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The Utilization of Image Texture Measures in Urban Change Detection

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Abstract: Image texture is increasingly being integrated into classification procedures using remotely sensed data. This research examined the utility of texture measures when integrated within established approaches for monitoring urban development. Landsat-7 satellite data for the years 1999 and 2002 were enhanced through a pansharpening process to provide 15 metre spatial resolution multispectral data. The images were acquired within the same approximate yearly time frame to help minimize seasonal vegetation differences and the effects of varying sun positions. Texture proved valuable in accounting for and distinguishing varying degrees of "greenness" in the imagery and the dissimilarity option was useful in locating recently excavated land. The measures were also helpful in separating agricultural fields from urban features. An increase of 3 % in overall classification accuracy was realized when texture information was included as a classification variable. An integrated unsupervised classification/ image differencing change detection process with a combination of inputs including texture, principal components, and the Normalized Difference Vegetation Index (NDVI) provided enhanced classification results and allowed for the estimation of urban expansion rates (4.62 square kilometres per year for the 1999–2002 period).

Zusammenfassung: *Die Verwendung von Image Texturwerten in der Stadtentwicklungsanalyse.* Texturwerte werden zunehmend für Satellitenbild-Klassifikationsverfahren verwendet. Dieser Artikel überprüft die Nützlichkeit von Texturwerten und integriert sie innerhalb einer herkömmlichen städtischen Entwicklungsüberwachungsanalyse. Landsat-7 Daten wurden für die Jahre 1999 und 2002 durch ein „pansharpening" bearbeitet, um die Multispektraldaten auf 15 Meter in der räumlichen Auflösung zu verbessern. Die Bilder wurden etwa zur gleichen Jahreszeit aufgezeichnet, um saisonale Vegetationsunterschiede und die Effekte bei der Veränderung der Sonnenposition herabzusetzen. Die Textur von Objekten war wertvoll in der Erkennung unterschiedlicher Grün-Abstufungen in den Bildern, und die „dissimilarity" Option war nützlich, um kürzlich gerodetes Land zu lokalisieren. Die Maßnahmen waren auch hilfreich bei der Trennung von landwirtschaftlichen Flächen und städtischen Strukturen. Eine Zunahme von 3 % der gesamten Klassifizierungsgenauigkeit konnte festgestellt werden, da Texturwerte in die Klassifikationsverfahren eingeschlossen sind. Es wurde versucht, mehrere Parameter in die Klassifikation zu integrieren, wie die Textur, die Hauptkomponenten und der normalisierte Vegetationsindex (NDVI), welche schlussendlich bessere Klassifizierungsergebnisse hervorgebracht haben. Die Untersuchungen führten zu dem Resultat, dass sich die Fläche der Stadt im Untersuchungszeitraum um jährlich 4,62 km^2 vergrößert.

Introduction

Research into texture measures has mostly focused on which statistics and window sizes provide the biggest gains in feature extraction, as well as ways in which texture bands can be combined with spectral data to increase classification accuracy. Traditionally, texture features are combined with or integrated into classification procedures

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(Karathanassi et al. 2000, Marceau et al. 1990, Pesaresi 2000, Pusissant et al. 2005, Shaban & Dikshit 2001, Tatem et al. 2004, Zhang et al. 2003). Tatem et al. (2004) utilized texture and found that a "superresolution" classification produced higher accuracies, but involved increased computational expense. In studying CO_2 emissions in Copenhagen, Soegaard & Møller-Jensen (2003) used a grey level co-occurrence matrix combined with a parallelepiped classification to define urban areas. In this case, only a few pixels had their texture statistics calculated, and each parallelepiped was assumed to be texturally homogeneous and assigned the value of pixels it encompassed. It has also been found that using at least three different texture bands, combined with spectral data, produced the highest gains in classification accuracy (Zhang et al. 2003).

Remote sensing methods are very effective in the analysis of urban change (Forsythe 2004, Hostert & Diermayer 2003, Masek et al. 2000, Ridd & Liu 1998). The use of fused or sharpened data for urban applications is also well-documented (Forsythe 2004, Steinnocher 1997, Zhang 2002, Zhang 2004). In this research, a combined unsupervised classification/image differencing change detection process that includes texture measures is utilized to examine urban growth.

Study Area

Calgary, Alberta is the fastest growing major metropolitan area in Canada (Statistics

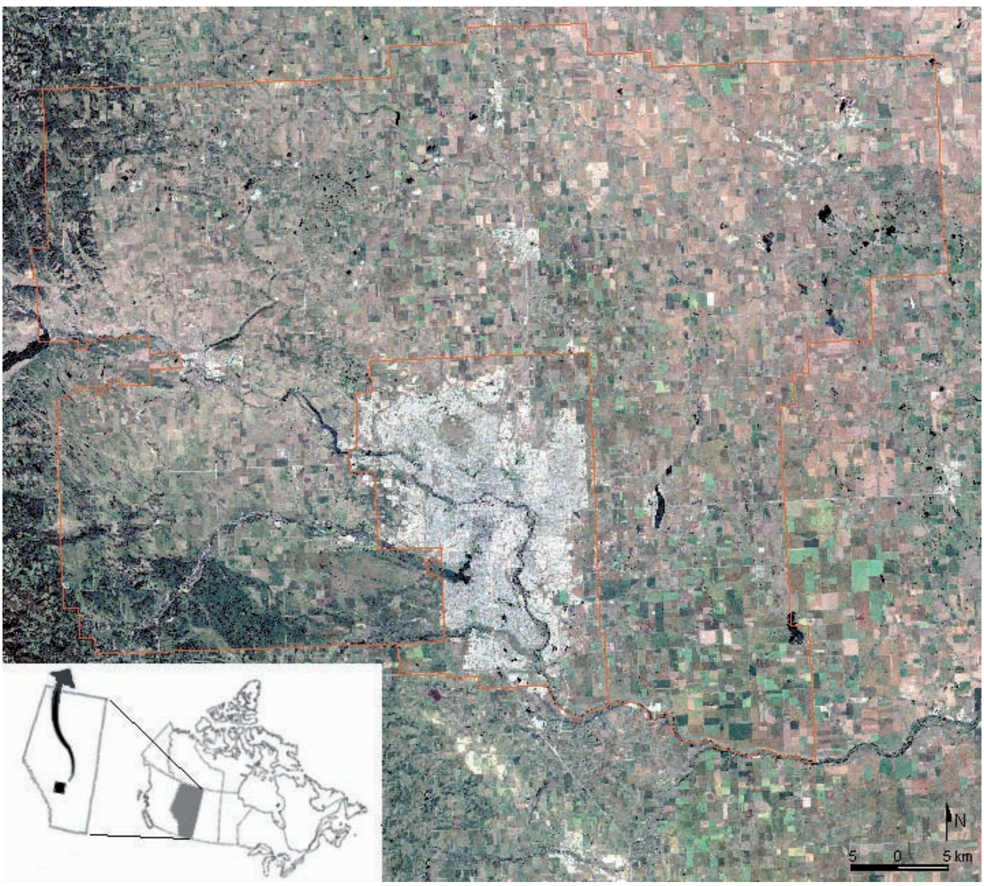

Fig. 1: Calgary Census Metropolitan Area (boundaries in red).

Canada 2005). The Census Metropolitan Area (CMA) – (Fig. 1) contains the smaller communities of Cochrane and Airdrie which are also developing rapidly. In addition, surrounding communities such as Okotoks and Strathmore are growing in part due to the economic prosperity that Calgary is currently experiencing. Two distinct growth phases can be identified from census data for Calgary over the last 30 years. During the 1970's, the population grew by over 50 % from 400000 in 1971 to 625000 in 1981. From the mid-1990's onward, large annual increases in population occurred, indicating, in part, a shift from a natural resource based economy to a more diversified financial system.

Data

Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery was acquired, ortho-rectified (NAD83-GRS1980 UTM Zone 11 projection), and subset (to the city limits of Calgary) for the dates of July 9, 1999 (Fig. 2) and August 18, 2002 (Fig. 3).

The images were the best available in terms of being "cloud free" and the dates encompass the same approximate yearly time frame to help minimize seasonal vegetation differences and the effects of varying sun positions. It is however quite apparent from the large areas of "green" in the 1999 data, that moister conditions existed at the time of image acquisition in 1999 compared to 2002.

Methods and Analysis

To enhance urban features within the data and assist with boundary delineation, the PANSHARP algorithm (as implemented in the PCI Geomatica software) was used to upgrade the spatial resolution of the images from 30 to 15 metres. This process eliminates problems (such as the destruction of data spectral characteristics, colour distortion, and operator and data set dependence) that can occur during the data fusion or sharpening process (Zhang 2002). A more detailed discussion of the process can be found in Zhang (2004).

Image classification has been successfully used to distinguish urban expansion from land cover changes that occur due to other factors such as agricultural practices (For-

Fig. 2: Landsat 7 subset image – July 9, 1999 (Path 42, Row 24).

Fig. 3: Landsat 7 subset image – August 18, 2002 (Path 42, Row 24, shifted 20 % south).

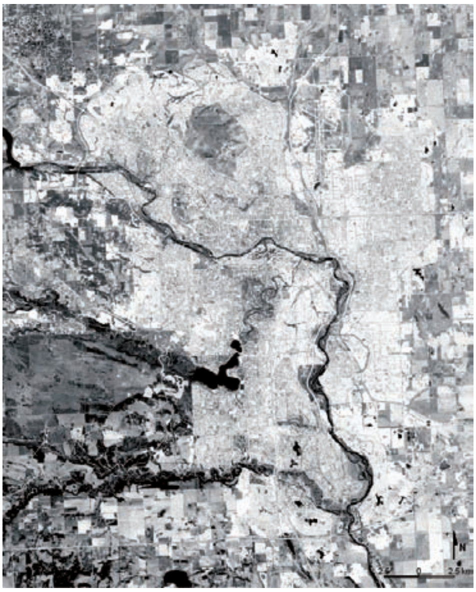

Fig. 4: Mean Texture.

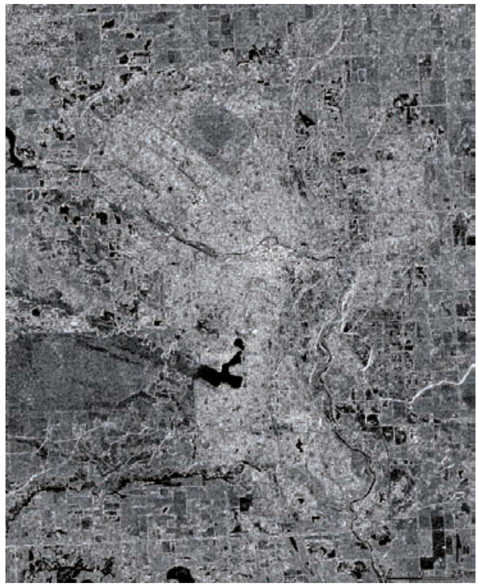

Fig. 5: Dissimilarity Texture (black areas on the urban fringe indicate excavated land).

sythe 2004, Masek et al. 2000). Previous studies (Du 2005, Forsythe 2004, Masek et al. 2000, Shaban & Dikshit 2001, Yeh & Li 2001) have shown that a number of features derived from the original satellite bands can be useful in distinguishing classes. De Kok et al. (2003), Forsythe (2004), and Shaban & Dikshit (2001) found that texture measures were a great asset for urban change detection. Of the many options that are available, mean, dissimilarity, contrast, and homogeneity texture measures were generated with both 3×3 and 7×7 windows using band 2 of the ETM+ data. These parameters were chosen based on the authors' previous urban change detection research and results reported in the literature (De Kok et al. 2003, Forsythe 2004, Shaban & Dikshit 2001, Steinnocher 1997). The 3×3 results were clearly superior to the 7×7 results in terms of the amount of detail that could be discerned, especially in areas where urban growth had occurred. Mean texture measures (Fig. 4) delineated urban built-up areas very well, and distinguished urban and agricultural features having similar spectral characteristics. Dissimilarity (Fig. 5) detailed newly excavated areas in remarkable detail, while homogeneity was somewhat less successful in locating these areas. Contrast was the least successful of the texture options which does not correspond with the results of Pesaresi (2000) who found that the contrast measure was especially well-suited to discerning the differences between built and non-built environments.

Determining the optimal window size and texture statistics is still a process requiring many trials. While it has been found that the window size used is overwhelmingly responsible for the homogeneity and accuracy of a texture class (Marceau et al. 1990), there is no one best size. This is because such an optimal size depends on the spatial resolution of the image and the land use being captured (Pesaresi 2000). Windows must be large enough to encompass the whole of the texture pattern, but small enough not to include more than one (Pesaresi 2000, Pusissant et al. 2005). Traditionally, large window sizes, ranging from 31×31 to 40×40 to 51×51, have been recommended (Karathanassi et al. 2000, Pesaresi 2000).

However, some researchers have found that with higher spatial resolution images, smaller window sizes must be used due to the greater variability seen in urban areas. In these cases, a window size of 7×7 was recommended (PUSISSANT et al. 2005, ZHANG

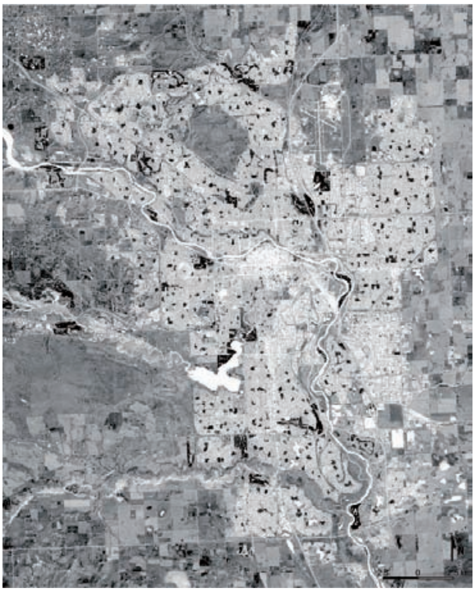

Fig. 6: Principal Component 2 (small black areas within the city limits are parks with larger black areas representing golf courses and other large manicured green areas).

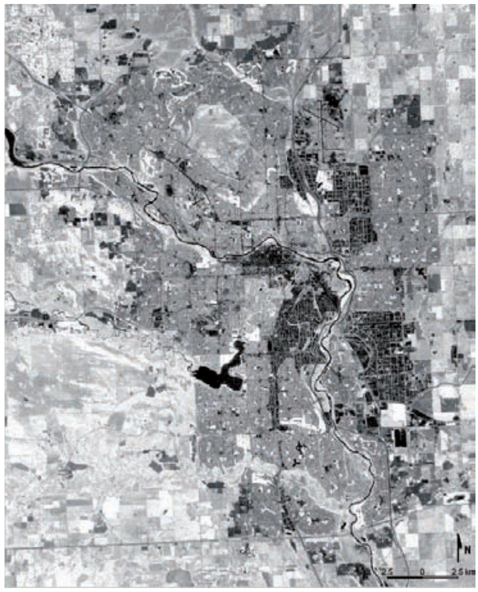

Fig. 7: NDVI (black areas within the city limits represent industrial and manufacturing land uses with black areas on the fringe indicating excavated land).

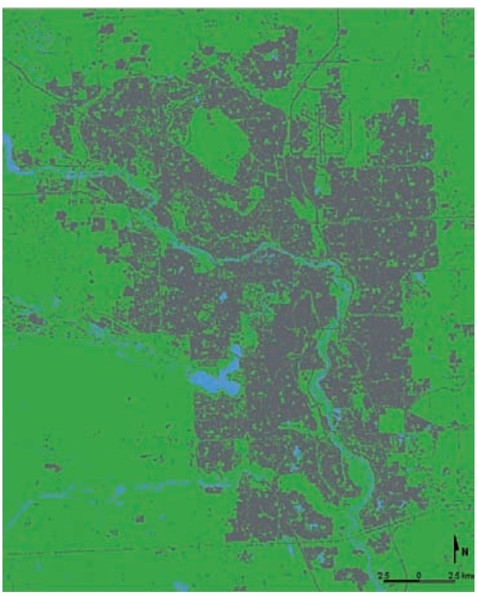

Fig. 8: Aggregate 2002 Classification (green = greenspace, grey = built, blue = water).

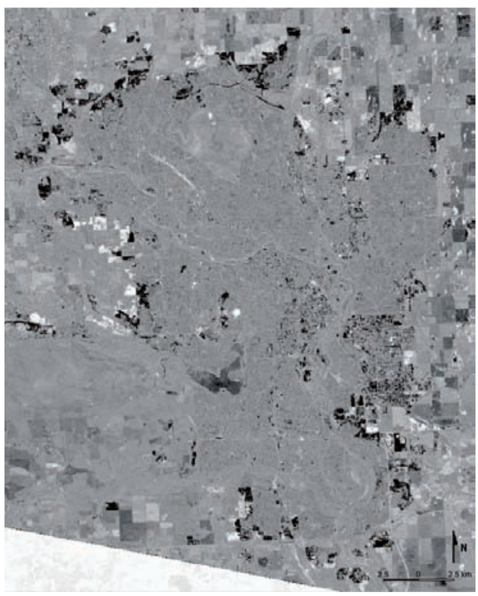

Fig. 9: 2002 Band 2 – 1999 Band 2.

et al. 2003), but this was found to be unsuitable for the imagery used and objectives of this research.

Similar problems have been encountered in determining which of the texture statistics derived from the matrices should be used. Depending on the land cover, certain measures will provide more or less accuracy (PESARESI 2000, SHABAN & DIKSHIT 2001, ZHANG et al. 2003). No one measure provides the best results, so a combination may be a better solution. However, the mean measure (DU 2005, ZHANG et al. 2003) and contrast measure (PESARESI 2000, SHABAN & DIKSHIT 2001) stand out as two of the best for urban applications.

In addition to texture, Principal Components and a Normalized Difference Vegetation Index (NDVI) were generated as inputs for the classification procedures in a process similar to that utilized by DU (2005), FORSYTHE (2004) and MASEK et al. (2000). Principal Component 2 (Fig. 6) was effective in distinguishing urban green areas including parks and golf courses. NDVI (Fig. 7) was useful for distinguishing urban industrial/manufacturing and newly excavated areas from residential districts.

Two distinct classification procedures were performed. One did not include texture, while the other had mean texture added as an additional classification input. Fig. 8 represents the aggregate classification results that were derived using the six Landsat bands (1, 2, 3, 4, 5, 7), mean texture, principal component 2, and NDVI. These data were then combined with the results of image differencing operations (Fig. 9) using band2 (2002 band 2 minus 1999 band 2). The overall classification accuracy for the three classes (greenspace, built, and water) was 88% (Kappa 0.75) compared to 85.3% (Kappa 0.69) when texture measures were not included (full accuracy statistics are presented in Tab. 1 and 2).

Some interesting features in the difference image include white areas generally representing excavated areas where previous agricultural or forested land has been replaced by land being prepared for building and darker (blacker) areas mainly representing areas where housing developments have replaced excavated land (FORSYTHE 2003).

The use of an unsupervised classification layer as an agricultural mask was necessary to complete the data analyses. It can be seen in from the large black/grey square/rectangle agricultural fields in Fig. 9 that these areas have also changed (due to crop rotation or harvesting) in addition to the urban areas that were either newly developed (or redeveloped) and excavated. Image texture

Tab. 1a: Accuracy Statistics for Classification with Texture Measures.
Overall Accuracy: 88% – 95% Confidence Interval (82.47% – 93.53%).
Overall Kappa Statistic: 0.75% – Overall Kappa Variance: −0.10%.

Class Name	Producer's Accuracy	95% Confidence Interval	User's Accuracy	95% Confidence Interval	Kappa Statistic
Greenspace	95.56%	(90.74% 100.37%)	86.87%	(79.71% 94.03%)	0.67
Built	76.27%	(64.57% 87.97%)	91.84%	(83.15% 100.52%)	0.87
Water	100.00%	(50.00% 150.00%)	50.00%	(−44.30% 144.30%)	0.50

Tab. 1b: Accuracy Statistics – Error (Confusion) Matrix.

Classified Data	Reference Data Greenspace	Built	Water	Totals
Greenspace	86	13	0	99
Built	4	45	0	49
Water	0	1	1	2
Totals	90	59	1	150

Tab. 2a: Accuracy Statistics for Classification with No Texture Measures.
Overall Accuracy: 85.33% – 95% Confidence Interval (79.34% – 91.33%).
Overall Kappa Statistic: 0.69% – Overall Kappa Variance: −0.04%

Class Name	Producer's Accuracy	95% Confidence Interval	User's Accuracy	95% Confidence Interval	Kappa Statistic
Greenspace	94.32%	(88.91% 99.72%)	83.84%	(76.08% 91.60%)	0.61
Built	72.13%	(60.06% 84.20%)	89.80%	(80.30% 99.29%)	0.83
Water	100.00%	(50.00% 150.00%)	50.00%	(−44.30% 144.30%)	0.50

Tab. 2b: Accuracy Statistics – Error (Confusion) Matrix.

Classified Data	Reference Data Greenspace	Built	Water	Totals
Greenspace	83	16	0	99
Built	5	44	0	49
Water	0	1	1	2
Totals	88	61	1	150

(as noted above) was very useful when included in the unsupervised classification procedures. It helped to discriminate between the urban and agricultural areas where spectral signatures were similar compared with when it was not included as a classification input variable. The aggregate classifications consisting of urban, greenspace, and water were developed from 64 original unsupervised K-means classes. This allowed for small features that may have caused classification problems (i.e. aggregated into the incorrect class when fewer original K-means classes were used) to be clearly separated and delineated. They were then assigned to the appropriate aggregate class.

ArcGIS software was used to combine the difference and unsupervised classification images and to calculate areas. Fig. 10 illustrates the overall urban change that occurred during the 1999–2002 period. A total of 13.86 square kilometres was identified as new urban development over the three year period (an average was 4.62 square kilometres per year). A small cloud in the middle of the 2002 image has introduced some error into the final result and some omission errors can be found in the southern part of the image in addition to some commission errors to the east of the city (related to the a lack of water in low-lying areas in the 2002 image compared to the 1999 data). Overall, the results are very good with changed urban areas well represented and the excavated and newly developed areas clearly delineated.

Conclusion

Image texture provided for an increased level of accuracy when it was included as an input in classification procedures. A 3×3 window was found to improve the delineation of urban features as compared to the 7×7 option. The mean measure was useful in distinguishing urban from agricultural areas, while the dissimilarity option was very proficient in locating excavated areas of the urban fringe.

A combined approach including image differencing and unsupervised classification allowed for the measurement of urban development. The pansharpened images enabled finer detail to be distinguished (including excavated vs. newly built land) than is possible with coarser resolution data. Calgary is a rapidly expanding urban centre. The use of additional parameters (especially image texture) that can be generated from image data proved particularly effective in determining urban growth. Although the

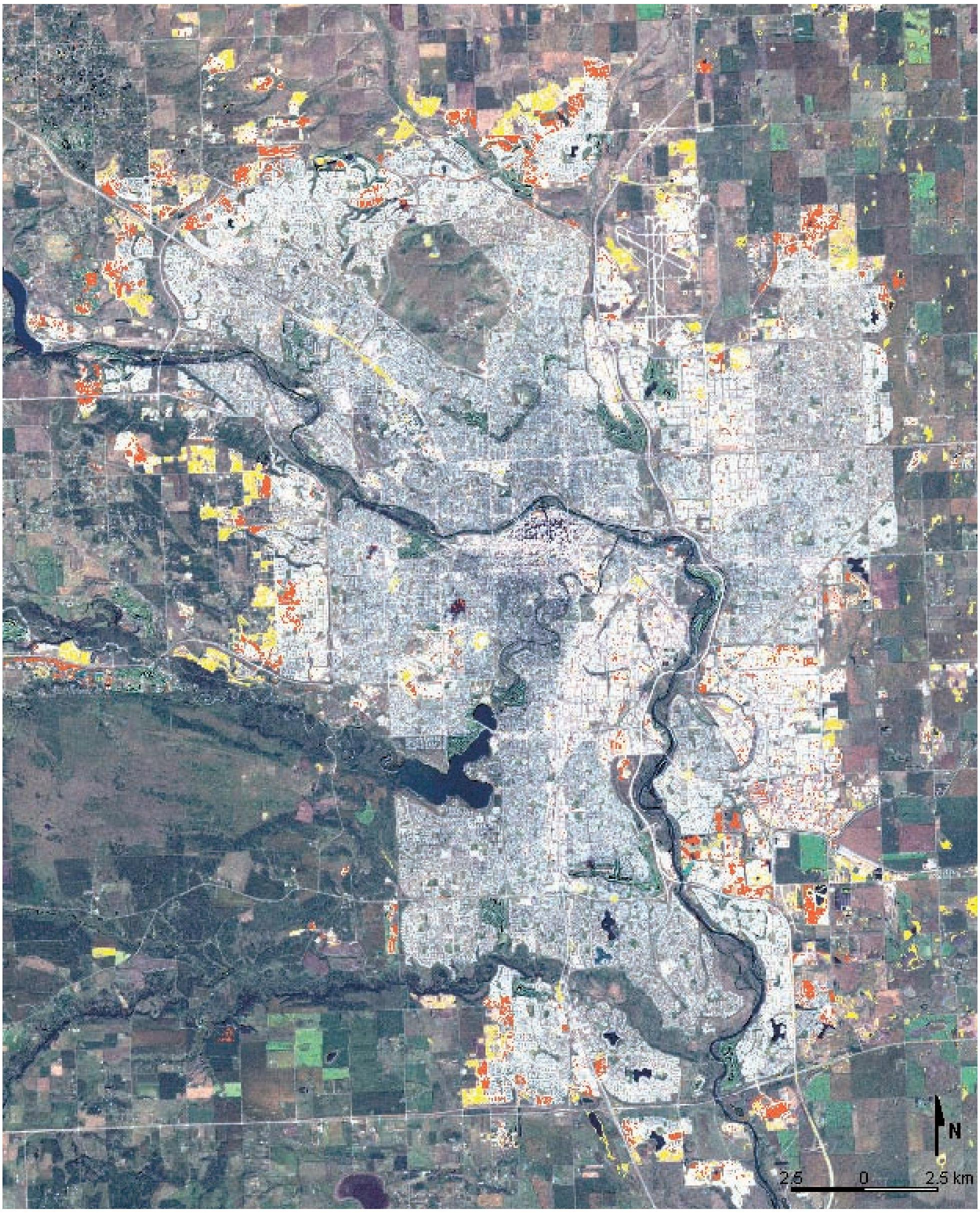

Fig. 10: Overall Urban Change from 1999 to 2002 (Yellow: excavated land replaces vegetation; Red: developed land replaces excavated land; background image Landsat 2002 Bands 3, 2, 1).

images were acquired during the same season (year to year), it was necessary to compensate for differences in greenness to obtain suitable urban classification results. The use of texture measures was very advantageous as they provided additional information to assist in classification procedures and define boundaries between various land cover features.

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