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Modeling Urban Sprawls in Northeastern Illinois

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Abstract Like many metropolitan regions Chicago area characterized by Urban Sprawl. The ability to manage this Urban Sprawl for a sustainable future presents numerous challenges for geographers and planners. Nowadays remotely sensed data are inherently suited to provide information on urban land cover (LC) characteristics, change over time, and modeling. This paper has attempted to investigate Urban Sprawl in northeastern Illinois, and analyze its impact on the agricultural land and nature over time. The satellite images were acquired and classified to prepare the base maps, change detection was employed to analyze changes overtime. The Land Change modeler was used to predict the future urban growth of the area in 2020 and 2030. The results indicated that between (1989 and 2010) the built up area increased by 82.2%, which associated with a loss of 25.8% of the valuable agricultural lands and a decline in the urban open spaces and other landscape categories by 32.5%. The predicted maps showed an increase of built up land, which will cause further loss of agricultural lands mainly in the suburbs.

Keywords: *simulation of urban sprawl, land change modeler, multi-layer perceptron, markov chain, northeastern illinois, remote sensing*

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1. Introduction

Urban sprawl has received increasing attention from planners, geographers and policy makers who are advocating in sustainable urban development. Urban sprawl is a land transformation patterns characterized by low-density settlement, often random development and rapidly expanding in a manner that radiates from urban centers [1]. It is characterized by development patterns along the periphery of cities and highways or roads connecting major settlements. Urban sprawl has several social and economic consequences, such as but not limited to loss of open space, environmental pollution, and congestion [1,2]. It is also associated with loss or fragmentation of natural areas (e.g. wetlands, wildlife corridors), increased flood risks, and overall reductions in quality of life [2].

The Chicago metropolitan region provides a classic example of this urban land transformation. For instance, between 1970 and 1990, Northeastern Illinois lost 440 square miles of farmland [2]. This is an amount equal to twice the current land area occupied by the City of Chicago. The transformation hasn't stopped, and factors such as city's roads and transportation systems, ongoing federal subsidies for housing, permissive local governments, and politically weak regional planning agencies are effecting continued urbanization [3,4]. According to the Northeastern Illinois Planning Commission (NIPC) (now the Chicago Metropolitan Agency for Planning (CMAP)), rapid population growth (i.e., at rate of 25%) was predicted for the Chicago metropolitan region between 1990 and 2020. In other words, the metro population is expected to grow by about 1.8 million between 1990 and 2020, which higher than the 4% growth recorded preceding decades i.e., between 1970 and 1990 [4].

Simulation models, integrating remote sensing and GIS, have greatly expanded the opportunities for providing accurate and up-to-date information of modeling the changes and predictions of Urban expansion. Since the Landsat data dates back to 1972, the remote sensing techniques evaluated patterns of cities' growth over time. The techniques have also evaluated drivers of changes including, but not limited to, bio physical factors (i.e., temperature, rainfall, slope, drainage etc.) and socio-economic drivers (i.e., the growth of population, industrialization, infrastructure and technological [5]. These findings have enhanced the understanding of causes, consequences and drivers of growth of many cities around the world.

However, simulation models vary in strengths by which they evaluate urban growth patterns and predict future changes. For instance, while some models (e.g., Markov chain) [6] produce the prediction of land use categories without spatial details [7], i.e., the future land use depends only on the current state and not on the sequence of events that preceded it [8,9]; others (e.g., Geomod, [10]) consider the spatial details, but predict only a one-way transition from one category to one alternative category [11]. Studies have started using cellular automata and Markov chain (i.e., CA_Markov) together to give spatial dimension to Markov model which is weak in spatial side [10,11,12]. The CA_Markov has an ability to predict any transition among any number of categories which makes it a better choice than when Geomod is used standalone [10,11]. Recently, Land Change Modeler (LCM), which uses the combination of Multi-layer perceptron (MLP) Neural Network and Markov chain modeling technique is employed to simulate urban growth. The method uniquely finds the best fitting and hence suitable for modeling complex relationships among factors involved in Land changes [7,13,14,15]. Besides, the MLP in the model also enhances the ability of the model to accommodate relationships that are perhaps non-linear [16,17]. This study investigated the urban sprawl in Northeastern Illinois, especially the impacts on the agricultural and natural landscapes. Similar studies have been done for the neighboring area in the past [12,18]. However, the studies were conducted using the data covering the period between 1972 and 1997 and an approach referred to as dynamic landscape simulation (DLS) approach, necessitating the need for a study with recent data and a more robust approach.

2. Materials and Methods

2.1. Study Area

The study area for this research stretched over a large portion of Northeastern Illinois. The area includes a large part of the Chicago metropolitan area (9.4 million), which is the third largest metro in the USA following New York (19 million) and Los Angeles (12 Million) [19]. It includes Cook, DuPage, Kane, Kendall, McHenry, Will, Grundy, Boone, De Kalb and a large part of lake and Kankakee counties and covers an area of 6,853.8 square miles Figure 1.

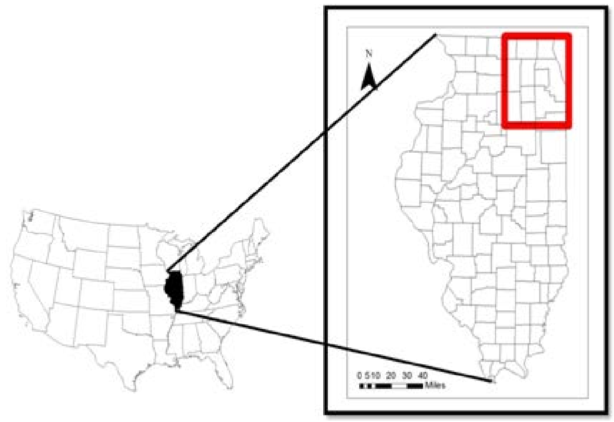

Figure 1. Study Area Location Within US and Illinois counties

The majority of the population resides in Cook county (60%) followed by DePage (10%) and Lake (8%) counties. The census data over the study period depicts that the region has experienced significant population growth, which is a major driver of urban land transformation and expansion. For example, from 1990 – 2000, the population of metro Chicago increased by 11.58%. Though the rate reduced in the subsequent decade, i.e., between 2000 and 2010, population still grew by 3.86% (See Table 1).

The population growth has impacted the metro area is characterized by diverse land cover types including some of the world's best remaining rare natural habitats, and expansive agricultural lands. Agriculture was the dominant land cover type in the past decades, though like most metropolitan areas, it is experiencing dramatic land cover changes. From 1972 to 1997 there were 37% and 21% losses, respectively, of agricultural and natural lands in Chicago metropolitan area [18]. According to the study [18], the suburban land transformation was associated with human settlement triggered by redistribution of population, decentralization of metropolitan functions, and the growth and development of suburban areas.

Table 1. Population, and Population Growth in the Study Area between 1990-2000 and 2000-2010

County	1990	2000	2010	Growth 1990-2000 (%)	Growth 2000-2010 (%)
Cook	5,105,067	5,376,741	5,194,675	5.3	-3.4
DeKalb	77,932	88,969	105,160	14.2	18.2
DePage	781,666	904,161	916,924	15.6	1.4
Grundy	32,337	37,535	50,063	16.1	33.4
Kane	317,471	404,119	515,269	27.3	27.5
Kendall	39,413	54,544	114,736	38.4	110.2
Mchenry	183,241	260,077	308,760	41.9	18.7
Will	357,313	502,266	677,560	40.6	34.9
Lake	516,418	644,356	703,462	24.7	9.2
Kankakee	96,255	103,833	113,449	7.9	9.3
Total	7,507,113	8,376,601	8,700,058	11.6	3.7

Source: US Census Bureau. Note: LU/LC change was calculated between 1989, 1999, and 2010, while the population growth was found for 1990, 2000 and 2010.

2.2. Data

Three cloud-free Landsat satellite images/scenes were downloaded from a U.S. Geological Survey (USGS) web site (http://glovis.usgs.gov/) to conduct this research. Two of these images, October 4th 1989, and September 12th 2010 images, were Landsat 5 Thematic Mapper (TM) images while the third image, September 22nd 1999 image, was a Landsat 7 Enhanced Thematic Mapper (ETM+) image. The images referenced to the World Geodetic System (WGS) 1984 ellipsoid and the Universal Transverse Mercator (UTM), Zone_16N coordinate system. Additionally, the images were characterized by a spatial resolution (pixel size) of 30 meters in the visible and IR (infrared) bands and each image covers 170 km *183 km. The Properties of the selected Landsat Images are shown in Table 2.

Table 2. Specifications of Landsat Images Selected

Year	Date of Acquisition mm/dd/yyyy	Sensor	Cloud cover (%)	Quality	Path/ row
1989	10/04/1989	Landsat 4-5 TM	0	9	23/31
1999	09/22/1999	Landsat7 ETM+	0	9	23/31
2010	09/12/2010	Landsat 4-5 TM	0	9	23/31

Ancillary data needed for this study, particularly, for ground truthing, referencing and modeling. These includes; Chicago Land Green Infrastructure-Land Use 2004, 4-meter spatial resolution IKONOS multispectral satellite imagery and land cover maps of the Illinois counties of the Chicago area. The Chicago Land Green Infrastructure was obtained from Green Mapping Organization (GMO) and the IKONOS imagery was obtained from the Chicago State University (CSU) GIS Lab were used as a references to get some ideas about land cover types in the study area. On the other hand, the land cover maps of the Illinois counties of Chicago Wilderness for 1985, and 1997 were used for identifying information classes and training a supervised image classifier. Additionally, Google Earth 2010 was also used to assist training signature selection and get some ideas about the recent land cover of the study area. Main roads and water bodies' data prepared by Chicago Metropolitan Agency for Planning (CMAP), were used for Land Use Land Cover (LU/LC) modeling.

2.3. Methods

2.3.1. Image Processing

Image preprocessing needed for this study include image stacking, band selection and combination. Image stacking is the process converting a multiple band Landsat images into a multispectral image [20]. While image stacking, both thermal band 6 and panchromatic band were excluded because their overall contribution to this study is infinitesimal. The false color composite in which bands 4, 3 and 2 are displayed in the red, green and blue, respectively, was used for this study to enhance distinction among different LU/LC types [7]. In this band combination, urban areas appear in cyan blue, vegetation in shades of red, water bodies from dark blue to black, soils with no vegetation from white (sand, salt) to brown.

2.3.2. Image Classification

This research focuses mainly on the urban sprawl and its effect on the agricultural lands and natural areas. Therefore, it was determined to limit the classification results as five information classes, namely; built up land, agricultural land, water, forest and woodlands, and a category referred to as "others" (See Table 3). The digital classifications were done using the maximum likelihood image classifier (Equation 1 &2). The maximum likelihood decision rule is assign pixel to the classes based on probability. The probability density function for a class (W_i) is given by:

$$P(X / W_i) = \frac{1}{(2\pi)^{1/2}\sigma_i} \exp\left[-\frac{1}{2} * \frac{(X-\mu_i)^2}{\sigma_i^2}\right] \quad (1)$$

Where:
P = probability density function
W_i = LULC class (e.g., Urban land)
X = brightness values
μ_i = estimated mean of all values in LULC class (e.g., Urban land) training class
σ_i^2 = estimated variance of all the measurements in this class

For multiple done, n-dimensional multivariate normal density function equation is given as:

$$P(X / W_i) = \frac{1}{(2\pi)^{1/2}|V_i|^{1/2}} \exp\left[-\frac{1}{2} * (X-M)^T V_i^{-1} (X-M_i)\right] \quad (2)$$

Where:
$|V_i|$ = the determinant of the covariance matrix,
$|V_i^{-1}|$ = the inverse of covariance matrix
$(X - M_i)^T$ = transpose of the vector $(X - M_i)$
M_i = mean vector
V = covariance matrix

This classifier is the most common classification algorithms and successful [21,22,23] as it involves training of the information classes. The classifier is trained using information (training) classes obtained directly from the ground truth thereby facilitating a classification on the basis of a likelihood probability of pixel's belongingness to each training class [20].

Table 3. The LU/LC classification scheme

LU/LC Class	Descriptions
1. Urban land	All man-made features (residential, commercial and industrial areas, settlements and transportation infrastructure and mixed urban)
2. Agricultural land	Includes cropland and other types of agricultural practices
3. Water	Waterbodies such as (lakes,rivers, streams and canals)
4. Forest and woodlands	Deciduous and evergreen forest , and transitional woodland
5. Others	Includes mixed pixel containing Built up mixed with Agricultural land, Urban mixed with Nature (i.e., Forests and Woodlands or Waterbodies mixed with Built up. and other land cover types

Note: Classes description was adopted from U.S Geological survey LU/LC Classification system for use with remote sensor data

The training sites were selected with the help of reference and ancillary data such as Google Earth 2010, Chicago Land Green Infrastructure-Land use 2004, IKONOS and the land cover maps of the Illinois counties of Chicago. Training polygons were digitized for each training site, and spectral signature were developed for LU/LC category, to derive statistics that categorizes pixels. Several methods were used for evaluating separability of the training signatures. Only training sites with separable signatures were used to perform the classification. At least 30 training sites per class and a total of 360 sites were selected for supervised image classification and subsequent accuracy assessment.

Following image classification, isolated incidences of individual group of pixel(s) independent from its neighbors were identified. Post-classification smoothing was conducted to smooth the image and eliminate such isolated incidences. This was done with a 3x3 MAJOROTY filter, which removed the isolated pixels based on the most popular values within the filter window. Smoothed images were then clipped into the shape and size of the study area.

2.3.3. Accuracy Assessments

Accuracy assessments of the classified maps (1989, 1999 and 2010) were evaluated using the error matrix. The error matrix evaluated accuracy using parameters such as overall accuracy, producer's accuracy, user's accuracy and the Kappa Index of agreement. The overall accuracy specifies the total correctly classified pixels and is determined by dividing the total number of correctly classified pixels by the total number of pixels in the error matrix. The producer's accuracy indicates the probability of a reference pixel being correctly classified; while the user's accuracy indicates the probability that a pixel classified on a map actually represents that category on the ground. On the other, the Kappa index measures the agreement between classification map and reference data [24]. All accuracy parameters have index values between

0 and 1, where 0 symbolize poor and 1 strong classification accuracy/agreement.

2.3.4. Change Detection

A number of remote sensing system and environmental considerations were made in selecting the images appropriate for the change detection analysis. For instance, with regards to the system considerations, attempts were made to acquire data on anniversary or near anniversary dates. Accordingly, images near or at the anniversary dates i.e., 10/04/1989, 09/26/1999, and 09/12/2010 were acquired. Additionally, attempts were made to select images with same spatial, spatial and radiometric resolutions. Other consideration included atmospheric conditions, soil moisture condition, and plant phonological cycle of the times when the images were recorded. The images selected were recorded when the atmosphere was cloud free (0%), the landscape has similar moisture condition and stages of vegetation development.

Many change detection algorithms are available (e.g., [7,11,15,22,23,25,26]. These are post classification change detection, image algebra-based change detection i.e., image differencing, image ratioing, multi date composite image [25]. While image algebra-based change detection, particularly, image differencing can only provide change or non-change information, post classification technique can provide "from-to" change matrix [26]. Besides, post classification technique is the most common change detection method, and has successfully employed for detecting and monitoring Urban sprawl and changes occurring in urban areas [7,11,15,22,23]. Therefore, post classification method was used in the change panel of the Land Change Modeler (LCM) in IDRISI to determine changes LU/LC between 1989 and 1999, 1999 and 2010, and 1989 and 2010. The Land change panel also created a variety of change graphs and maps, which help to understand prevailing land cover gains, losses and change "from-to" map. The spatiotemporal changes of Urban sprawl was also evaluated by creating the LU/LC maps for the three time periods (1989, 1999, and 2010) on maps reclassified into built up and non-built up land.

2.3.5. Urban Growth Prediction

Different models have been developed for the purpose of modeling urban growth and land use changes. These are Markov Chain, Geomod, CA-Markov, and Land Change Modeler (LCM). The LCM is also referred as Multi-Layer Perceptron (MLP) - Markov in some cases because it represents combination of Markov and MLP techniques and was selected to predict the urban growth in the study area. The method is found as most suitable for the simulation of the complex relationships in the LU/LC change in recent studies [7,13,14,15]. The LCM, which predicts future LU/LC based on the historical change of LU/LC maps [17], consisted of three major steps. These are Change Analysis (discussed in the previous section), Transition Potential Modeling and Change Prediction. The schematic of LCM is indicated in Figure 2.

The modeling requires two LU/LC maps for different dates 1989 and 2010 as project parameters. The LU/LC maps were used as references to understand the nature of change in the study area, and for establishing samples of transitions that should be modeled. The transition potential map is a product of Multi-Layer Perception (MLP) neural network algorithm that was selected owing to its ability to optimize non-linear relationships. The MLP running statistics are shown in Table 4. All combinations of driver variables were tested to assess relative influence of each. The MLP gave a good accuracy rate (i.e., 79.15%) using distance from Built-up land and likelihood driver variables, again high Cramer's V values does not guarantee a strong performance since it cannot account for the mathematical requirements of the modeling approach used and the complexity of the relationship, therefore many factors was excluded to reach higher accuracy in MLP. The minimum number of cells that transitioned from 1989 to 2010 was 361045, therefore this number represent the maximum sample size. Ideally the RMS error curve should be smooth and descent. In this study RMS error curve; both the training RMS and testing RMS curves showed decrease in the RMS errors which indicated increase in accuracy rate (i.e., 79.15%).

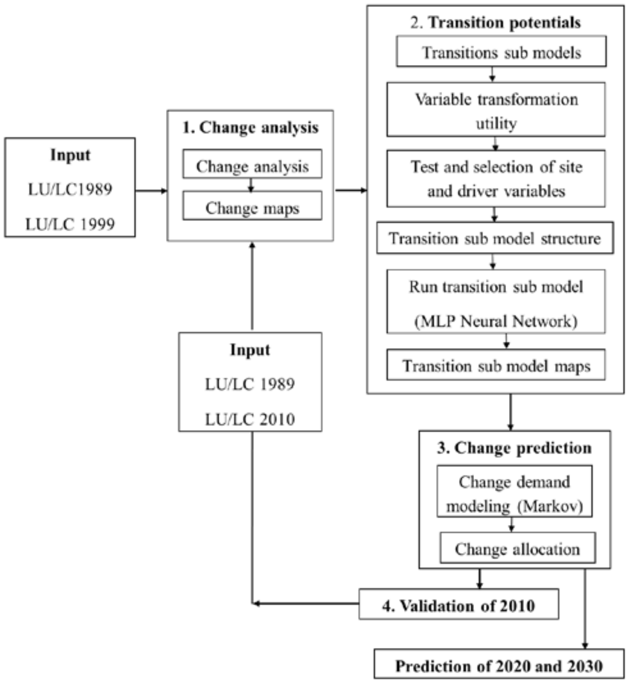

Figure 2. LULC Modeling using Land Change Modeler (LCM)

Table 4. Statistics of MLP Neural Network

Maximum Sample Size	361045
Iterations	10000
Training RMS	.2373
Testing RMS	.2386
Accuracy Rate	79.15%

MLP is an artificial neural network model that maps sets of input data onto a set of appropriate outputs. It is composed of an input layer, output layer, and hidden layers, which are between input and output layer (Figure 3). MLP works in such a way that activity of the input units represents the raw information that is fed into the network. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units

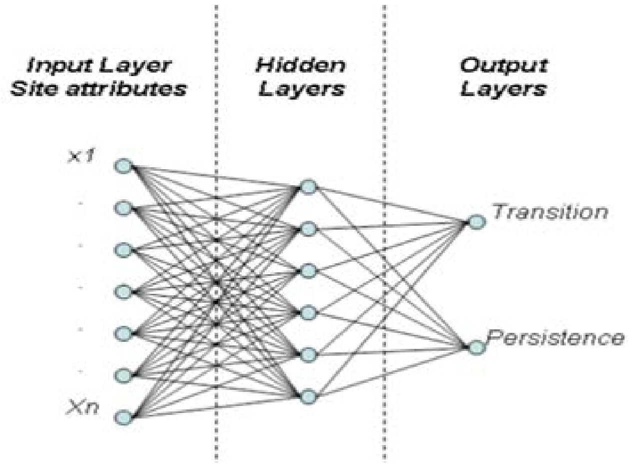

Figure 3. Architecture of the Multi-layer perceptron network applied to land use change modelling

The transition potential are maps of the land that would potentially be transformed. It is developed by the following steps: First the sub-models that are going to be used for computing the transition potential were identified using Transition Sub-Model Status panel. The panel lists all transitions that exist between the two land cover maps. Three sub models were considered, namely; built up land gain from agricultural land, built up land gain from "others", and "others" gain from agricultural land since the focus of the study is mainly modeling changes in built up land. In the next step, variables that explain the transitions were developed. A quick test of the potential explanatory power of a variable was done using Cramer's V test. Cramer's test has values between 0 – 1, where 0 signify lower explanatory power (association) and 1 imply a strong explanatory power [17]. With Satisfactory Cramer's Value, the driving and model variables were put together to model each transition. The transition potential maps, the Markov Chain modeler and the transition probability matrix were used to predict the 2010 LU/LC map. The method, which combines MLP and Markov chain was found to be efficient for predicting future LU/LC change [7,13,15].

2.3.6. Model validation

Model validation is conducted to determine the quality of the predicted LU/LC map [17]. After using the LU/LC maps for 1989 and 1999 to simulate the year the LU/LC in 2010, a cross-tabulation analysis was employed to compare the simulated image of 2010 with the base LU/LC map of 2010 produced using supervised classification, for validation. The analysis produces a tabular matrix, which depicts the proportion of the total number of pixels that are correctly predicted as in the classified 2010 map.

3. Results and Discussions

3.1. LU/LC Classification and Accuracy Assessment

The results of LU/LC classifications of Landsat images of 1989, 1999 and 2010 are shown in Figure 4. Accordingly, five major LULC types were identified in the northern Chicago counties. These are built up areas, agricultural lands, waterbodies, forest and woodlands and a category referred to as "others". The others category is consisted of mixed pixel containing Built up mixed with Agricultural land, Urban mixed with Nature (i.e., Forests and Woodlands or Waterbodies mixed with Built up.

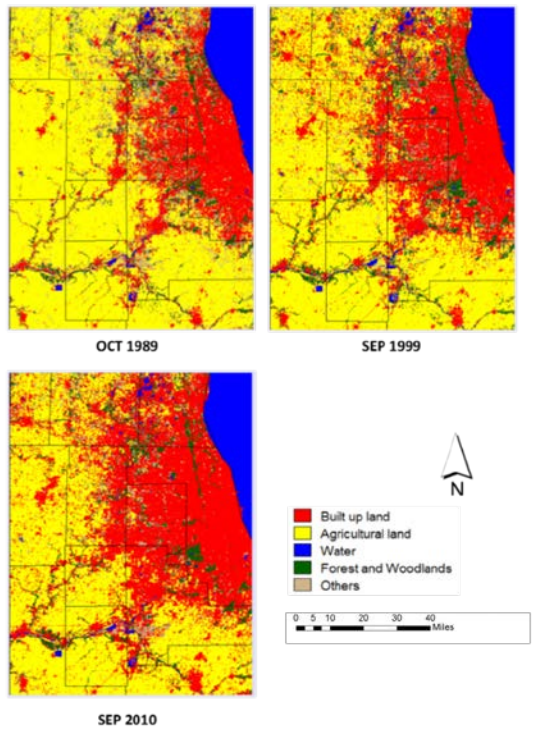

Figure 4. LU/LC maps obtained from classification of the 1989, 1999, and 2010 Landsat Images

The accuracy of the classified maps are shown in Table 5. The overall accuracy of the map for 2010 image is 100%, whereas the accuracies for 1989 and 1999 were 99%. On the other hand, the Kappa statistics, which evaluated the overall agreement between a classification map and reference data and is a more accurate measure than the overall accuracy measure as pointed out earlier, demonstrated an strong agreement (i.e., 99%) between the classification maps and the reference data. Producer's and User's accuracy were found consistently good ranging from (79%-100%) for all categories in each study year, except for "Others" category. The user's accuracies for "Others" ranges 31 – 80% and it was low (31%) for 1999 image. The possible reason for the lower producer accuracy of this category was the characteristic of this class, which are mixture of other land cover type and mixed pixel with varying ranges of different dominant land cover types. However, higher values of overall accuracy parameters and KIA indicate that the classification results are good enough for further analysis.

In 1989, agriculture was dominated the LU/LC types of the study area, accounting for approximately 56.2% of the landscape. This is followed by built up and "others" areas, which was stretched over 1468.8 sq miles (i.e., 21%) and 688.7 sq miles (i.e., 10%); respectively (Table 6). The proportion of waterbodies, and Forest and woodlands were the least accounting for only 7% and 5.3% of the landscape, respectively. In 1999, while still agriculture dominated the LU/LC types of the region (i.e., 50.3%) the proportion has decline from what it was in 1989. Conversely, the proportion of built up lands increased to

29.5% whereas Waterbodies, Forest and Woodlands and other categories, relatively, remained stable. In 2010, built up and agricultural land were about the same i.e., 39.1% and 41.7%, respectively.

Table 5. Summary of error matrixes for the classified images of 1989, 1999 and 2010.

Year	Category	Producer's	User's	KIA per Class
1989	Built up	1	.79	.79
	Agriculture	0.98	1	1
	Water	1	1	1
	Forest & Woodland	0.99	1	1
	Others	0.97	.62	0.62
	Overall accuracy	.99		
	Overall KIA	0.98		
1999	Built up	1	0.93	.93
	Agriculture	0.94	1	1
	Water	1	1	1
	Forest & Woodland	1	1	1
	Others	0.89	0.31	.31
	Overall accuracy	.99		
	Overall KIA	.98		
2010	Built up	1	.83	.83
	Agriculture	0.99	1	1
	Water	1	1	1
	Forest & Woodland	0.99	1	1
	Others	0.98	0.88	.88
	Overall accuracy	1		
	Overall KIA	1		

The higher proportion of Agricultural land in Northeastern Illinois is a characteristic of typical Midwest landscape of United States [27]). According the study [27], Agriculture is a single dominant LU/LC type of the Midwest covering approximately 49% of the landscape. Additionally, the result is consistent with the patterns of LU/LC map of the second largest metro city of the Midwest i.e., Twin cities, MN [22]. According to the study [22], the seven-county Twin Cities Metropolitan Area is consisted of Agriculture (41.1%), Urban (31.9%); Forest (21%) and Waterbodies (6.2%)corroborating our finding.

Table 6. LU/LC Area in square miles and percentage for each LU/LC category, during the 1989, 1999, and 2010

LU/LC Category	1989		1999		2010	
	Area (Sq. miles)	Area (%)	Area (Sq. miles)	Area (%)	Area (Sq. miles)	Area (%)
Built up land	1,468.8	21.4	2,022.5	29.5	2676.8	39.1
Agricultural land	3,853.5	56.2	3,446.2	50.3	2859.4	41.7
Water	481.2	7.0	500.0	7.3	485.9	7.1
Forest and Woodlands	361.7	5.3	439.6	6.4	366.9	5.4
Others	688.7	10.0	445.5	6.5	464.8	6.8
Total	6,853.8		6,853.8		6,853.8	

3.2. Change Detection Analysis.

Table 7 contains results of quantitative analysis of LU/LC changes of Northwestern Chicago between 1989 and 2010. The change analysis (Table 3) revealed that from 1989 to 1999, various LU/LC changes have occurred. For instance, the built up lands gained about 553.7 square miles (i.e., 37.7%), while the agricultural areas lost about 407 square miles(i.e., -10.6%). The category of “Others" class also declined by 35.3 %. Waterbodies, forest and woodlands increased by 3.9% and 21.5% respectively. Similarly, in the second decade, between 1999 and 2010, built up lands registered the main change followed by agricultural areas. The built up lands gained approximately 654.3 square miles (i.e., 32.4%), whereas agricultural lands lost about 586.7 square miles (i.e., -17.0%). Forests and wood land decreased by 16.5%. Water and "others" didn't show a significant change during that time period. In summary, between 1989 and 2010 the urban areas expanded by about 1,208. 1 square miles (i.e., 82.2%), while agricultural lands and “others” class were reduced by 994.1 square miles and 223.9; respectively. Waterbodies, forest and woodlands stayed relatively unchanged.

Table 7. LU/LC change in square miles and percentage during the three time periods

LU/LC	1989 -1999		1999-2010		1989-2010	
	Change (sq. miles)	Change (%)	Change (sq. miles)	Change (%)	Change (sq. miles)	Change (%)
Built up land	553.7	37.7	654.3	32.4	1,208.1	82.2
Agricultural land	-407.3	-10.6	-586.7	-17.0	-994.1	-25.8
Water	18.9	3.9	-14.2	-2.8	4.7	1.0
Forest and Woodlands	77.9	21.5	-72.7	-16.5	5.2	1.4
Others	-243.2	-35.3	19.3	4.3	-223.9	-32.5

The result of LU/LC changes of Northwestern Chicagoland corroborates with prior study in Chicago Metro area [18]. The study [18] evaluated the LU/LC change within the greater eight counties of Chicago metropolitan area between 1972 and 1997, found that the region has experienced a dramatic land cover change. Accordingly, a significant increase of the built up area and decrease in the agricultural land and other natural areas were reported, indicating socio-economic drivers have not changed over time. Additionally, Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area produced identical results [22]. The multi-temporal Landsat data between 1986 and 2002 showed urbanization increased from 23.7% to 32.8% of the total area, while agriculture decreased from 49.6% to 40.5%; substantiating similar kinds of change in the neighboring metropolitan city.

Table 8. Total Population, and population growth in the study between 1990-2000 and 2000-2010.

Year	Population			Growth (%)	
	1990	2000	2010	1990-2000	2000-2010
Total	7,507,113	8,376,601	8,700,058	11.58	3.86

Table 8 compared observed increase in built up areas and population growth in metro areas. Accordingly, the population of Chicago metro area has increased by 11.6% between 1990 and 2000 built up land increased by 37.7% during the same period, which is 3 times lower than the rate of the urban growth. Similarly, from 2000 to 2010 the population increased by 4%, while the built up land grew by 32.4%. Similar observation [12] was after implementing a dynamic landscape simulation approach to investigate human induced LU/LC changes in Chicago metropolitan area revealed population increase by 4% from 1970 to 1990, while the urban land area was increased by 47% during the same period.

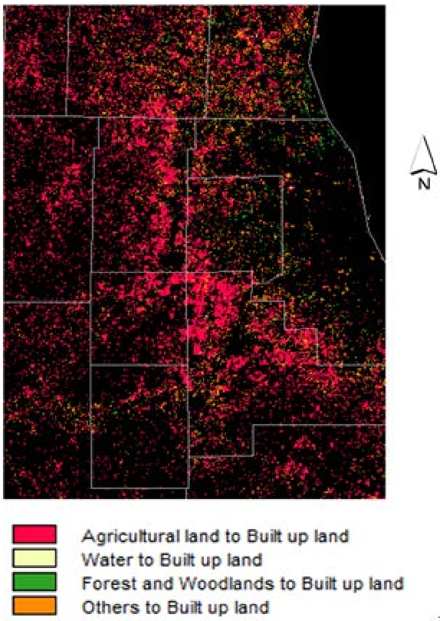

Figure 5. Transition from all classes to built up land between 1989-2010

While the dual population and built up area increase depict a logical causal relation, the disparity in their rates are a reminder of perhaps a changing behavior of the urban population. Urban residents are increasing leaving densely populated city center to suburban areas in search of larger space. For example, the population of Cook reduced by 3.39% between 2000 and 2010 (Table 1) confirming people movement from city center into the suburban counties. Therefore, increase in urban land expansion in Chicago metro area is not only due to population increase but also because of increasing demand for larger residential area. Additionally, more and more people needed a larger residential space in the latter decade than the former, indicating that the trend is not a matter of the past but present.

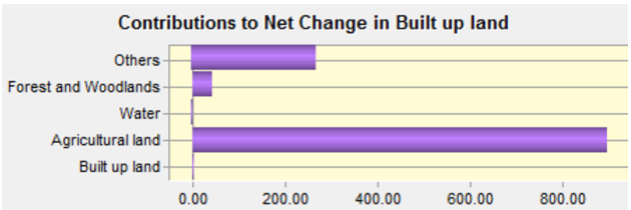

Figure 6. Contribution of other land classes to built up land (in square miles), from 1989 to 2010, computed in Land Change Modeler (LCM)

Figure 5 and Figure 6 are the analytical result of LU/LC types contributed to increase in built up area between 1989 and 2010. Accordingly, the dominant contributions to built up area increase was agricultural land followed by "others" category. Approximately 895.83 and 270.34 square miles of agricultural lands and “other” class were converted into built up land, respectively. Forests and woodlands contributions were very low and water bodies hasn’t changed into built up land. This finding is corroborated by the reports [12,18]. The reports found Agriculture as a major land cover type converted into urban, indicating its unique fragility to human footprint in Chicago area. Surprisingly, wetland ecosystem, though found sensitive in many parts of world, is stable in northwestern Chicago land.

3.3. Spatiotemporal Changes of Urbanization

Figure 7 presents result Spatiotemporal Change of Urban areas in 1989, 1999 and 2010. According to the result, the highest Urban Sprawl was experienced in the suburban areas where there are concentrations of agricultural lands and natural preserves. It shows the urban growth spilling beyond the boundary of the existing built up land into the rural areas of Kane, McHenry, and Will counties. The largest urban land expasion was in Will County, to the south, where the populations also increased by 89.6% between 1990 and 2010 (see Table 1). When it comes to the far suburbs, the fastest growth of built up area was in southern Kendall County. In General, the proportion of the built up land was only 21.4 % (i.e., 1,468.8 square miles) until 1989, and non-built up land (other landscape categories) amounts to 78.5% (i.e., 5,385.1 square miles). In 1999 and 2010 the built up area grew to 29.5% and 39.1%, respectively, indicating the trend of urban sprawl (Table 9).

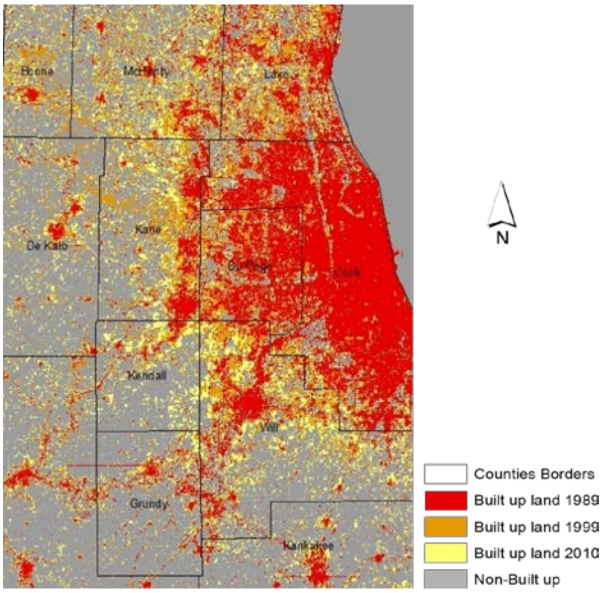

Figure 7. Spatiotemporal Change of Urban areas in 1989, 1999 and 2010

Table 9. Proportion of built up areas in Chicago metropolitan area in 1989, 1999 and 2010

LU/LC Category/Year	1989		1999		2010	
	Area (Sq. Miles)	Area (%)	Area (Sq. Miles)	Area (%)	Area (Sq. Miles)	Area (%)
Built up	1,468.8	21.4	2,022.5	29.5	2,676.8	39.1
Non Built up	5,385.1	78.5	4,831.3	70.5	4,177.0	60.9
Total	6,853.8	100	6,853.8	100	6,853.8	100

3.4. LU/LC Modeling and Validation

Model validation is an important step in case of predictive change modeling [17]. According to the cross-tabulation analysis conducted for model validation, the overall agreement between the classified and simulated 2010 map was found 77%. This is a strong agreement compared with studies such as [15] which was found 61% and [13] which was found 72%. Because the model passed the validation test, it was used to predict LU/LC of northeastern Illinois. Accordingly, Figure 8 is the prediction results of projected LU/LC of 2020 and 2030.

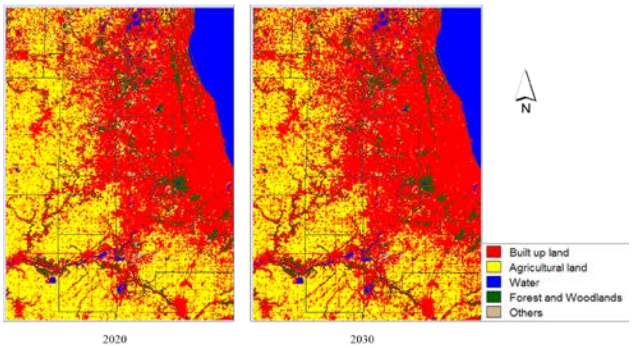

Figure 8. Future projection LU/LC map of northeastern Illinois for year 2020 and 2030

According to the prediction result, in 2020 built up land will dominate the LU/LC types of the study area accounting for approximately 46.5% of the landscape followed by agricultural land and “others” areas, which will be about 2367.6 sq miles (i.e., 34.5%) and 449.4 sq miles (i.e., 6.6%); respectively. Therefore, in the current trajectory continues, 2020 would mark the year when the proportion of Built up area would effectively surpass Agricultural land in Northeastern Illinois. In 2030, the proportion of built up land will increase further to amount to half of the study area accounting 6,853.8 square miles, whereas agricultural lands will decrease to 29.8% and “Others" category is predicted to decrease by 6.1% (See Table 10).

Table 10. Expected LU/LC in square miles and percentage of northeastern Illinois for 2020 and 2030

LU/LC Category	2020		2030	
	Area (Sq. Miles)	Area (%)	Area (Sq. Miles)	Area (%)
Built up land	3184.0	46.5	3538.5	51.6
Agricultural land	2367.6	34.5	2041.9	29.8
Water	481.2	7.0	500.0	7.3
Forest and Woodlands	361.7	5.3	439.6	6.4
Others	449.4	6.6	420.6	6.1
Total	6853.8		6853.8	

It is also revealed that between 2010 and 2020, the built up land will gain approximately 507.2 square miles (i.e., 19%), while the agricultural land is predicted to lose 492.8 square miles (See Table 11). During that same time period "Others" will decline by 3.3%. The predicted map of 2030 indicate that from 2010 until 2030, The LU/LC will continue the change in the same manner, i.e., greater loss of agricultural lands. Besides, Northeastern Illinois Planning Commission (NIPC) (now the Chicago Metropolitan Agency for Planning (CMAP) has predicted 25% population growth for the Chicago metropolitan region between1990 and 2020, compared with only 4% between 1970 and 1990 [4]. Therefore, considering that the prediction is, in part, made based on the information of the past slower population growth rate, this predicted, the current accelerated growth rate will likely lead to a huge increase of urbanization. Even with the increase in the population growth rate, the built up land will increase at faster rate the population growth.

Table 11. Comparison of the expected LU/LC map of 2010 and predicted LU/LC of 2020 and 2030

LU/LC category	2010-2020		2010-2030	
	Decrease/ increase (Sq. miles)	Change (%)	Decrease/ increase (Sq. miles)	Change (%)
Built up Land	507.2	19.0%	861.7	32.2%
Agricultural Land	-491.8	-17.2%	-817.5	-28.6%
Others	-15.3	-3.3%	-44.2	-9.5%

4. Conclusion

This study has attempted to investigate the urban growth in a large portion of northeastern Illinois region. Remote sensing, GIS and simulation models were employed for analyzing and modeling LU/LC change, the quantitative analysis of the LU/LC maps provided a strong evidence that during twenty one years (from 1989 to 2010) the area has experienced an extensive urban growth, associated with a huge loss of the valuable agricultural lands and a decline in the urban open spaces and other landscape categories. This tremendous growth was mainly taking place in suburb areas, and at times in an unstructured and fragmented fashion raising concerns over the present city’s urban planning. For example, during the study period, the urbanized or built up land area increased by more than 80%, which is tremendous. There is also imbalance between urban and population growth as the population was increased by only 15%, suggesting that major driving factors could possibly be the decentralization of population and metropolitan functions, and the increasing demand for larger residential area.

The results of the LU/LC prediction indicated that in the next two decades the growth trend is also likely to keep increasing. Accordingly, more population would shift from the city to the suburbs causes losses of agricultural lands and some open spaces corroborating the prediction made by NIPC indicating concerted efforts by all stakeholders to effect sustainable urban development of northeastern Illinois. In general, this study has demonstrated the capabilities of remote sensing, GIS and LCM simulation model for analyzing, monitoring and predicting urban growth thereby providing a useful information for urban planners and decision makers about the past LU/LC change and an early measure of a serious problem in Chicago metropolitan region and quantifying the impact of the suburban sprawl on the agricultural lands and natural areas. However, these results can further improved should the future works deploy a high resolution images, and the multi temporal ground truth. It can also improve should the complex decisions of land development system modelled with other important drivers such as but not limited to socio-economic conditions, and distances from important places like railway station.

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