

Exploring Land Use Change in a Twin-Cities Metro Suburban Area Between 2008 to 2017: City of Chaska Case Study

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Abstract

As urbanization increases, farmland and other land-use transitions into new classifications. Studies have detailed the effects of land-use on natural resources and the environment and factors that facilitate change in land-use. Studies have also compared best practice and methods of calculating change in land-use. To attain a sustainable pattern of land-use, there is necessity for useful and efficient methods of estimating changes in land-use. This project used remotely sensed land images to track land-use in Chaska, Minnesota – a suburban city of the Twin Cities metro area, over a ten-year period (2008-2017) starting in 2008 when residential home construction slowed. Classification and classification assessment methods were applied to aerial imagery and the classified data respectively. A transition matrix and land-use dynamic index methods were applied to track land-use trends from 2008 to 2017.

Introduction

Large-scale changes recorded in land-use generates a wave of significant effects with implications for numerous policy issues including international trade, climate change and wildlife habitat among other issues. This has caused land-use to figure prominently in international climate negotiation (Lubowski, Plantinga, and Stavins, 2008).

In the United States, dramatic land-use changes were recorded in the 1970s, 1980s, 1990s and the early part of the 2000s, including declines in cropland, and accelerated expansion of urban areas that depart from trends over previous decades (Lubowski *et al.*, 2008). Since 1967, more than two acres of farmland is lost to urban growth per minute; more than 25 million acres of land has been consumed by the

spread of cities in the United States (Rose, 2016). These trends led to a prediction that a widespread and fundamental land-use change process would increase urban land area in the United States by 79 percent between 1997 and 2025 (Alig, Kline, Lichtenstein, 2004).

Rapid urban growth is measurable based on the development of suburban expansion and urban sprawl (Harris and Ventura, 1995; Sajja, 2014). Between 1947 and 1953, the population of suburb cities in the United states grew by 43 percent while the population of the entire country grew by 11 percent (Lubowski *et al.*, 2008; Rose, 2016), and by 2001, the United States suburbs contained 57,983,000 housing units (Gruen, 2010).

The Minneapolis-St. Paul metro area of over 3,000 square miles has a population estimate of 3,113,338 people

distributed across 7 counties and 182 communities in 2018 with Hennepin and Ramsey counties accounting for more than half of the total figure (Metropolitan Council, 2018). Gruen (2010) noted that City development has generally been outward from the initial center of activity; this general pattern of urban development does not elude the Minneapolis-St. Paul metro area. The Twin Cities occupies the center of activity that influences development outwards to other cities around it in a generalized picture regardless of the influence smaller city centers have on their direct surrounding neighborhoods.

Urban growth in the Minneapolis-St. Paul area generates a significant change in land-use with factors including increasing population, transportation, suburbanization, zoning, housing policy, subprime mortgage and economic prosperity contributing to increased demand and supply of houses. Most new housing development in the United States took place in the suburbs from 1947 until recently (Gruen, 2010), with cities firmly adopting planning strategies that encourage mixed land-use, compact design and walkable neighborhoods for more effective and sustainable use of resources.

Land-use is generally monitored periodically by governmental agencies and other interested parties for the purpose of planning and evaluating plans implementation. Metropolitan Council (2018) reveals that the Metropolitan Council compiles and maps generalized land-use data for the Twin Cities every 5 years using aerial photographs together with parcel information, assessor's information, field checks and community review. The Twin Cities land-use is generalized into 16 categories of Single-Family-Residential, Multi-Family-Residential, Retail And Other

Commercial, Office, Mixed Use, Industrial And Utility, Extractive, Institutional, Park, Recreational Or Preserve, Golf Course, Major Highway, Railway, Airport, Agricultural, Undeveloped and Water.

In this project, land-use trends in the suburban Minneapolis-St. Paul metro city of Chaska is explored starting from 2008 when housing prices dropped and construction of new houses came close to a stop in the United States. The drop in housing prices and the rate of construction of new houses was a notable diversion from the trend of continuous expansion of urban frontiers. Builders had their stock of unsold houses pile up, many subprime mortgages and overextended prime mortgages went into default in contrast to trends of builders selling close to 2 million newly constructed houses in the United States in a year (Gruen, 2010).

Study Area (Chaska)

Located in the south-west Minneapolis-St. Paul metro area, Chaska is the most populous city in Carver County of Minnesota, United States (Figure 1). It had a population of 23,770 at the 2010 census and an estimated population of 26,765 in 2018 (Census, 2019).

The city incorporated the remaining portion of Chaska Township to its development plan in 2005 through a 600-acre (0.93 mi²) residential "smart growth" styled development for the area.

A major highway 212 realignment that passes through Chaska from south-west to east was completed in 2008. It is a 12-mile freeway on a completely new alignment between Carver County Road 147 west of Chaska and MN-5 just west of I-494 in Eden Prairie (Riner, n.d.).

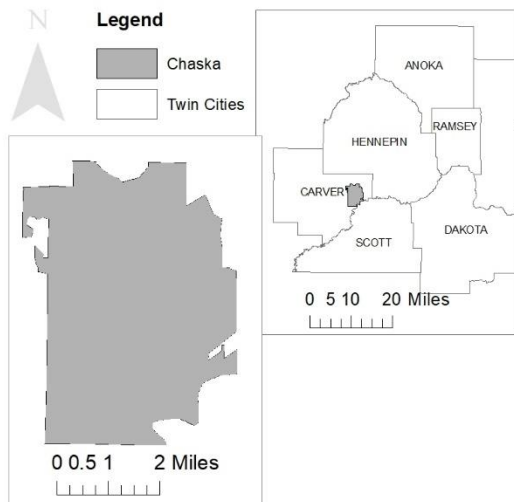


Figure 1. A map of Chaska city in grey and an inset map showing the location of the city (in grey) in the Twin Cities metro area counties.

Methods

Exploring land-use using remotely sensed imagery requires careful analysis of the imagery pixels. Thus, data collected were evaluated to ensure they covered the same extent and had the same resolution and projection before classification and analysis.

The output of the supervised classification process is critical in determining the accuracy of the entire analysis. Hence, it was put through an accuracy assessment test to determine data reliability and to have referential records of each class's accuracies and inaccuracies.

Lastly, a land-use transition matrix and land-use dynamic index were applied to track changes in land-use.

Data Collection and Processing

Data used in this project are remotely sensed land cover imagery from the National Agricultural Imagery Program (NAIP) titled "NAIP Digital Ortho Photo Image" with 1meter spatial resolution, 32-bit pixels and 4 band color. Tiles were

downloaded for years 2008, 2013 and 2017 from the USGS (US Geological Survey) website using the Earth Explorer webtool. Downloaded tiles were mosaicked into respective datasets which was used to derive land-use classification data for each year.

The Chaska city boundary data was derived from the Counties, Cities, and Townships shapefile of the Twin Cities Metropolitan Area sourced from the Minnesota Geospatial Commons website and used to mask the Chaska area in the Digital Ortho Photo Image datasets.

Both the NAIP imagery and city boundary data were available for free download and were projected in the NAD 1983 UTM Zone 15N projection.

Supervised Classification

The 2016 Twin Cities Metropolitan Council generalized land-use categories for the metro area were used to derive the land-use classification system used for the project. The sixteen land-use categories were regrouped into four categories. Single-Family-Residential, Multi-Family-Residential, Retail and Other Commercial, Office, Mixed Use, Industrial And Utility, Major Highway, Railway, Airport, Extractive, and Institutional were regrouped as Urban and Construction. Park, Recreational or Preserve were grouped as Forest, Trees and Shrubs. Golf Course, Agricultural, Undeveloped was grouped as Agriculture and Grass. Water includes only water.

A supervised classification was carried out following sequential steps of carefully drawing twenty polygons of training sites for each land-use category across the entire map extent (enough to adequately capture each class). Then a Maximum Likelihood Classification was used to extract data for the identified

categories of the training samples.

Accuracy Assessment

For each year, after the classification was completed, the accuracy of the classification was assessed following accuracy assessment guidelines of Texas A&M University (2016) by creating a confusion matrix and determining classification accuracies by comparing test pixels with their corresponding location in the classified image.

This was completed by creating a point shapefile, adding class field, and creating 40 points for each class with the guide of the pre-classified imagery. The points were carefully and evenly distributed across each class. After populating class fields accordingly, points were converted to pixels. The pixels layer and the classified image were then combined.

The output layer attribute table was exported as a dbase table from which meaningful figures of overall accuracy, class accuracy, omission, commissions, and producer's and user's accuracies were derived. While an overall accuracy (Sum of correctly classified cells/Total number of cells *100) of 85% is acceptable, an overall accuracy of 86.25% was recorded for year 2008, 91.25% for 2013, and 89.37% for 2017. Lastly, the kappa coefficient, defined by Texas A&M University (2016) as the measure of agreement between model-prediction/classified-image and reality (1 is perfect agreement and 0 is perfect randomness) was calculated using equation 1.

$$K = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r (X_{i+} * X_{+i})}{N^2 - \sum_{i=1}^r (X_{i+} * X_{+i})} \quad (1)$$

N = Total of sites in the matrix

r = Number of rows in the matrix

X_{ii} = Number in row i and column i

X_{i+} = Total for column i

X_{+i} = Total for row i

A kappa coefficient measure of 0.85 was marked for good data reliability. 0.84 was recorded for 2008, 0.88 for 2013 and 0.86 for 2017.

Land-Use Transition Matrix

A land-use transition matrix was applied to analyze the transfer of areas of land between different land-use categories at the end of research periods. It is described by Teferi, Bewket, Uhlenbrook, and Wenninger (2013) as a common approach in comparing maps of different sources because it provides details of “from-to” transition between land-use categories.

Land-use Dynamic Index

The single land-use dynamic degree can be used as a leverage to compare change in land-use between regions over time. It was described by Huang, Huang, Pontius, and Tu (2018) as the annual net change of a land-use category as a percentage of the initial size of the category. It is calculated using equation 2 adopted from Li, Liu, and Huang (2017).

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%. \quad (2)$$

U_b = Area of land category at the end of research period

U_a = Area land category at the beginning of research interval

T = Length of research period

Cumulative Land-use Dynamic Degree

The cumulative land-use dynamic index/degree is the total of year(s) change rate of area change of all land-use

categories. It was defined by Zhao, Zhu, Wu, HU (2012) as the transfer rate among land categories during the research period. It is derived from equation 3.

$$K_{total} = \frac{\sum_{i=1}^n |U_{bi} - U_{ai}|}{2 \sum_{i=1}^n |U_{ai}|} \times \frac{1}{T} \times 100\%. \quad (3)$$

U_{bi} = Area of land category at the end of research period

U_{ai} = Area land category at the beginning of research interval

T = Length of research period

n = Number of land use categories

Methods Summary

The four methods of analysis have outputs for specific application in the project. The outputs of data collection and data processing procedures were transformed through supervised classification into datasets that serve as the base data for all other analysis in the project. Accuracy assessment outputs serve as the verification and error table, and outputs of the land-use transition matrix and land-use dynamics indexes provide details of land-use change between 2008 and 2017.

Results

The results explain the outputs of the methods of analysis applied in each stage of the analysis. Land-use distribution is the result of the classification procedure applied to the imagery files. The result of the accuracy assessment procedure applied to the test pixels created to test the usability of the classification outputs are attached in Appendix A. The results of the land use transition matrix, single land-use dynamic index, and cumulative land-use dynamic degree are discussed in later sections.

Land-use Distribution

The output of land-use classification procedure applied to the NAIP digital ortho photo images are land-use distribution maps for 2008, 2013 and 2017 (Appendix B). The total area for each category of land-use was derived (Table 1) and charted for visual comparisons (Figure 2)

Table 1. Land-use distribution of the city of Chaska in 2008, 2013 and 2017. Derived from aerial image classification.

Land use	2008 (mi ²)	2013 (mi ²)	2017 (mi ²)
Water	1.09	0.97	0.92
Urban/Construction	3.49	2.80	3.98
Agric/Grass	7.83	7.64	7.67
Forest/Trees	5.28	6.28	5.13
Total	17.69	17.69	17.69

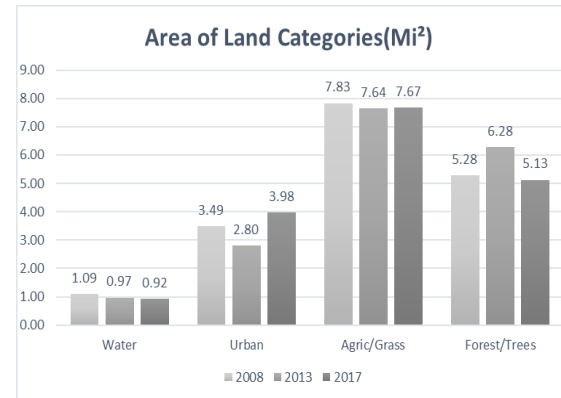


Figure 2. A chart of land-use distribution in the city of Chaska for 2008, 2013 and 2017.

Table 1 and Figure 2 reveal a reduction in total area of water bodies between 2008 and 2013 and between 2013 and 2017. Urban area reduced between 2008 and 2013 and increased significantly between 2013 and 2017. Agricultural and grass land area reduced between 2008 and 2013 and increased between 2013 and 2017. Forest and trees total area increased

between 2008 and 2013 and reduced between 2013 and 2017

Land-use Transition Matrix

The output table (Table 2) has rows of classes at start time (From) and the column has classes at end time (To).

Table 2. Land-use transition matrix for study periods 2008-2013, 2013-2017 and 2008-2017.

Land-use transition matrix from year 2008 (rows) to 2013 (column). All values in are mi ² .						
2013 \ 2008	Water	Urban	Agric/ Grass	Forest/ Trees	Total	Loss
Water	0.81	0.11	0.07	0.10	1.09	0.28
Urban	0.04	2.20	1.10	0.16	3.49	1.29
Agric/ Grass	0.04	0.35	5.47	1.96	7.83	2.36
Forest/ Trees	0.08	0.14	1.00	4.06	5.28	1.22
Total	0.97	2.80	7.64	6.28	17.69	
Gain	0.16	0.60	2.17	2.22		
Land-use transition matrix from year 2013 (rows) to 2017 (column). All values are in mi ² .						
2017 \ 2013	Water	Urban	Agric/ Grass	Forest/ Trees	Total	Loss
Water	0.76	0.13	0.04	0.03	0.97	0.21
Urban	0.06	2.44	0.19	0.11	2.80	0.36
Agric/ Grass	0.05	1.17	5.00	1.43	7.64	2.64
Forest/ Trees	0.05	0.23	2.44	3.56	6.28	2.72
Total	0.92	3.98	7.67	5.13	17.69	
Gain	0.16	1.54	2.67	1.57		
Land-use transition matrix from year 2008 (rows) to 2017 (column). All values are in mi ² .						
2017 \ 2008	Water	Urban	Agric/ Grass	Forest/ Trees	Total	Loss
Water	0.74	0.20	0.09	0.06	1.09	0.35
Urban	0.06	2.56	0.69	0.19	3.49	0.94
Agric/ Grass	0.05	0.90	5.09	1.79	7.83	2.74
Forest/ Trees	0.07	0.32	1.80	3.09	5.28	2.19
Total	0.92	3.98	7.67	5.13	17.69	
Gain	0.18	1.42	2.58	2.04		

The diagonal cells are areas that persist in same category through time, while the gains are the differences between the columns total and the persistent cells and the losses are the differences between the row totals and the persistent cells. Total area of each land-use category is recorded in the total column and total row. The actual area gained and lost in each land-use category during the study period is the difference between gain row and loss column for each land-use category. Detailed land-use transition maps are attached in Appendix C.

Table 2 reveals a 0.12 mi² reduction in total area of water bodies between 2008 and 2013 and a 0.05 mi² reduction between 2013 and 2017. Urban areas lost 0.69 mi² of its total area between 2008 and 2013 and gained 1.18 mi² between 2013 and 2017 with a general increase of 0.49 mi² between 2008 and 2017. Agricultural and grass land area reduced by 0.19 mi² between 2008 and 2013 and increased by 0.03 mi² between 2013 and 2017. Between 2008 and 2013, forest and trees total area increased by 1 mi² and reduced by 1.15 mi² between 2013 and 2017.

Land-Use Dynamic Degree/Index and Cumulative Land-use Dynamic Degree/Index

The result of the Single Land-use Dynamic Index (Table 3, Figure 3) shows loss of urban/construction area between 2008 and 2013 and a significant increase between 2013 and 2017. Agricultural and grass land recorded the least loss between 2008 and 2013 and increased by 0.08% between 2013 and 2017. Water surfaces reduced through the entire study period with an overall loss of -1.74%. While forest, trees, and shrubs area increased in the first half of the study period, it

recorded the highest loss of -4.59% in the second half.

Table 3. Single land-use dynamic degree/Index and cumulative land-use dynamic degree/Index table for years interval 2008-2013, 2013-2017 and 2008-2017.

Single Land-use Dynamic Index (%)			
Time	2008-2013	2013-2017	2008-2017
Water	-2.26	-1.29	-1.74
Urban Construction	-3.98	10.53	1.52
Agric/ Grass	-0.47	0.08	-0.22
Forest/ Trees	3.80	-4.59	-0.38
CCLUDD %	1.1	1.7	0.76

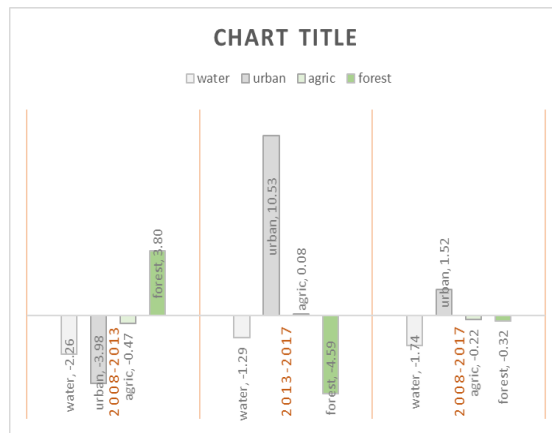


Figure 3. Chart of dynamic degree of land-use categories. Values above 0.00 measures percentage area gain. 0.00 indicates no change in area of land-use category. Values below 0.00 measures percentage of area loss.

The result of the Cumulative Land-use Dynamic Degree (Table 3) indicate an increase in rate of change in land-use between 2013 and 2017 (1.7%) than between 2008 and 2013 (1.1%).

Results Summary

Land-use distribution is the total area of each land class into which all land use was categorized in this project. The accuracy assessment table (Appendix A) verifies the

usability of the data and gives useful knowledge of the data including each class accuracy, overall data accuracy, and distribution of errors. The land-use transition matrix details changes in land-use between 2008 and 2013, 2013 and 2017, and between 2008 and 2017. The dynamic index takes account of gains and losses of total area in each category to derive percentage degree for the same time intervals as the transition matrix including the overall time interval.

Discussion

A close look at the tables and figures would raise question which are deemed essential to shed light on the details of how land-use has changed in the city of Chaska through the years of study. These questions include: What situations could lead to a negative growth of urban and construction area? How did the data affect the analysis?

Growth Pattern

Generally, urban and construction area increased between 2008 and 2017, while other land-use categories reduced.

The city of Chaska's 0.93 mi² residential development plan of 2005, the 2008 completion of freeway 212 on a completely new alignment in Chaska, and a buoyant housing market in the United States indicate significant construction in Chaska before 2008. The decline in urban and construction area between 2008 and 2013 coincides with a period of rapid drop in construction of new houses and roads in the United States. However, completing ongoing construction usually includes landscaping. Cleared land surfaces initially classified as urban and construction are later covered with lawn and trees. Likewise, roadsides and highway divides

are covered with vegetation after construction. The conversion of urban/construction area to agriculture/grass accounts the transfer of 0.69 mi² from urban land-use to agriculture/grass land-use between 2008 and 2013.

A 1.18 mi² increase in urban and construction area between 2013 and 2017 indicate periods of rapid construction and economic improvement that meets demand with supply of new constructions.

Data Effects

In 2008, 2013 and 2017, respectively. Water has 82%, 100%, and 95% producer's accuracy, and 96%, 100% and 100% user accuracy. Urban/construction has 92.5%, 95%, and 100% producer's accuracy, and 97%, 100% and 100% user accuracy. Agriculture/grass has 87%, 80%, and 90% producer's accuracy, and 85%, 84% and 76% user accuracy. Forest/trees have 89%, 90%, and 72% producer's accuracy, and 76%, 81% and 82% user accuracy.

One hundred percent of the user's accuracy values recorded for both water and urban/construction in 2013 and 2017 categories imply that no agriculture/grass or forest/trees area was misclassified as either water or urban in 2013 and 2017. Except for water in 2008, both water and urban/construction have producer's and user's accuracy values above overall accuracy of 85%. Also, 3.03% is the highest commission (misclassification rate) value for both classes, compared to agriculture/grass and forest/trees area with a minimum of 15% commission value and a high of 23.9%.

Generally, agriculture/grass and forest/trees have low producer's and user's accuracy values and high misclassification rate. 89%, 100% and 100% of

misclassified pixels in 2008, 2013 and 2017 respectively were misclassified as either agriculture/grass or forest/trees.

Conclusion

Exploring land-use using remotely sensed imagery can be affected by the qualities of the imagery, such as cloud cover and shadows. Area of water surfaces in Chaska reduced slightly between 2008 and 2017, the exact area loss cannot be accurately estimated because to the low producer's accuracy of water in 2008.

Urban/construction increased significantly in Chaska between 2008 to 2017. The area of land gained by urban and construction is estimated to have increased by a minimum of 0.31 mi². The land gained by urban and construction was transferred from agriculture/grass and forest/trees. Comparing results with accuracy tables reveals that agriculture/grass and forest/trees combined area reduced in Chaska between 2008 and 2017 by a minimum of 0.31 mi². Misclassification records in the accuracy table makes it ambiguous to accept the amount of area transferred between the two classes.

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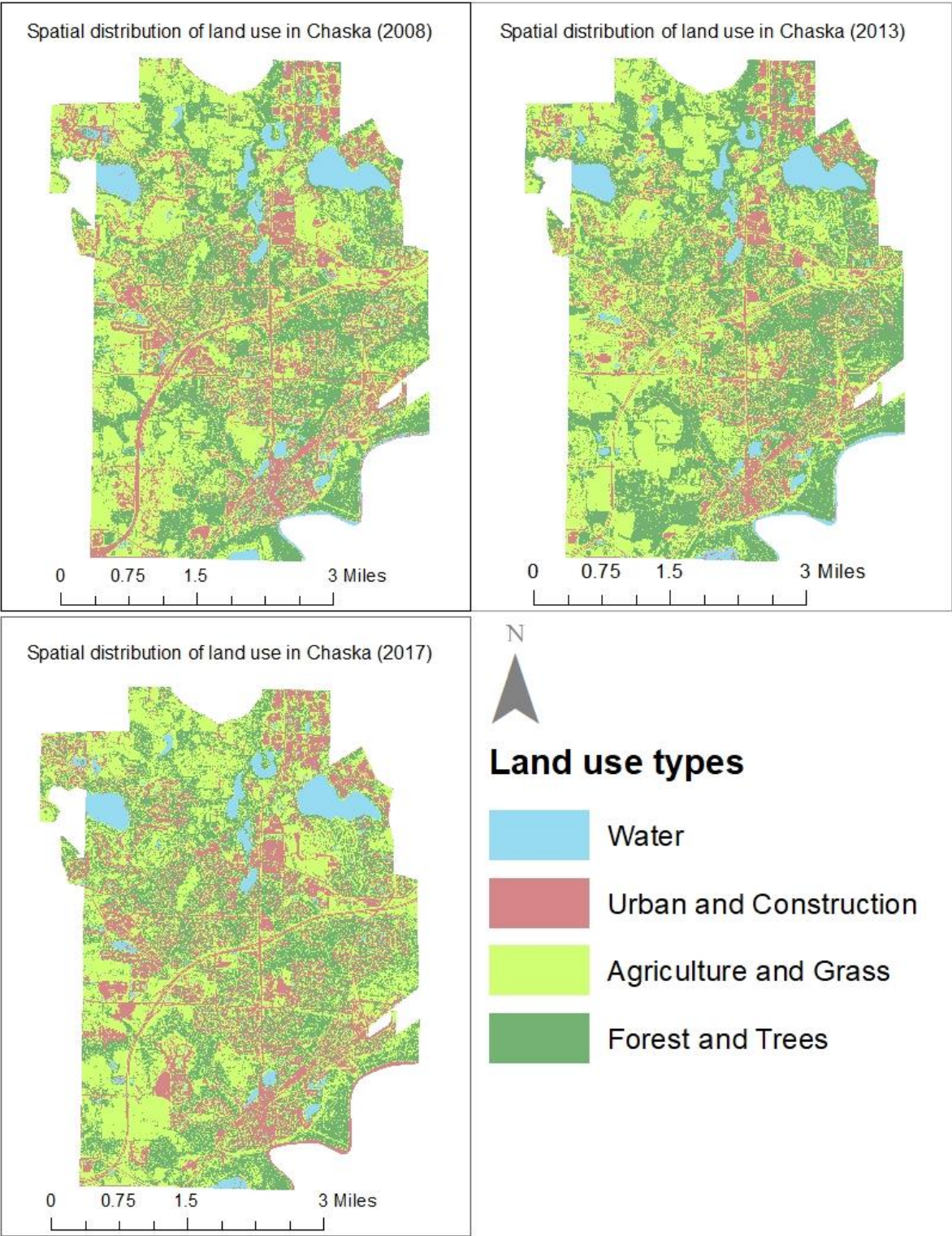
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Appendix A. Accuracy assessment tables computed using test pixels to derive confusion matrix, ground truth, commission, omission, producer's accuracy, and user's accuracy for years 2008, 2013 and 2018 land-use supervised classification output layer.

Accuracy Assessment Table					
Confusion Matrix					
Class	Water	Urban	Agric/Grass	Forest/Trees	Ground Truth
2008					
Water	32	1	0	0	33
Urban	1	37	0	0	38
Agric/Grass	0	2	34	4	40
Forest/Trees	6	0	5	35	46
Total	39	40	39	39	157
2013					
Water	40	0	0	0	40
Urban	0	38	0	0	38
Agric/Grass	0	2	32	4	38
Forest/Trees	0	0	8	36	44
Total	40	40	40	40	160
2017					
Water	38	0	0	0	38
Urban	0	40	0	0	40
Agric/Grass	0	0	36	11	47
Forest/Trees	2	0	4	29	35
Total	40	40	40	40	160
Ground Truth /Class accuracies (%)					
2008					
Class	Water	Urban	Agric/Grass	Forest/Trees	
Water	82	2.5	0	0	
Urban	2.6	92.5	0	0	
Agric/Grass	0	5	87.2	10.3	
Forest/Trees	15.4	0	12.8	89.7	
2013					
Water	100	0	0	0	
Urban	0	95	0	0	

Agric/Grass	0	5	80	10
Forest/Trees	0	0	20	90
2017				
Water	95	0	0	0
Urban	0	100	0	0
Agric/Grass	0	0	90	27.5
Forest/Trees	5	0	10	72.5
Commission (% of test pixels incorrectly classified as a class) or over-classification rate. It is the total of incorrectly classified pixels in a row divided by total Ground truth pixels in a row.				
	2008	2013	2017	
Water	3.03	0	0	
Urban	2.6	2.63	2.5	
Agric/Grass	15	15.8	23.40	
Forest/Trees	23.9	18.2	17.14	
Omission (% of incorrectly classified pixels in a column divided by total pixels in the column)				
	2008	2013	2017	
Water	18	0	5	
Urban	7.5	5	0	
Agric/Grass	12.8	20	10	
Forest/Trees	10	10	27	
Producers Accuracy (% Correctly classified pixels divided by total pixels for each class).				
	2008	2013	2017	
Water	82	100	95	
Urban	92.5	95	100	
Agric/Grass	87	80	90	
Forest/Trees	89.7	90	72.5	
Users Accuracy (% of correctly classified Pixels in a class divided by total Ground truth pixels in the class).				
	2008	2013	2017	
Water	96.97	100	100	
Urban	97.37	100	100	
Agric/Grass	85	84.21	76.60	
Forest	76.09	81.82	82.86	

Appendix B. Land-use classification map of the city of Chaska for years 2008, 2013, and 2017.



Appendix C. Land-use transfer distribution maps of the city of Chaska for 2008-2013, 2013-2017 and 2008-2017.

