LAND COVER CHANGE AND LANDSCAPE DYNAMICS IN THE URBANIZING AREA OF A MEXICAN BORDER CITY

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ABSTRACT

Land cover change associated to urbanization processes represents one of the most insidious forms of ecosystem alteration and links frequently to other types of environmental degradation. Timely and accurate remotely sensed detection of land cover change is therefore an essential requirement for a better understanding of coupled natural and human systems in urban expansion areas. Landscape dynamics represent the spatio-temporal manifestations of land cover change and are potentially useful to track the capacity of natural ecosystems to perform intrinsic functions that support socioeconomic systems. This capacity can be affected when changes occur in areas with highly vulnerable environmental conditions, such as in desert regions. Accelerated and miss-planned urban growth in the Mexican border region of Ciudad Juárez, Chihuahua threats surrounding desert ecosystems viability and jeopardizes the provision of supporting environmental services. In this work, we used an integrated remote sensing approach to assess land cover change from high-resolution imagery and to derive metrics to evaluate landscape attributes and dynamic during a five-year period. Landscape attributes were estimated for each of the observation dates and potential changes in landscape function and structure were evaluated. We found an increasing trend in landscape fragmentation, which might be related to many of the environmental problems faced by the city, including atmospheric and surface water pollution, and flood risk. An extended period of analysis and more detailed data are, however, essential to establish more robust relationships between the character of the recent urbanization process and the landscape dynamics in the region.

INTRODUCTION

Among the scientific community and the society in general there has been an increasing concern for a better understanding of the complex environmental problems derived from the human alteration of natural ecosystems. Some of the most evident manifestations of this phenomenon are the land cover changes linked to urbanization processes, which are subsequently the cause of many other types of environmental degradation (Watson, *et al.*, 2000). Densely populated landscapes represent, in fact, the most altered terrestrial ecosystems (Forman, 1995). The impacts of land cover change are of such magnitude that have motivated the emergence of new sub disciplines devoted entirely to its monitoring and to the study of its biophysical and human triggering mechanisms and consequences (Rindfuss, *et al.*, 2005). In the last decades, remote sensing technology has provided the means for a timely and accurate monitoring of land cover change, facilitating the track of spatio-temporal trends useful for the assessment of critical regional and global ecological processes. Due to its inherent advantages including synoptic view, multi-temporal coverage, and feasibility of processing in digital format, remotely sensed products are increasinly used for land cover change monitoring (Lu, *et al.*, 2004). The results of their applications are serving to evaluate not just the environmental but the economic effects of land cover change at many different scales around the globe.

The Remote Sensing Approach to Landscape Dynamics Assessment

In the remote sensing context, change detection consists in identifying the differences in the state of an object or phenomenon by observing it at two different times (Singh 1989). The phenomena of interest are the changes in the initial land cover conditions along a time series captured in an image set. Land cover change, therefore, can be defined as the difference in the reflectance values of two image pixels or objects recorded at two different dates (Lambin and Strahler 1994). Once land cover changes are detected, change spatial units can be used to assess spatial reconfiguration of the landscape. At regional scales land cover change from natural to anthropogenic conditions motivates the modification of landscape patterns that support essential ecological services (Luck *et al.*, 2001). Landscape —as an area with homogeneous land cover characteristics— hence represents an optimal spatial unit to assess land cover change patterns derived, for example, from urbanization processes.

Landscape ecology provides the conceptual and methodological framework to analyze the spatial landscape configuration and its complex relationships with ecological processes and environmental risks (Turner *et al.*, 2001). Landscapes are viewed as spatially complex, heterogeneous assemblages of patch types. Patches usually represent discrete areas of relatively homogeneous environmental conditions at a particular scale, such as polygons representing different land cover types (Forman *et al.*, 1986). Landscape spatial dysfunctions affect critical ecological services including surface water supply and regulation, erosion control and sediment retention, waste assimilation, soil formation processes, genetic resources banking, and provision of recreation and leisure opportunities (Costanza *et al.*, 1997). Landscape capability to perform these functions is determined by three main landscape characteristics: 1. Structure, related to its shape, size, number, and configuration; 2. Function, determining the interactions among the spatial elements in terms of energy and matter flows; and 3. Change, considering the alteration of structure and function through time (Turner 2005). These characteristics can be assessed by using quantitative measures or 'metrics' of landscape patterns revealing different aspects of ecosystems function (O'Neill *et al.*, 1988). Integration of landscape ecology and remote sesning thus, can be very useful for an accurate and timely evaluation of landscape dynamics and fucntion derived from land cover changes (Crews-Meyer 2002).

Research Problem and Objective

Fragmentation effects on landscape structure and function derived from recent land cover changes have not been assessed with an integrated approach in the region of the study. Some related effects studied individually include hydro meteorological risks (Granados-Olivas 2006); aquifers recharge decrease (Sheng *et al.*, 2001); habitat and biodiversity loss (PRONATURA 2002); and agriculture productivity reduction (Salas-Plata *et al.*, 2004). It is needed, however, to achieve a comprehensive understanding of the relationships of these effects with land cover changes that might be altering landscape functions. Despite the efforts to direct urban growth and land use assignation according to the physical potential and constraints of the environment (IMIP 2003), there is still an incomplete understanding of the effects that miss-planned urbanization may have on the landscape.

In this work we aim to identify the land cover changes in the main urbanizing area of Ciudad Juárez, Chihuahua and to assess their potential effects in the landscape dynamic. It is hypothesized that land cover changes associated to urbanization processes in the area of study have caused a landscape fragmentation that might be affecting landscape structure and function.

DATA AND METHODS

For this study we used a rule base object oriented classification approach to derive natural and manmade land cover classes from high spatial resolution imagery. Post classification comparison was applied to detect significant changes in cover characteristics linked to urbanization processes. Landscape metrics were derived from land cover classes in each date and compared to establish relationships with potential alterations to the structure and function of landscape.

Study Area

Ciudad Juarez, Chihuahua is an actively growing city located in the northern plains of the Chihuahuan Desert on the southern shore of the Río Bravo / Rio Grande in northern Mexico. Being the fourth largest Mexican city with more than 1,300, 000 inhabitants, Ciudad Juárez occupies an approximate area of 290 sq. km. Its strategic location on the international border between Mexico and the U.S. across from El Paso, TX and its economic activity dominated by the maquiladora industry attracts more than 20 thousand people every year (INEGI, 2005). This pace of growing places an enormous pressure on the desert land needed for the expansion of industrial and residential uses around the city, propitiating an accelerated landscape fragmentation (Liverman and Breuing 1999). It is estimated that approximately 450 ha. of land have been incorporated to the city every year since 2002.

The study area for this project is defined by a 78.29 sq. km. polygon with and elevation range of 107 meter located in the southeastern portion of Ciudad Juárez (SECJ). This area, formerly occupied by desert scrub communities of *Larrea tridentata* and agriculture encompasses 70% of the urbanization occurred in Ciudad Juárez within the last five years. Most of the future growing plans for the city are located within or further south of this polygon.

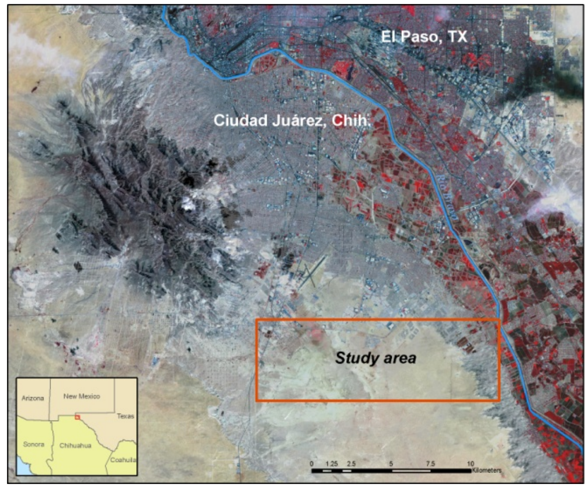

Figure 1. Study area in the southeastern portion of Ciudad Juárez, Chih. (SECJ) Background image: Aster 2001, RGB 432.

High Resolution Satellite Data

We used 2007 cloud free 2.44 m. multispectral QuickBird pan sharpened images and 2002 0.7 m. spatial resolution natural color composites (NCC) to derive the land cover data needed for the analysis. The two dates available for the study were November 25 2002 and August 15, 2007. Despite of this almost three-month lapse, potential classification errors derived from phenological differences were not considered critical given the sparse vegetation cover and the urban nature of most of the cover types being identified. The five year span in the collection date, however, was considered more important to detect the fast land cover changes occurring in the SECJ area. QuickBird products were acquired radiometrically and geometrically corrected with a total positional accuracy of 23 m. CE 90% and a RMSE of 14 m. All data were referenced to UTM Zone 13N, datum WGS84.

Image Pre-processing

High resolution images were first pre-processed to standardize scenes for classification. Given the location and extent of the SECJ study area, we first created mosaics to concatenate two swaths for each date both for panchromatic and multispectral scenes. We resolved swath illumination differences applying a histogram matching process. Since no atmosphere parameters were available for absolute atmospheric correction, we applied a generic inverse point spread convolution to dehaze multispectral images. 2007 panchromatic and multispectral mosaics were then co-registered to each other applying a first order polynomial transformation with a RMSE of 0.084 m. After this first geometric correction, we used a pan sharpening function (King and Wang 2001) to increase the spatial resolution of the 2007 multispectral scene. This mosaic was re-sampled to 0.7 m. to match the 2002 spatial resolution. Since no IR was available for 2002, we created a natural color composite for the 2007 image. Both composites were finally co-registered to each other with a RMSE of 0.153m.

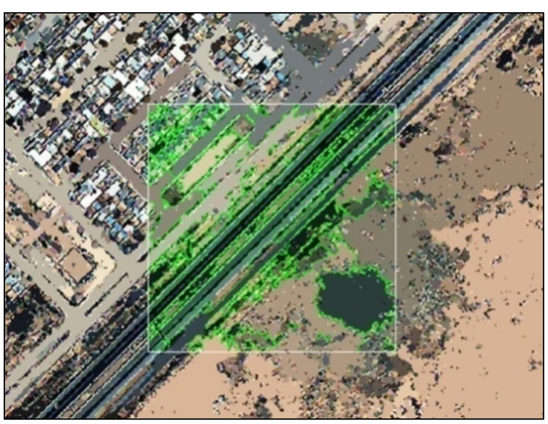

Figure 2. Image segmentation and merging sample on the Region Means image of a SECJ area section.

Land Cover Classification and Change Detection

For this study we used a supervised object oriented approach to classify natural and manmade land cover classes in a test portion of the SECJ area using the ENVI feature extraction tool. For this purpose, we first tested different segmentation scale levels and chose 45.9 for both dates. This parameter provided a good delineation of individual objects representing the main land cover classes in the area (Figure 2). Given the high spatial resolution of the images, the objects extracted initially were merged using a 75.7 threshold λ value to iteratively merge adjacent segments based on a combination of spectral and spatial information (Robinson *et al.*, 2002). This step allowed integrating small objects to reduce over-segmentation. We computed spatial, spectral, and texture attributes from the extracted objects to serve as the basis for the rule based classification.

Extracted objects associated to desert scrub and bare soils were aggregated as samples into a natural land cover class. Objects associated to residential, industrial, pavement and developing areas were grouped into a manmade land cover class. The classification was performed with the K Nearest Neighbor classification algorithm with a 3 K parameter. Configured this way, this method considers the Euclidean distance of the target to 3 neighbors in the training data in an n-dimensional space defined by the number of object attributes used for classification. This method is much less sensitive to outliers and noise in the dataset and performs better than traditional nearest-neighbor classifier because the K nearest distances are used as a majority vote to determine the target membership class (Schowengerdt 2007). Accuracy assessment was performed with a random stratified sample of 47 field points. The two classified dates were compared by computing a difference map to detect the changes in the natural and manmade land cover classes.

Landscape Metrics Computation

Classified datasets were generalized to eliminate patches with an area smaller than 50 sq m but keeping the 0.7 pixel size. This allowed landscape metrics were less affected by classification errors derived from high information content in the high spatial resolution imagery. In preparation for the landscape metrics calculation, datasets were converted into 8-bit binary format. Landscape metrics were calculated with Fragstats (McGarigal and Marks, 1995), a spatial pattern analysis program for categorical raster data. Given the extent of the test area and the nature of the land cover classes extracted, we chose to compute only 8 representative metrics that provided a general idea of the effects of urbanization processes on landscape structure and function in the SECJ area (Table 1).

Table 1. Selected Fragstats landscape metrics (McGarigal and Marks, 1995)

Metric type	Level	Metric	Key	Description
Area/ Density/ Edge	Class	Patch density	PD	Measures the number of patches per 100 hectares
		Largest patch index	LPI	Quantifies the percentage of total landscape area comprised by the largest patch
	Landscape	Number of patches	NP	Measures the extent of subdivision or fragmentation of the landscape
Shape	Patch/ Class/ Landscape	Contiguity index	CONTIG	Assesses the spatial connectedness or contiguity of cells within a patch
		Shape index	SHAPE	Measure shape complexity
Contagion/ Interspersion	Class/ Landscape	Contagion	CONTAG	Measures the level of compactness
		Landscape Division index	DIVISION	Measures the probability that two randomly chosen pixels in the landscape are not located in the same patch
Connectivity	Class/ Landscape	Connectance index	CONNECT	Represents the percentage of the maximum possible functional joins between patches of the corresponding patch type based on a 100 m threshold distance.

RESULTS AND DISCUSION

Classification and Land Cover Change

Aggregation of segmented objects and supervised classification of natural and manmade land cover classes produced two models. In 2002, 88.26% of the test area was classified as natural land cover, which could be considered unaltered landscape patches. Only 11.73% of this area was classified as manmade land cover (Figure 3a). In the 2007 classification the natural land cover classes represent the 56.48% of the test area, while the manmade classes represent 43.51% (Figure 3b). The difference map in fact, depicts and increment of 31.78% in manmade land cover between 2002 and 2007 (Figure 3c). This means an approximate growing rate of 24 ha per year, way below the estimated growth rate for the whole city. However, because of their discontinue distribution; these new urbanizing areas show a clear fragmentation of the consolidated natural landscape units.

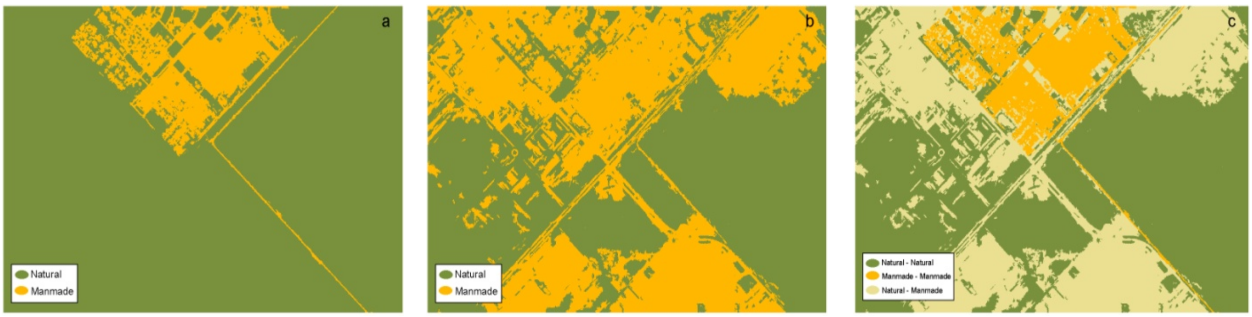

Figure 3. Object based supervised classification results from the 2002 (a) and 2007 (b) images, and land cover change (c).

Overall accuracy for the 2002 classification was of 87.23%, with a user's accuracy (UA) of 89.47% for the natural and 77.78% for the manmade land cover class (Table 2). The higher commission error (CE) in the manmade class was due to the many small interstitial bare soil areas located within the residential cluster. Conversely, the lower CE in the natural class might be due to its extent and compactness. When compared with a typical spectral based supervised classification, the overall accuracy decreased to only 64.35%. In the 2007 object based classification, the overall accuracy was of 82.98%, which was 27.63% above the overall accuracy of test spectral based classification of the same year. The object base classification reported a UA of 77.78% for the natural and 86.21% for the manmade class (Table 2). The higher fragmentation in the natural land cover and the increase in the manmade land cover caused a higher CE for both land cover classes in the 2007 classification.

Table 2. Error matrix of the 2002 and 2007 classifications

	2002 Classification					**2007 Classification**				
Reference	Natural	Manmade	Total	PA*	OE**	Natural	Manmade	Total	PA*	OE**
Natural	34	2	36	94.44%	5.56%	14	4	18	77.78%	22.22%
Manmade	4	7	11	63.64%	36.36%	4	25	29	86.21%	13.79%
Total	38	9	47			18	29	47		
UA	89.47%	77.78%				77.78%	86.21%			
CE	10.53%	22.22%				22.22%	13.79%			

**Producer's accuracy, **Omission error*

We observed some advantages in using the object based classification for this study. Since we only had available visible bands, we were not able to fully exploit the spectral differences between impervious and vegetated surfaces. The object segmentation was performed based not only on spectral but spatial and texture attributes ensuring the better identification of ground features. In addition, interactive sample selection allowed classifying features such as developing areas in the manmade class. Since many of these objects were just bare soil, the use of object segmentation based on spatial attributes and the application of location criteria by the operator avoided these features to be assigned automatically to the natural class.

Landscape Dynamic Characterization

At the landscape levels metrics reveal an increasing land cover fragmentation in the test area (Table 3). The number of patches (NP), in fact, increased in 250% between the two dates. This indicates an intense ongoing process of desert scrub land opening for urbanization. Many of the recent emerging small manmade patches were identified in the 2007 image as campsites, unpaved roads, and dumpsites linked to the construction of new residential developments. Patch density (PD), accordantly, increased from 72.44 to 182.55 patches per 100 ha, which agrees with the fragmentation trend in the area. Regularity in the shape (SHAPE) of the land cover patches with a value of 1 for maximally compact patch, also registered a small increase. The increase was expected to be higher, but there seems to be a strong influence of the small patches in both dates.

Table 3. Landscape level metrics computed from the 2002 and 2007 land cover classifications

Year	NP	PD	SHAPE	CONTIG	CONTAG	CONNECT	DIVISION
2002	275	72.44	2.09	0.83	71.66	9.64	0.59
2007	693	182.55	2.18	0.64	44.84	3.38	0.73

The contiguity index (CONTIG), representing the spatial connectedness of cells within a patch and measured between 0 and 1, decreased in 22.89%. This might confirm the opening of small manmade areas in the desert scrub patches and reveal limitations in the classification protocol to assign correctly small patches within large manmade patches. The level of compactness, measured by the contagion index (CONTAG) with a range from 0 to 100 shows an even large decrease, mostly because the two large desert scrub patches in 2002 were split into several small patches in 2007. Connectance index (CONNECT) representing the percentage of functional joining between patches of the same type was in fact very slow in both dates; in part due to the existence of only two classes, but is even lower for 2007. When looking at the probability of two random pixels not occurring in the same patch, the landscape division index (DIVISION) increased 14% due to the larger number of patches and increased fragmentation.

Most metrics at the class level (Table 4) coincide with the pattern showed at the landscape level. The only exceptions are a decrease in SHAPE and DIVISION metrics for the manmade class between 2002 and 2007. The first difference can be interpreted as decrease in the complexity of the manmade patches due to the large residential and industrial regular patches that appeared in 2007, which might help also to understand the lower probability of random locations not occurring in the same patch.

Table 4. Class level metrics computed from the 2002 and 2007 land cover classifications

Year	Class	PD	LPI	SHAPE	CONTIG	CONNECT	DIVISION
2002	1*	58.743	55.13	1.99	0.83	9.48	0.60
	2**	13.69	10.65	2.53	0.79	12.44	0.98
2007	1	142.77	23.09	2.11	0.62	3.31	0.91
	2	39.77	42.88	2.41	0.69	4.20	0.81

**1 = natural, ** 2 = manmade*

At the patch level, shape index for 2007 classification shows a relatively higher complexity for both natural (Figure 4a) and manmade (Figure 4b) land cover classes. The presence of atypical high values is, however, more frequent in the 2007 sets, which might indicate the intra fragmentation of large patches by the occurrence of small manmade islands increasing shape complexity. This trend is confirmed by the inversely proportional pattern showed in the contiguity index values distribution (Figure 5). In this case, the 2007 classification shows a higher number of patches with very low values of spatial cell connectedness within a patch, which confirms the landscape fragmentation trend along the five year period of the study.

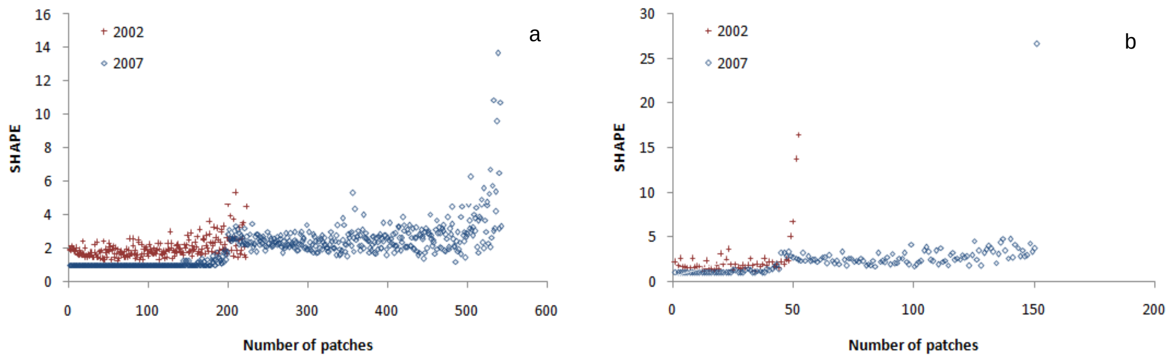

Figure 4. Patch level Shape Index values distribution for natural (a) and manmade (b) land cover classes.

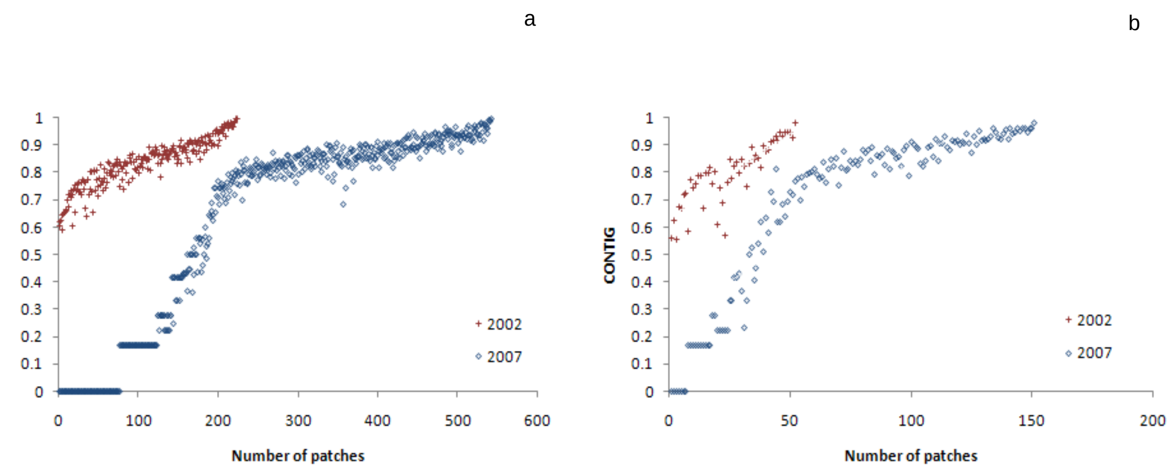

Figure 5 Patch level Contiguity Index values distribution for natural (a) and manmade (b) land cover classes.

The effects of this landscape fragmentation, showed by the selected landscape metrics, might have different implications in the structure and function of desert scrub natural landscape in the area. For example, removal of vegetated cover and alteration of topographic conditions for land developing, without the appropriate urban infrastructure, might make some areas more vulnerable to flood risk. This can be confirmed by the presence of large flooded areas in the 2007 image, confined by roads and terrain alterations for residential and industrial development (Figure 6). From the ecological, perspective, increasing landscape fragmentation might be affecting vital ecosystems functions such as matter and nutrient exchange, soil formation processes, trophic chain preservation and habitat provision for small species. A more precise assessment of these potential fragmentation effects requires, however, empirical studies at different spatio-temporal scales.

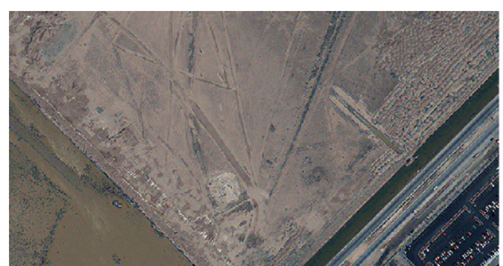

Figure 6. Natural color composite of the QuickBird 2007 image showing flood areas in the southern portion of the SECJ.

CONCLUSIONS

Land cover change in the SECJ area changed dramatically between 2002 and 2007. Urban related land cover increased in a third of the area. This increment occurred in both large compact patches and small opening areas that caused a marked landscape fragmentation, mostly in natural land cover types represented by desert scrub communities. This trend was confirmed by most landscape metrics selected for the analysis. Some of the effects of this over fragmentation might be related to environmental risks for the new developing urban areas and to alteration of subtle ecological functions essential for the provision of critical environmental services. Residential and industrial development has been determinant factors in the spatial configuration of land cover change in the study area. This study demonstrates an integrated remote sensing-landscape ecology approach to understand the relationship of land cover change and landscape structure and functions in the SECJ. An extended period of analysis and more detailed field data are, however, needed to establish more robust relationships between the character of the recent urbanization process and landscape dynamics in the area.

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