DN values for the same spectral class for different places or at different times over the same area may be different to some extent. This may decrease the performance of the introduced GWR method for gap-filling of missing information. Converting the DN values into the surface reflectance values through atmospheric and topographic correction models might improve the gap-filling results. To answer the question whether the radiometric correction would lead to more accurate gap-filling results in this study, the radiometric correction processing was performed on a data set with medium–wide gaps using Geomatica 2013 software. Figure 13(a) shows the image with medium–wide gaps after radiometric correction obtained on 16 April 2005. Figure 13(b) shows the image after radiometric correction obtained on 24 April 2002. Figures 13(c)–(e) show the filled images obtained using the simple replacement method, GWR, and the cokriging method, respectively. From these images, it can be seen that the reflectance values are still different in the 2005 image and the 2002 image even after radiometric correction, thus the simple replacement method did not work well. However, both GWR and cokriging methods worked well for filling the medium–wide gaps as they

Figure 13. The results of gap-filling using different methods based on the radiometrically corrected images from 2002 and 2005. (a) is the radiometrically corrected image from 16 April 2005 and (b) shows the radiometrically corrected image from 24 April 2002. (c) shows the simple composite image and (d) and (e) show the results of the gap filling using GWR and cokriging, respectively.
did in the third case study. In fact, both GWR and cokriging methods do not consider whether DN values or reflectance values are used as long as the variables involved have spatial correlations at some scale. Compared with the results for the images (with medium–wide gaps) without the radiometric correction (Figure 4), it can be seen that there is no significant difference between the results for the images with and without the radiometric correction. However, for application studies, converting DN values into reflectance values is recommended before performing gap-filling.

6. Conclusions
Although Landsat 7 ETM+ imagery acquired since early 2003 has data gaps caused by the abnormal function of the SLC, it is still a very useful data source for many applications, especially at regional scales. Efforts have been made to find suitable techniques to fill the data gaps in the SLC-off imagery. There seems no perfect method for the purpose. Each of the methods suggested so far may have its own advantages and disadvantages. The objective of this study was to introduce an alternative technique – the GWR method – for filling the gaps of the Landsat ETM+ imagery and examine its effectiveness. GWR has been widely applied to model spatial distributions and relationships in a variety of fields in the literature. Studies using this method for directly processing remotely sensed imagery have not yet been published. This study demonstrated the feasibility of this method in filling gaps in Landsat ETM+ imagery. Although there are visible seam lines at the edges of wide gaps filled using GWR for some bands, the validation results, including RMSE values, error distribution maps, and classification results in the case studies, demonstrate that the DN values estimated by GWR are in fact closer to those of the original image than the corresponding values estimated by cokriging. The filling of SLC gaps using GWR in this study was also found to be fast.

The development of efficient implementation of GWR in readily available GIS software facilitates the expedient processing of remote-sensing imagery and other geospatial data, and hence, the speed of filling gaps using GWR should be fast.

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References


