

Modeling Urban Land Use Change and Urban Sprawl: Calgary, Alberta, Canada

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Abstract This paper implements a land use classification for the City of Calgary, Alberta, Canada, using an object-oriented approach for six Landsat TM and ETM+ images and simulates the land use pattern in the future using Markov Chain analysis and Cellular Automata analysis based on the interactions between these land uses and the transportation network. Shannon's Entropy (an urban sprawl index) based on the land use classification results is used to measure urban sprawl. This research proves that an object-oriented approach can produce satisfactory classification results. It reveals the manner in which land use is likely to develop in the future, and demonstrates that urban sprawl continued to grow in Calgary during the years between 1985 and 2001. Such models are useful for providing the building blocks for traditional four-step transportation planning models.

Keywords Urban sprawl · Road networks · Entropy · Object-oriented classification · Cellular automata · Markov chain analysis

The research reported here used six satellite images for the City of Calgary (1985, 1990, 1992, 1999, 2000, 2001), together with land use files for the major road networks, parks and water bodies and the eCognition software (Definiens Imaging GmbH, 2002) to produce an object-oriented land use classification. The land use classifications in 1985 and 1992 were then used to “predict” land use in 1999 using two geosimulation techniques: Markov Chain and Cellular Automata analysis. This

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“prediction,” based on the interactions between the transportation network and industrial and residential land uses among others, was then compared to the actual land use pattern for 1999. Once the methodology had been deemed successful a new prediction for 2010 was developed based on the change that had occurred between 1990 and 2000. In order to determine the degree of urban sprawl Shannon’s Entropy statistic was calculated for the six time periods. These figures were shown to be high when compared to the same statistic calculated for other cities. Moreover, during the five time periods of this study the relative entropy increased in all but one of the five time periods showing that the City of Calgary continues to have a problem with urban sprawl. Concern over Calgary’s perceived problem with sprawl is also evident on various websites (www.calgarysprawl.ca/; www.urbansprawl.ca/) and in the popular press as well (Davis 2006; Graveland 2006) where it has been noted that Calgary’s geographical footprint is the same as New York City’s but with only a tenth of the population. Knowledge of where new residential areas will appear as the city grows is of fundamental importance in each of the four steps of the traditional transportation planning model (Waddell et al. 2003): trip generation (Marchal 2005), trip distribution (Boyce and Bar-Gera 2004), modal choice (Espino et al. 2006) and traffic assignment (Nie and Zhang 2005).

1 Study area and data sets

1.1 Study area

Studying a city’s past land development trend and predicting its future land use pattern are critical for city planners to be able to design a sustainable development strategy. This study focused on the City of Calgary, Alberta, Canada, and included all the land within the city limits, as well as the surrounding areas of cropland, grassland and forest. The population of Calgary is predicted to reach one million in 2007 or 2008.

1.2 Data sets

Landsat TM and ETM+ satellite data for the years 1985, 1990, 1992, 1999, 2000, and 2001 (Table 1) were utilized in this study. The images were acquired within the same approximate yearly time frame to help minimize seasonal vegetation differences and the effects of varying sun positions. They were also the best available during the analysis period in terms of image quality and the percentage of each image that was not obscured by clouds and their shadows. Six of the available

Table 1 Data sets (Landsat TM and ETM+ images)

| Acquisition date | Image format | Spatial resolution | Projection |
|------------------|--------------|--------------------|--------------------|
| 1985-07-26 | TM | 28.5 m | NAD83 UTM Zone 12N |
| 1990-09-10 | TM | 28.5 m (Resampled) | NAD83 UTM Zone 12N |
| 1992-08-14 | TM | 28.5 m | NAD83 UTM Zone 12N |
| 1999-07-29 | ETM+ | 28.5 m | NAD83 UTM Zone 12N |
| 2000-08-28 | ETM+ | 28.5 m | NAD83 UTM Zone 12N |
| 2001-08-15 | ETM+ | 28.5 m | NAD83 UTM Zone 12N |

spectral bands (1, 2, 3, 4, 5 and 7) were included in the analyses due to their constant spatial and spectral resolutions. The thermal band (Band 6) was omitted because of its lower spatial resolution (120 m for TM imagery and 60 m for ETM+ imagery) with the higher resolution 15 m ETM+ panchromatic data (Band 8) also being excluded as they were only available for the 1999–2001 images. In addition, the 2001 Calgary land use map (an ESRI shapefile) supplied by the City of Calgary was utilized together with other data sets (including Calgary's major roads, parks and water bodies) supplied by DMTI Spatial Inc. (<http://www.dmtispatial.com/>).

2 Methodology

2.1 Data pre-processing

All data sets were projected to *NAD83 UTM Zone 12N* to avoid image distortion. All GIS shapefiles were clipped in ArcMap using the boundary of the 2001 Landsat ETM+ image to ensure that all files covered the same area. In order to classify the data using the eCognition software each band of the six satellite images was exported to a .tif file. Industrial, residential and commercial lands were extracted from the 2001 Calgary Land Use map in ArcMap, although the latter two categories were merged into one owing to the difficulty of separating the two classes using the Landsat images. The 1996 Calgary road map was edited to remove roads that were not built in the earlier years.

2.2 Land use classification

The eCognition software was used to classify the six Landsat images. According to the software manufacturer the guiding principle for the land use classification is that objects should be generated as large as possible and as fine as necessary (Definiens Imaging GmbH, 2002)—somewhat reminiscent of Einstein's, perhaps apocryphal, admonition to keep things as simple as possible but not simpler. The .tif files were loaded into eCognition as image layers and the shape files representing the major roads, parks, water bodies, industrial land, residential and commercial land were loaded as thematic layers.

The analysis produced three levels. The initial level (eventually labelled as Level 3) was simply a division between urban and rural. Segmentation of the image requires various parameters to be set:

Layer weight: varying from 0 to 1 indicating the importance of a layer in the segmentation process;

Scale parameter: determines the average size of image objects;

Colour: determines the homogeneity of the image;

Shape: controls the degree of object shape homogeneity; it is in turn influenced by the *smoothness* and *compactness* parameters.

As was the case here, these parameters are often set in a trial and error fashion (Proudfoot 2004). In level 2, the second level generated, the major roads were segmented. Finally, for level 1 all the thematic layers were set to the “used” option.

Table 2 Classification scheme

| Level I | Level II |
|-------------------|--|
| Built-up Land | Residential and commercial Industrial Transportation |
| Non Built-up Land | Parks Vacant area |
| Water Bodies | |

Once the multiresolution segmentation was finished, classification was implemented. Land use classification requires a classification scheme. Some classification schemes that have been developed provide good possibilities. In this project, a hybrid classification scheme (Table 2) was developed according to the *U.S. Geological Survey Land Use/Land Cover Classification System* (Jensen 1996).

The Membership Functions offered in eCognition 2.1 are soft classifiers that are based on a fuzzy classification system, in which the feature values of arbitrary range were translated into a value between 0 (no membership) and 1 (full membership) (Benz et al. 2004). Using the Membership Functions approach, a class can be described with one or at most a few features (e.g., spectral number, shape property, and neighbourhood characteristics) and each feature is described by a membership function expression.

Feature View in eCognition 2.1 is a useful tool that provides all the information of a selected image object, not only the spectral features, but also any feature usable for classification. With the help of Feature View, exclusive features of each class could

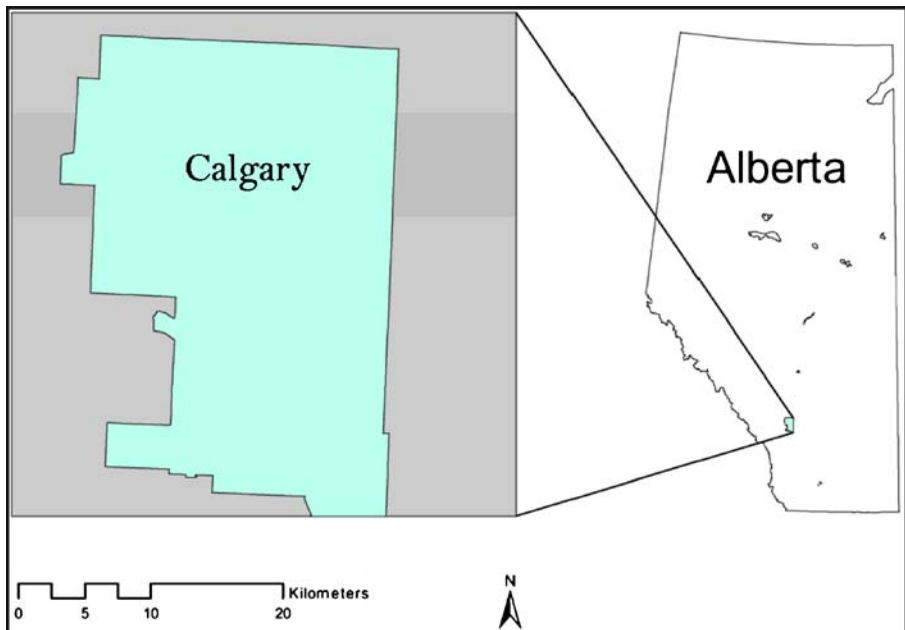
**Fig. 1** Study area location map

Table 3 Re-classification of FCUS map

| Original classes in FCUS map | Reclassified classes |
|--|----------------------------|
| Existing General Urban Use | Residential and Commercial |
| Future General Urban Use | |
| General Commercial | |
| Employment Concentrations | |
| Institutional | |
| Under Policy Review | Industrial |
| Industrial | |
| Transportation Utility Corridor | |
| Existing Open Space System | Transportation |
| Roads (not shown in the Legend) | Others |
| Water Bodies (not shown in the Legend) | |

be found easily. Membership functions require both a range and a choice of one of eight slope possibilities.

Spectral information alone may be insufficient to classify an image. eCognition allows the use of thematic layers to aid the separation of classes with similar spectral properties such as residential and industrial land. This was the procedure used to classify the 2001 image. All of the other five satellite images were classified in a similar way. When the thematic layers, which were extracted from the 2001 Calgary land use map, were applied to the older satellite images (e.g., the 1985 Landsat TM image), they were modified to match the reality on those images. This procedure used the *Manual Classification tool* in eCognition 2.1, which offers easy class assignment of selected image objects. This is only suitable for classes that have not changed very much. For example, the thematic layer of industrial land could be easily modified to classify the industrial class on all of the other five images since

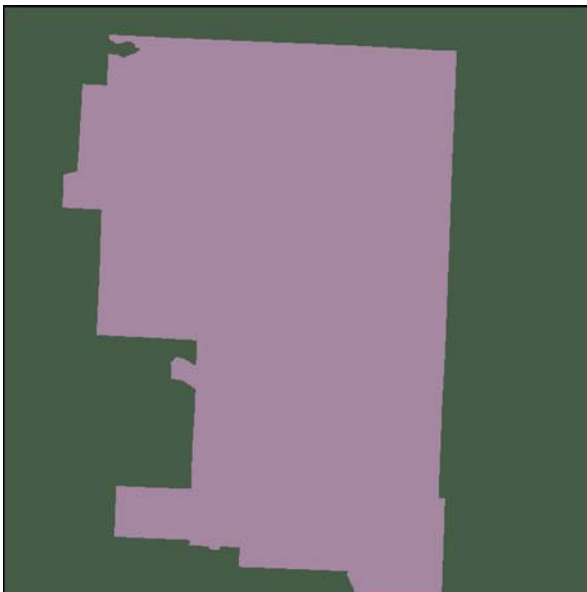
**Fig. 2** Level 3 of the multiresolution segmentation



Fig. 3 Level 2 of the multiresolution segmentation

the industrial land in Calgary has not expanded very much. For the residential and commercial class, this solution is not appropriate because these classes have grown significantly over these years. The residential and commercial class was classified using only object features for the other five images.

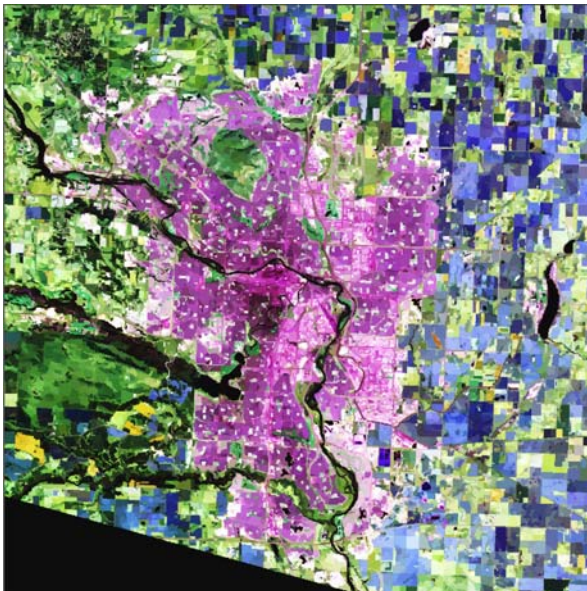


Fig. 4 Level 1 of the multiresolution segmentation

Land Use Classification Result of 2001

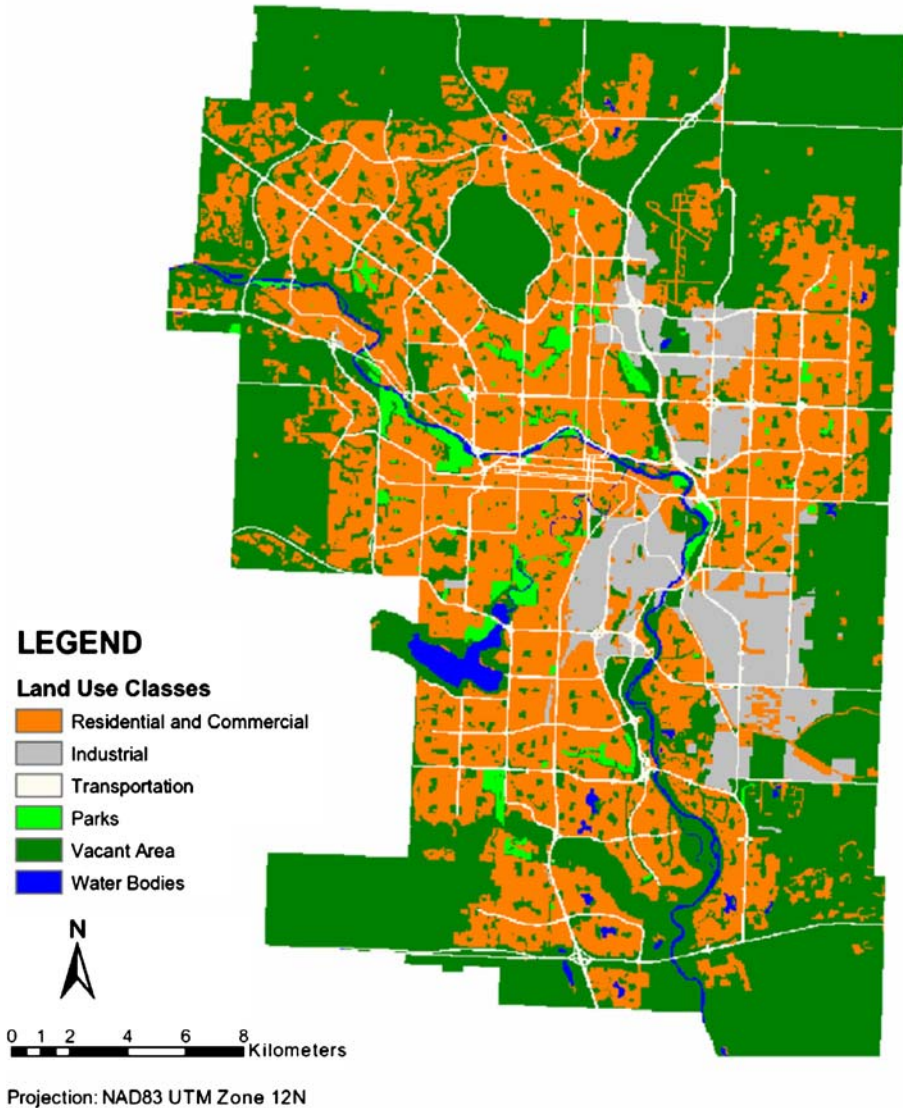


Fig. 5 Land use classification results for 2001

2.3 Land use prediction

In order to develop and validate a methodology for prediction of future land use, the 1985 and 1992 land use maps were used to “predict” land use in 1999. This prediction was then compared to the actual land use for 1999. Once the methodology had been validated as successful the 1990 and 2000 land use maps were used in the same way to provide a prediction for the year 2010. Land use prediction involves

Residential and Commercial Suitability Map of 1999



Fig. 6 Residential and commercial suitability map of 1999

examining the land use change between two points in time and then extrapolating this change into the future (Eastman 2003). This process has been termed “geosimulation” in a recent text by Benenson and Torrens (2004) and has been referred to as the “next big thing” in land use prediction (<http://ca.wiley.com/WileyCDA/WileyTitle/productCd-0470843497.html>). Two geosimulation techniques were used to produce the predictions: Markov Chain and Cellular Automata analysis.

The Markov Chain analysis was implemented using the Markov module in the Idrisi Kilimanjaro software (<http://www.clarklabs.org/>). Change in land use patterns between the two known dates was used to develop a transition probability matrix and this in turn was used to make the prediction. In the past, most implementations

Industrial Suitability Map of 1999

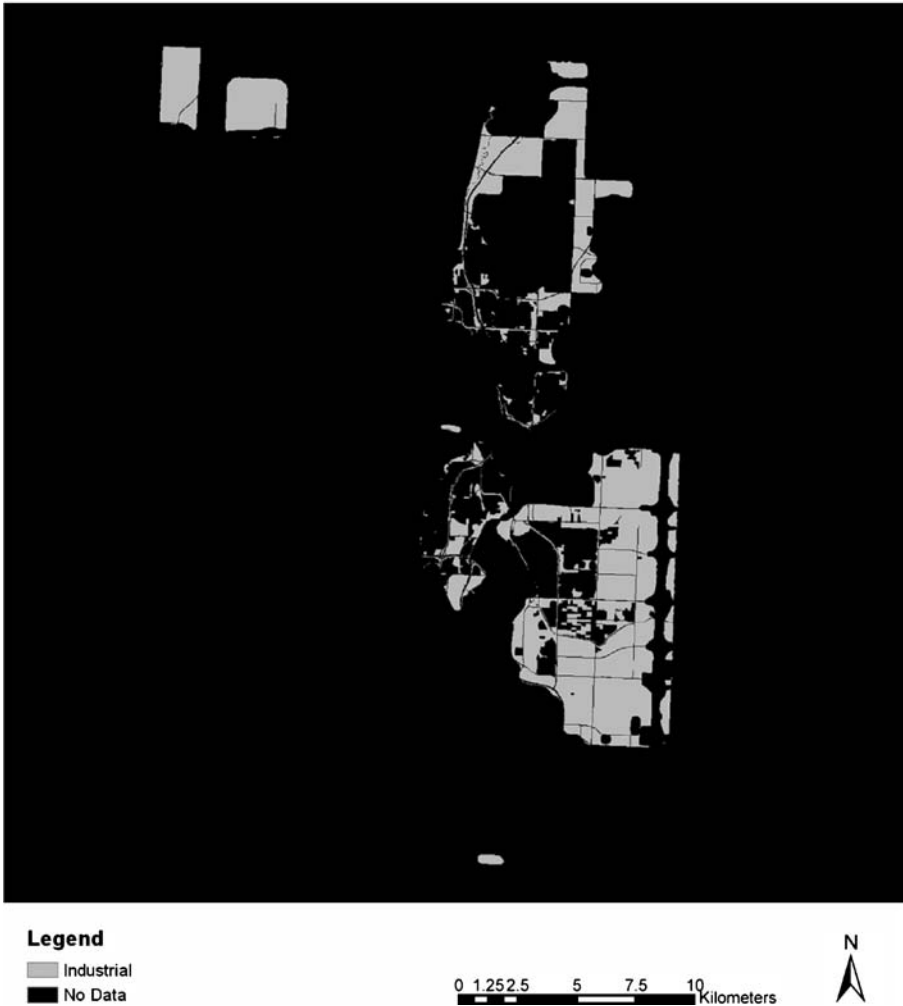


Fig. 7 Industrial suitability map of 1999

of Markov Chain analysis have been for time series analysis (Davis 2002) the extension of the technique to space–time series is an exciting, new development.

In the Cellular Automata (CA) analysis the land use was treated as a dynamic system in which space, time and the states of the system were treated discretely (White and Engelen 1993; Dadson 1999; Li and Yeh 2000, 2002). In the CA system, space was represented by a grid, time by uniform steps, and the states of the system were finite, integer numbers. The CA system consisted of four elements—cells, states, neighbourhoods and rules.

- *Cells* were the smallest of spatial units.
- *States* were attributes of the cells for a given time step.

Transportation Suitability Map of 1999

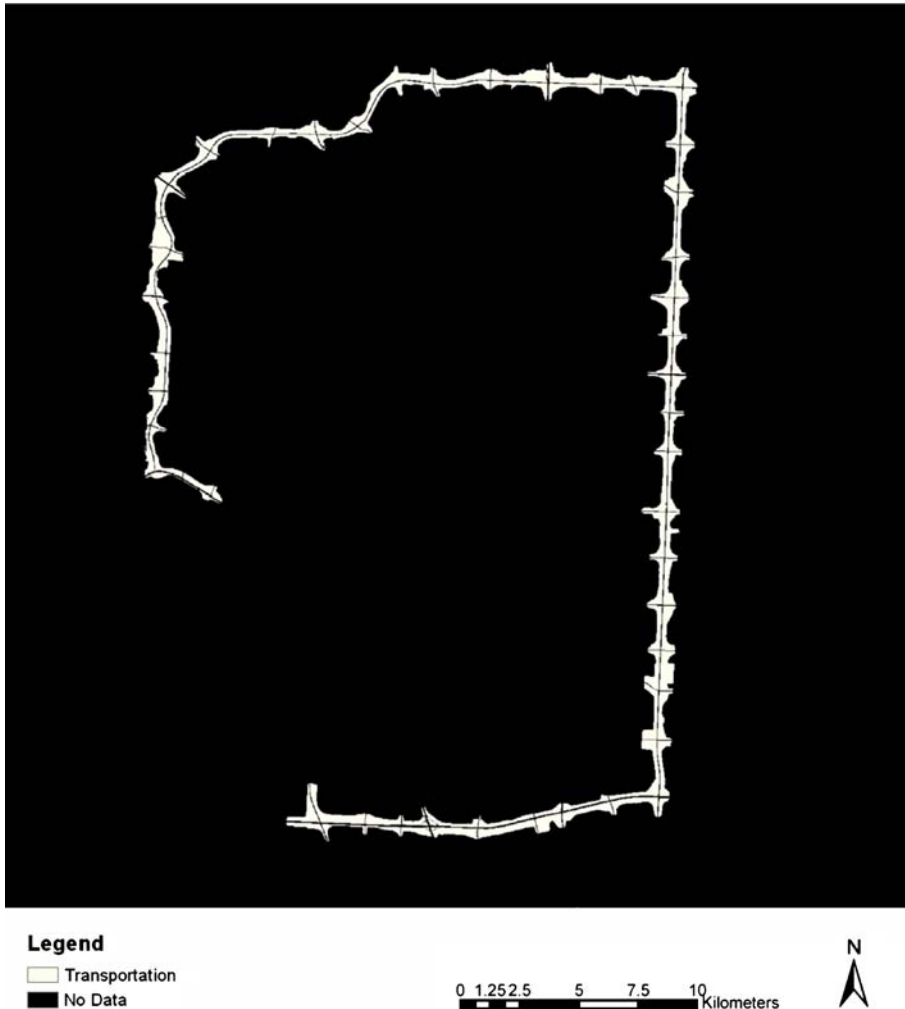


Fig. 8 Transportation suitability map of 1999

- *Relationships* among the cells were defined within neighbourhoods. The next state of each cell was determined by the states of its neighboring cells.
- *Rules* were used to define the states of the cells in the next time step.

In Idrisi Kilimanjaro, Cellular Automata analysis is accomplished by the CA_Markov module, which uses the output of the Markov Chain analysis and applies a contiguity filter to predict land use from time period two to a later time period.

To make the predictions of land use the land classifications for the six time periods that were produced by eCognition were imported into the Idrisi GIS as raster files. For this research land use suitability was determined using the City of Calgary's Future Conceptual Urban Structure (FCUS; <http://www.calgary.ca/docgallery/BU/>

Parks Suitability Map of 1999

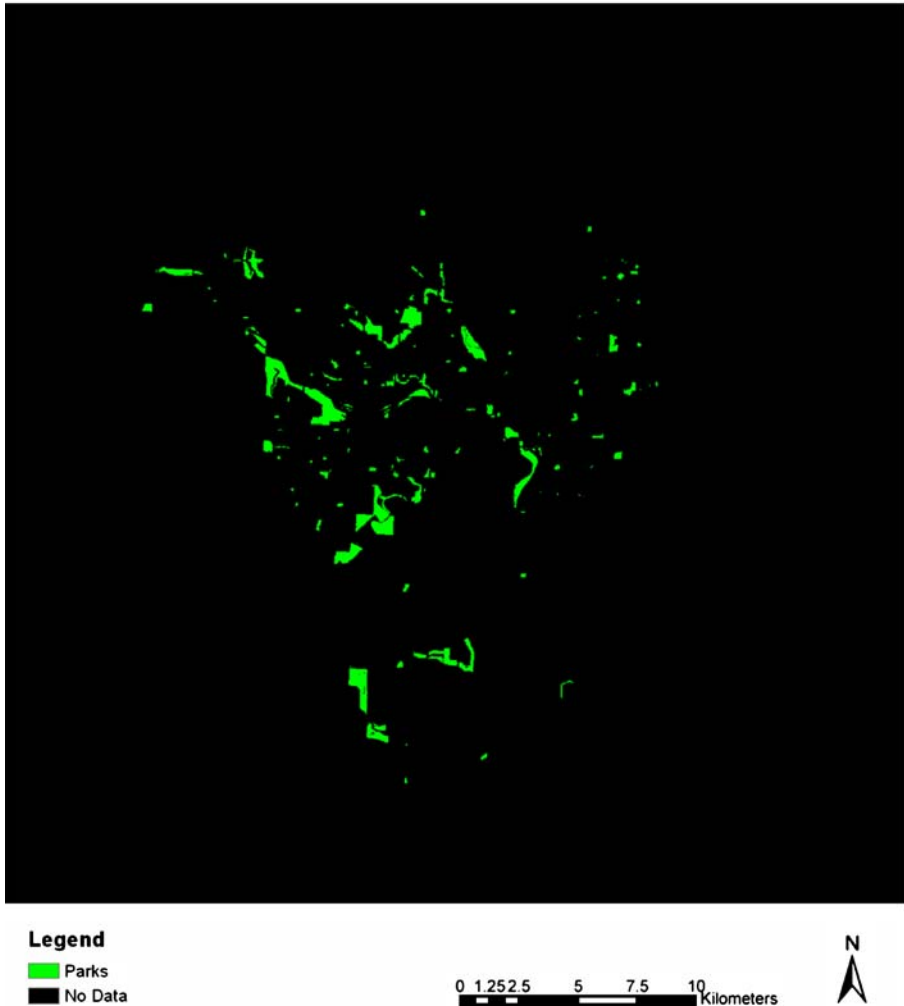


Fig. 9 Parks suitability map of 1999

[planning/pdf/calgary_plan.pdf](#)); the location of the City within the Province of Alberta is shown as Fig. 1). The original pdf file was converted to a .bmp file and then to an ERDAS Imagine file in ArcCatalog. This image was classified in eCognition, exported back to an ERDAS Imagine file and reclassified as shown in Table 3.

Parks and water bodies were considered not to change during the period from 1985 to 2001. Vacant area is a special class. Since the process of urban development is a process of consuming vacant area, vacant area in the later land use map of each group was used as the suitability map of vacant area in the future. A transition suitability image collection was created using the six suitability maps.

Vacant Area Suitability Map of 1999

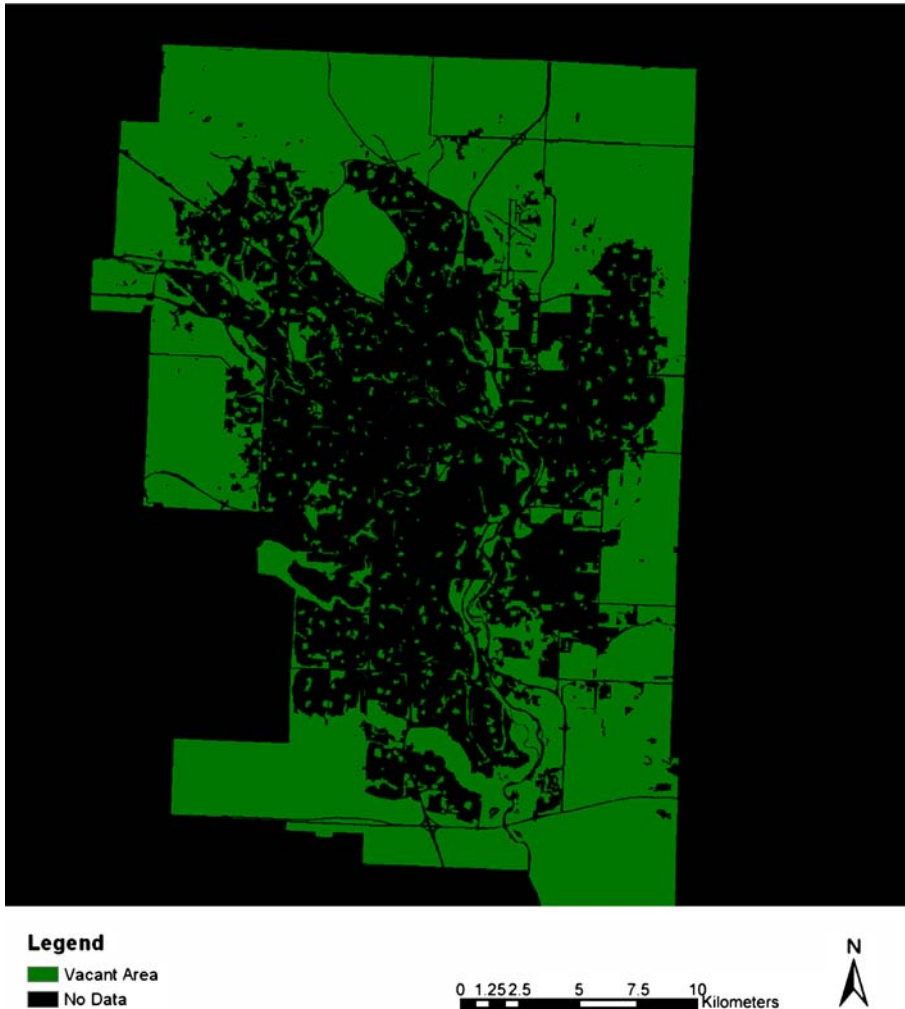


Fig. 10 Vacant area suitability map of 1999

2.4 Implementing the land use prediction

The trial prediction for the 1999 time period used the Markov module in Idrisi. This required a proportional error statistic to be assigned. Normally this might be difficult to determine but the City of Calgary has recently had a land use shapefile built that indicates the date when each land use parcel was incorporated into the city boundaries. In addition, the land use type is also indicated. For each of the six time periods, 4,000 random locations were generated and the Classified Data was compared to the Reference Data from the shapefile using the PCI Geomatica V9.1 software (<http://www.pcigeomatics.com/>). Four categories were used (residential/commercial; industrial; parks; and vacant areas) and the results recorded in an error

Water Bodies Suitability Map of 1999

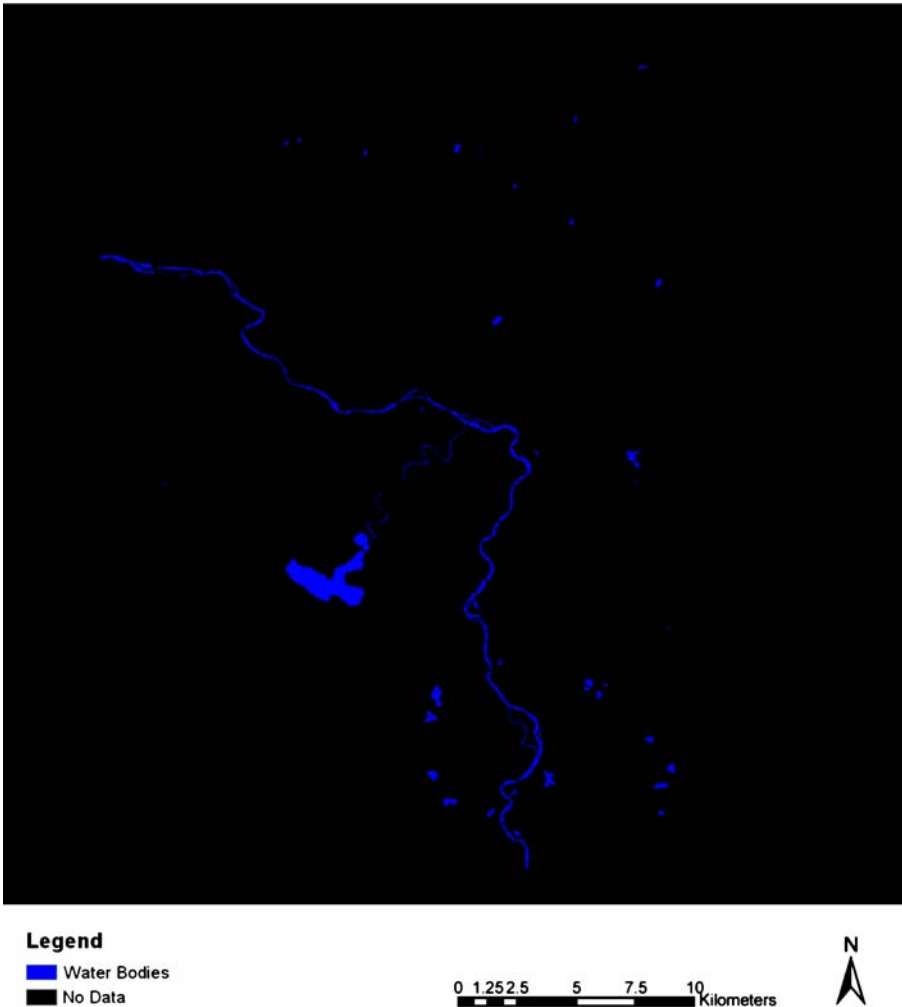


Fig. 11 Water bodies suitability map of 1999

(or confusion) matrix (Jensen 1996) where diagonal entries indicate an accurate classification. The overall accuracy varied from a low of 89.8% for the 1992 image to a high of a 92.5% for the 2001 image, while the average for the six images was 91.3%.

This accuracy assessment was used to set the proportional error parameter at 0.1 during the running of the Markov and CA_Markov modules. The initial analysis used the 1985 and 1992 classified images to “predict” the 1999 land use pattern based on Idrisi’s default contiguity filter. Once this had been deemed to be a success a “real” prediction for the year 2010 was produced based on the change that occurred between 1990 and 2000.

Table 4 Transition areas matrix

| Cells in | Expected to transition to | | | | | |
|----------------------------|----------------------------|------------|----------------|-------|-------------|--------------|
| | Residential and commercial | Industrial | Transportation | Parks | Vacant area | Water bodies |
| Residential and commercial | 205600 | 0 | 47 | 0 | 38878 | 482 |
| Industrial | 0 | 39606 | 0 | 0 | 5045 | 0 |
| Transportation | 0 | 0 | 46182 | 0 | 5152 | 0 |
| Parks | 350 | 350 | 350 | 15760 | 350 | 350 |
| Vacant area | 83837 | 5957 | 2653 | 0 | 414966 | 2530 |
| Water bodies | 839 | 0 | 0 | 0 | 560 | 12133 |

The diagonal elements of the matrix indicate no change in land use between the two time periods.

2.5 The measurement of urban sprawl using Shannon’s entropy

Urban sprawl is a complex phenomenon, which not only has environmental impacts, but also social impacts (Barnes et al. 2001; www.sprawwatch.org/). Due to its complexity, there is no specific, measurable, and generally accepted definition of urban sprawl (Sutton 2003). Many attempts have been made to measure urban sprawl (Ewing,1997; Nelson 1999; Galster et al. 2000; Yeh and Li 2001; Sudhira et al. 2004). The percentage of an area covered by impervious surfaces and concrete is a straightforward measure of urban development (Barnes et al. 2001). Based on this idea, Shannon’s Entropy, when integrated with GIS, has proved to be a simple but efficient approach for the measurement of urban sprawl (Shekhar 2004).

Since there were six land use maps derived from the object-oriented classification, in order to make the measurement of the 6 years of sprawl comparable, relative entropy instead of standard entropy was utilized because the range of relative entropy is always between 0 and 1. Relative entropy (E_n) can be expressed in this formula:

$$E_n = \sum_i^n p_i \log (1/p_i)/\log (n) \tag{1}$$

Where $p_i = x_i / \sum_i^n x_i$ and x_i is the density of land development, which equals the amount of built-up land divided by the total amount of land in the i th zone in the total of n zones. The number of zones means the number of buffer zones around the city center (22, 1 km concentric rings around the downtown area were needed to cover all parts of the city) or around selected roads (Yeh and Li 2001).

Since entropy can be used to measure the distribution of a geographical phenomenon, the difference in entropy between two different periods of time can also be used to indicate the change in the degree of dispersal of land development or urban sprawl (Yeh and Li 2001).

$$\Delta E_n = E_n(t + 1) - E_n(t) \tag{2}$$

Where ΔE_n is the difference of the relative entropy values between two time periods, $E_n(t+1)$ is the relative entropy value at time period $t+1$, $E_n(t)$ is the relative entropy value at time period t .

In this case, six land use maps had been derived from the classification process. The only task left for calculating the entropy was to create the buffer

Predicted Land Use Map of 1999

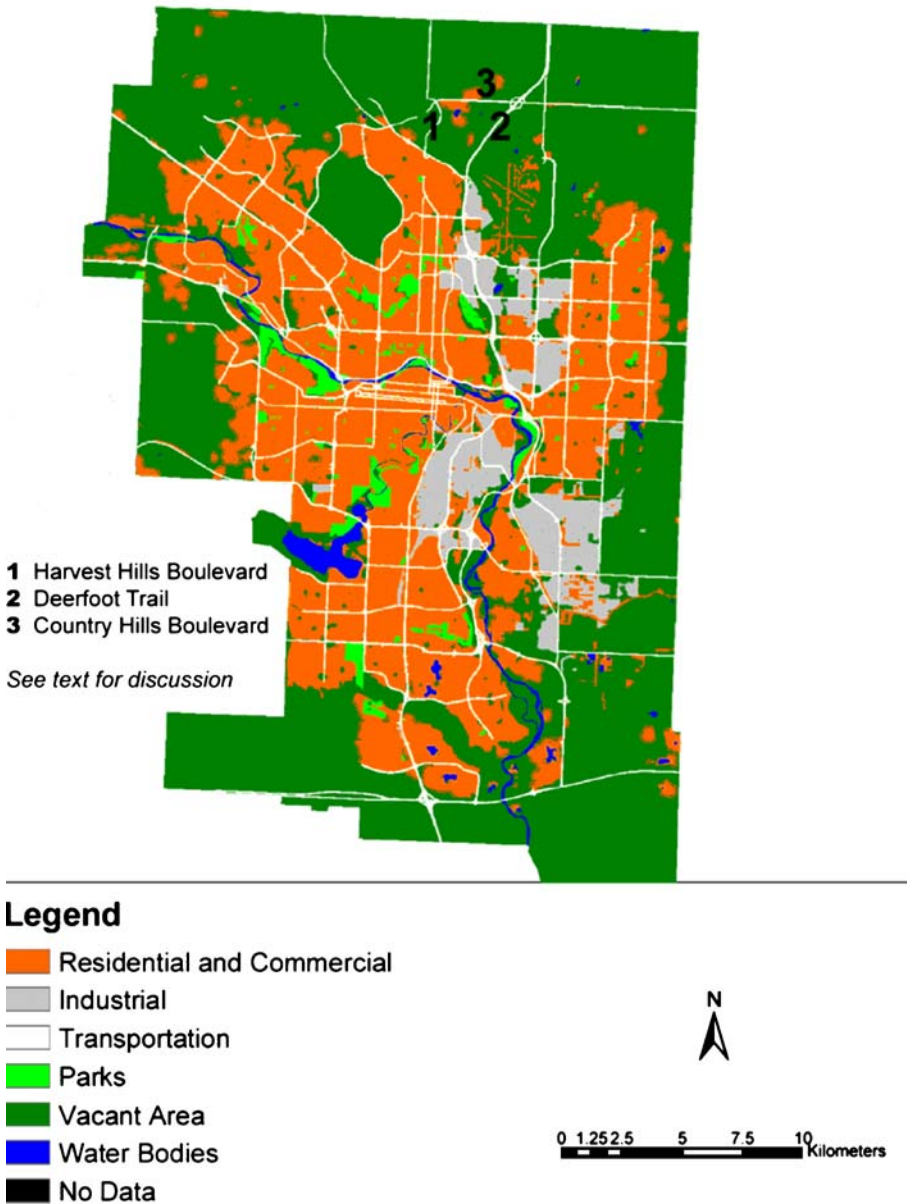


Fig. 12 Predicted land use map of 1999

zones. Accurate data for roads for all 6 years were not available for this project, but fortunately, Calgary has a very clearly defined downtown area. So, Shannon’s Entropy was computed on the basis of the buffer zones around the town center.

Table 5 Results of the validation analysis (see text for discussion)

| Variations | Formula | Values |
|------------|----------------------------------|--------|
| Kno | $\frac{P_o - NQNL}{1 - NQNL}$ | 0.9293 |
| Klocation | $\frac{P_o - MQNL}{MQPL - MQNL}$ | 0.9194 |
| Kquantity | $\frac{P_o - NQML}{PQML - NQML}$ | 0.9826 |

3 Results

3.1 Land use classification and prediction

Each satellite image was segmented into three levels for the purpose of classification. An example, of these three levels for the 2001 image is shown as Figs. 2, 3, and 4. Figure 5 shows the Land Use Classification Results for 2001 as produced by the eCognition software.

The ASCII eCognition file was then exported into the Idrisi software and converted to the Idrisi raster format so that the land use prediction could be carried out using the Idrisi Kilimanjaro software as described above. In order to make the process operational, suitability maps were created to display the future development for each of the three land use classes: transportation network; residential and commercial; and industrial. These three land use classes were extracted from the FCUS Map mentioned above.

In order to produce the prediction for 1999 six suitability maps had to be created, one for each of the following six land use classes: residential and commercial (Fig. 6); industrial (Fig. 7); transportation network (Fig. 8); parks (Fig. 9); vacant areas (Fig. 10); and, finally, water bodies (Fig. 11). Since the latter three were assumed not to change over the 7 years the 1992 classification results were used as the corresponding three suitability maps. The residential and commercial suitability map of 1999 was created by subtracting the residential and commercial map of 1992 from the residential and commercial map for the future (i.e., the FCUS Map referred to above). The industrial suitability map of 1999 was created in the same way. The transportation in the future map was used directly as the transportation suitability map of 1999. The resulting six suitability maps were collected together using Idrisi's Collection Editor to produce a transition suitability image collection for use in Idrisi's CA_Markov module.

Table 4 shows the transition areas matrix produced by running Idrisi's Markov module. The off-diagonal elements indicate the number of cells that are expected to change from each existing land use class in 1985 to each new class in 1992. Using the 1985 and 1992 land use maps, the transition areas matrix and the transition suitability collection, Idrisi's CA_Markov module was used to simulate the land use pattern of 1999 (Fig. 12). In order to compare the 1999 "prediction" with the actual land use in that year, Idrisi's Validate module was used to calculate the Kno, Klocation and Kquantity values. Respectively, these were 0.93, 0.92 and 0.98 (Table 5). Values above 0.9 indicate good agreement between the actual and predicted maps (Pontius 2000). Since the land use prediction of 1999 was so successful, the land use prediction of 2010 was implemented in the same way. The result is shown in Fig. 13.

Predicted Land Use Map of 2010

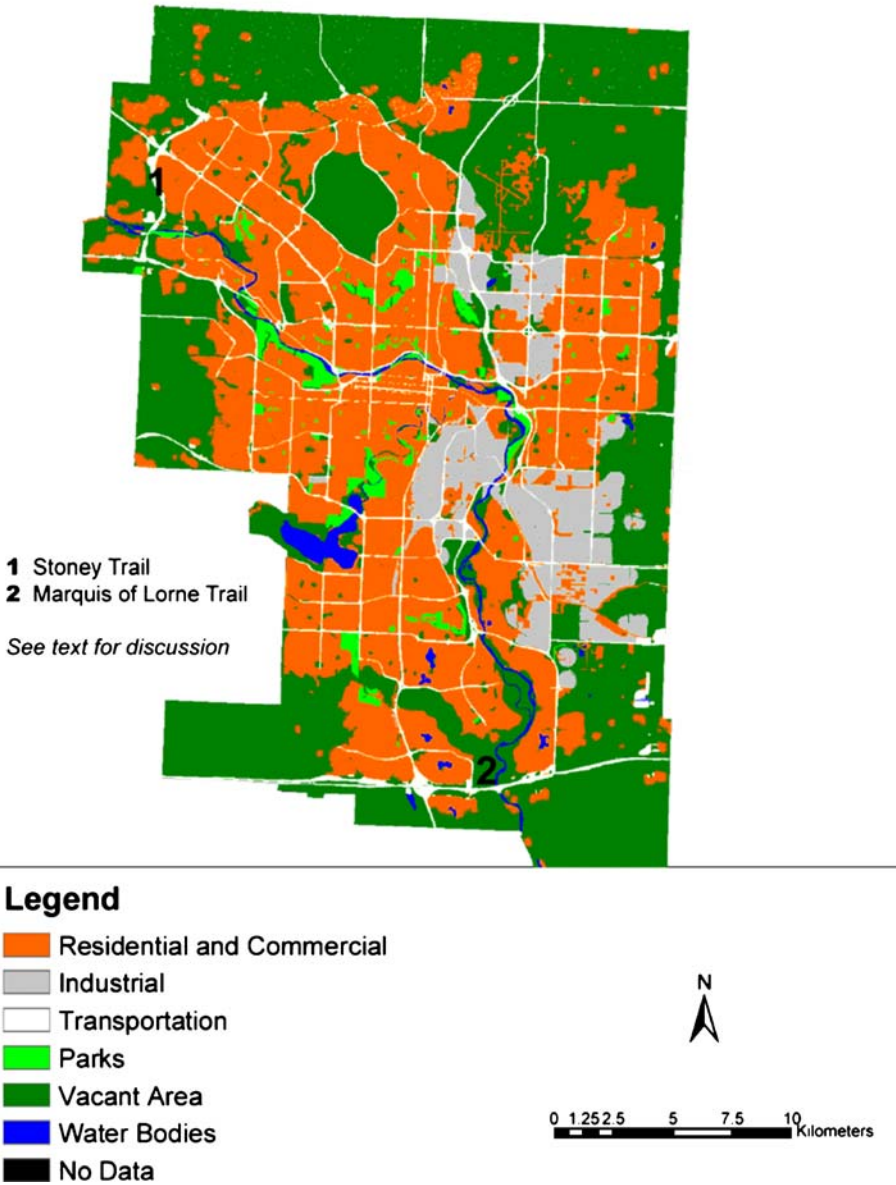


Fig. 13 Predicted land use map of 2010

3.2 Measuring urban sprawl in Calgary

The six land use maps were reclassified into two categories: built-up land and non-built-up land in order to calculate Shannon’s Entropy. The entropy statistic was calculated using Eq. (1) above and the twenty-two, one km buffer zones around

Buffer Zones around Downtown Calgary

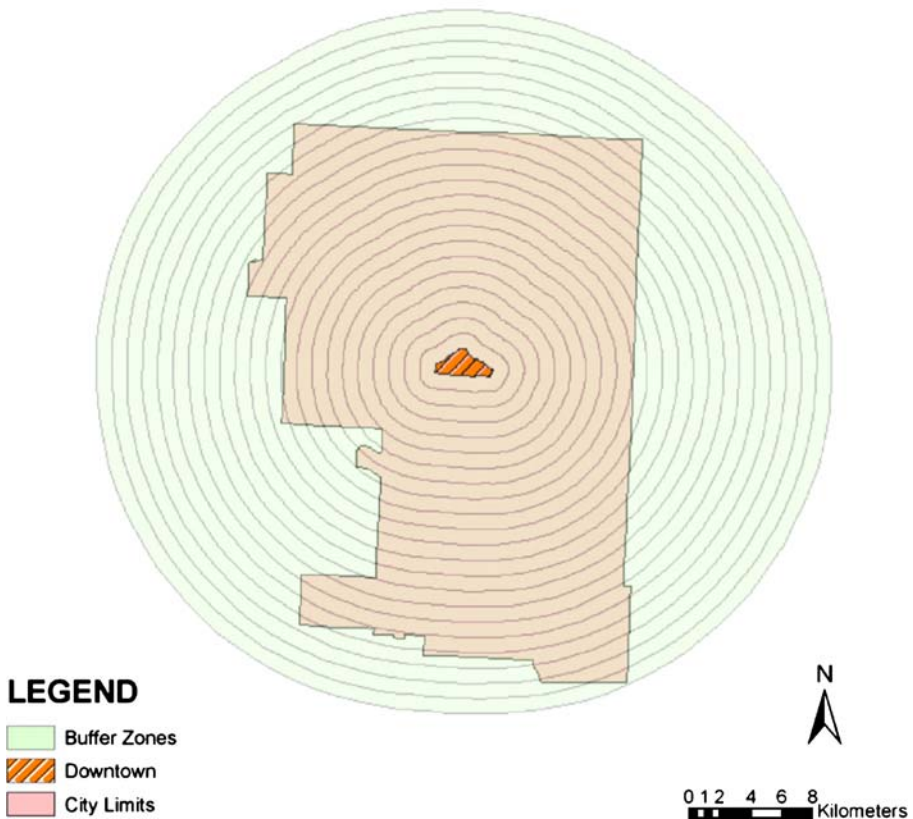


Fig. 14 Buffer zones around downtown Calgary

Calgary's downtown core (Fig. 14). The map of the built-up land is shown as Fig. 15. The results of the entropy calculation are shown in Table 6 and Fig. 16 and the change in the entropy measure is shown in Table 7 and Fig. 17.

4 Discussion

4.1 The process of land use classification

The object oriented classification approach used in the eCognition software successfully avoided the so-called “salt-and-pepper” effect that commonly results when pixel-based remote sensing classification approaches are used.

The multiresolution segmentation approach used by eCognition aided the process of classification by allowing the object mean value for the urban area to be used to distinguish the rural area beyond the city limits. The eCognition software has six

Built-up Land and Non Built-up Land of 2001

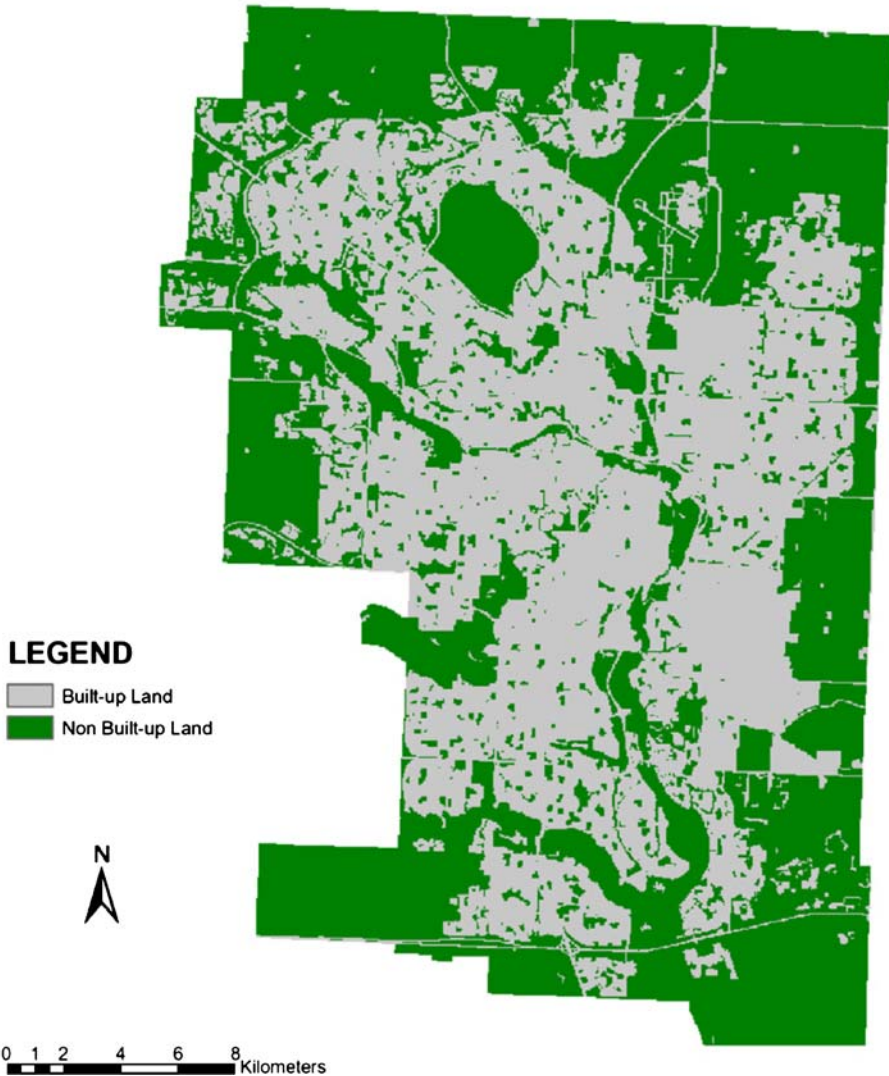


Fig. 15 Built-up land and non built-up land of 2001

parameters that can be adjusted in the multiresolution segmentation process. Although this increases the flexibility and adaptability of the software to various environments the choice of values to be entered for these parameters is not always straightforward and may require the use of additional local knowledge that is not always available (Flanders et al. 2003). Only six classes could be extracted using the spectral information from the images. This research showed that the eCognition software is a powerful tool for image classification but that its use requires considerable trial-and-error manipulation of the input parameters.

Table 6 Shannon's Entropy values of Calgary in the 6 years

| Year | | | | | |
|-------------|------------|-------------|-------------|-------------|-------------|
| 1985 | 1990 | 1992 | 1999 | 2000 | 2001 |
| 0.850928091 | 0.86418883 | 0.860065433 | 0.886924987 | 0.891793962 | 0.905053353 |

4.2 The limits to land use prediction

The suitability maps used in this research had a great influence on the land use predictions. This is because they act as the rules for the CA model. Different maps will lead to different rules that in turn may produce totally different results. The sensitivity of the predictions to the suitability maps will require further research.

Although the procedures used in the Markov Chain analysis in this research proved to be an effective approach for calculating the land use transition probabilities, these procedures assumed that the transition probabilities do not change over time. In other words, Markov Chain analysis predicts the future land use pattern only on the basis of the known land use patterns of the past. This is a weakness of the method in terms of simulating urban growth since new influences on the urban structure cannot be evaluated.

Although Table 5 (see Section 3.1) gave strong evidence that the predicted land use map of 1999 was similar to the actual land use map of 1999 it is still easy to see discrepancies between the two maps. Many commercial and residential land developments that occurred along the edge of the built-up area between 1992 and 1999 were not predicted precisely by the CA model. The predicted land use map of 1999 did show a number of development trends that can be found on the actual land use map of 1999. For example, the predicted map showed there would be residential and commercial land development between Harvest Hills Boulevard and Deerfoot Trail (Highway 2) along Country Hills Boulevard in the extreme northern-central region of the map (Fig. 12). In reality, the land development not only happened there, but also grew faster than the prediction. Such examples can also be found in other places around the city. These underestimates indicate that the residential and commercial land was developed faster from 1992 to 1999 than from 1985 to 1992, confirming the weakness of the Markov Chain Analysis that was noted above.

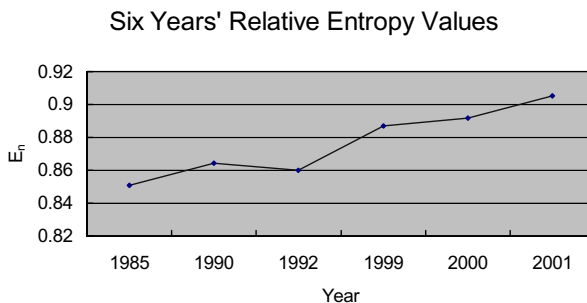
**Fig. 16** Six years' relative entropy values

Table 7 Differences of Shannon’s Entropy

| Time period | ΔE_n |
|-------------|--------------|
| 1990–1985 | 0.013260739 |
| 1992–1990 | -0.004123397 |
| 1999–1992 | 0.026859554 |
| 2000–1999 | 0.004868975 |
| 2001–2000 | 0.013259391 |

The shape of the contiguity filter used in this analysis may have influenced the results of the simulation. The filter develops a spatially-explicit weighting factor which will be applied to each of the suitability maps, weighting more heavily areas that are next to existing land uses. This ensures that land use change occurs next to existing similar land use classes, and is not wholly random (Eastman 2003). Due to the nature of the contiguity filter, the land that was deemed suitable for industrial and commercial development on the FCUS map did not always receive the expected development in the simulation and the converse was also true. A different filter with a different set of weights might have produced different results and again research on the sensitivity of the results to various weightings for the contiguity filter is warranted.

A much clearer trend can be detected when comparing the predicted land use map of 2010 with the land use map of 2000. In the Northwest quadrant the residential and commercial land would be further developed in the northwest direction, in the Northeast quadrant development will occur in a northerly direction and in the Southeast quadrant it will move due east. Industrial land is expected to expand on the city’s eastern edge. Stoney Trail, a major in-city freeway on the western side of the city, and the Marquis of Lorne Trail, an east–west freeway in the extreme south of the city, (see Fig. 13) were predicted to become more important links in Calgary’s transportation network. Although it is impossible to evaluate how accurate the prediction for 2010 is, it did yield some suggestions about where the city will develop in the next several years.

4.3 The on-going rise of urban sprawl

The calculation of Shannon’s entropy measure indicated that Calgary was continuing to sprawl between 1985 and 2001. The entropy value for 1992 is a little lower than

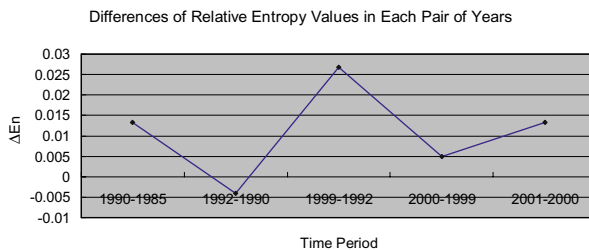


Fig. 17 Differences of relative entropy values in each pair of years. (The sign “-” means minus.)

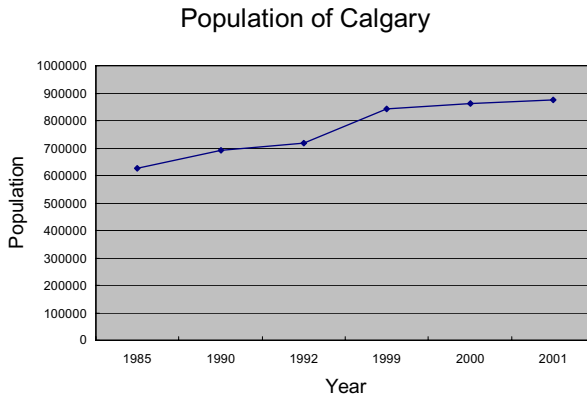


Fig. 18 Population of Calgary from 1985 to 2001

that of 1990. This is probably a result of the incompleteness of the 1992 image. In comparison to the 1993 average relative entropy value of 0.767, calculated by Yeh and Li (2001) for the 24 buffer zones around the 29 towns of Dongguan City in Guangdong Province in China, all 6 entropy values for Calgary are higher. This implies that urban sprawl in Calgary was a far more serious matter than that detected by Yeh and Li in their study.

Given an existing set of land development policies or lack thereof, the driving force behind urban sprawl in Calgary is population growth. Figure 18 shows Calgary's population growth between 1985 and 2001 demonstrating a strong correlation with the growth of sprawl.

Urban sprawl is occurring around the world. In recent years, the negative social and environmental effects of urban sprawl have been realized by more and more researchers and city planners. Smart Growth is a policy oriented strategy for fighting sprawl (Freilich 1999) and is primarily based on the implementation of higher residential densities (Danielson et al. 1999). This approach to combating urban sprawl now has a strong advocacy presence on the Internet (www.smartgrowth.org/). Faced with ongoing urban sprawl and strong population growth, the City of Calgary needs to consider smart growth policies to encourage the efficient and effective use of newly developed land or the re-use of established land. The City of Calgary's new emphasis on Transit Oriented Design where higher residential densities are promoted around light rail transit stations is a new policy that may do much to reverse the historic trend toward urban sprawl (www.calgary.ca/DocGallery/BU/planning/pdf/3405_tod_policy_guidelines.pdf). Our results suggest that while Calgary's mayor, Dave Bronconnier, is correct in his assertion that urban sprawl was a problem in the 1980s he is incorrect in assuming that the problem has been dealt with and that it will not be a concern for the future (Graveland 2006).

5 Conclusions

This paper has demonstrated a methodology for producing land use classification from Landsat images using the object-oriented methodologies contained in the

eCognition software. The classified images were then used to predict future land use change in the City of Calgary, Alberta, using Markov Chain analysis and Cellular Automata approaches based on the interactions between the transportation network and various other types of land use. Shannon's entropy statistic was used to measure the degree of sprawl in the city. This was shown to be high and increasing. Smart Growth policies were advocated as a remedy to problems generated by high rates of urban sprawl. Models such as those described here can provide simulated inputs for the variables commonly used in the four step transportation planning process.

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