Land Use Change Analysis for Regina

Department of Computer Science

University of Regina

Author Note

A report for project in the course CS890EQ – Topics in GIS & Geoprocessing

By

Sagarkumar Patel – 200398889

Shirish B. Soni – 200392271

Contents

Table of Figures 3
1. Introduction 4
2.1 Problem Statement 4
2.2 Proposed Solution 4
2. Study Area 6
3. Literature Review 7
4. Dataset and Data Preprocessing 12
4.1 Developing the geodatabase 12
5. Methodology 13
5.1 Major methods used in the project 13
5.2 Custom Models 16
6. Implementation 18
7. Result and Discussion 26
8. Assumption and Limitation 28
9. Conclusion and Future Work 28
10. References 31
11. Appendix 32
11.1 Metadata 32
11.2 Custom Scripts 39
11.2.1 Generate Clusters.py 39
11.2.2 Reclassify Cluster Script.py 44

Table of Figures

Figure 1 Study Area - City of Regina, Saskatchewan 6
Figure 2 Workflow of the processing (Wang, Wang, Li, & Li, 2014) 10
Figure 3 Model Generating Iso Clusters 16
Figure 4 Model to Reclassify Clusters 17
Figure 5 Flow diagram of the work in ArcMap 18
Figure 6 Flow diagram of the work in IDRISI TerrSet LCM 19
Figure 7 Land Cover of 2002 20
Figure 8 Land Cover of 2017 20
Figure 9 Change from 2002 to 2017 21
Figure 10 Persistence from 2002 to 2017 21
Figure 11 Trend Analysis of Unused to Commercial 22
Figure 12 Trend Analysis of Unused to Residential 22
Figure 13 Trend Analysis of Unused to Vegetation 23
Figure 14 Transition potential from Unused to Residential 23
Figure 15 Transition potential from Unused to Commercial 23
Figure 16 Transition potential from Unused to Water 23
Figure 17 Transition potential from Unused to Vegetation 23
Figure 18 Transition potential from Vegetation to Unused 24
Figure 19 Transition potential from Vegetation to Commercial 24
Figure 20 Soft prediction for Unused to Residential 24
Figure 21 Soft prediction for Unused to Commercial 24
Figure 22 Soft prediction for Unused to Water 24
Figure 23 Soft prediction for Unused to Water 25
Figure 24 Soft prediction for Unused to Vegetation 25
Figure 25 Soft prediction for Vegetation to Unused 25
Figure 26 Gains and Losses between 2002 to 2017 26
Figure 27 Changes from 2017 to 2032 26
Figure 28 Projected Land Cover for 2032 26
Figure 29 Comparison Matrix 27
Figure 30 Variable accuracy and skill 28
Figure 31 City Limit Map 29
Figure 32 Water Feature Map 29
Figure 33 Road Network Map 30
Figure 34 Address Points Map 30
Figure 35 Park Locations Map 30

1. Introduction

Considering the traditional or the conventional methods for performing land use survey with use of statistics may not provide with the reliable result as it can be influenced by the low authenticity of the data due to fluctuations in the spatial accuracy, instability, and disunity, moreover, it is not cost efficient and consumes a lot of time. On the other hand, we have seen major growth in space technology with respect to monitoring of environments and resource using satellites. These sources provide real-time and accurate data in spatial aspects and multi-temporal view for a large area, which can be utilized for studying the geospatial change dynamics of the ground.

The importance of the spatial trends, that have occurred in any city over a course of a couple of years, is to understand the direction where the development of various land uses is going. With an understanding of such trends one can manipulate and forecast the probability of the growth of various sectors of land uses for the upcoming years. The same concept is taken to establish the working ground for the performed research, where the study area in focus is the city of Regina, Saskatchewan in Canada.

1.1 Problem Statement

With time the development of any city brings in many changes in its distribution of land uses. These land uses mainly, make the use of the presently barren or unused land and new establishments are built on them to facilitate the growth. Now, these usages have their requirements and effects on the environment, along with this they also have reasons to utilize the land for the specific task. As there are many factors linked to the decision-making process of the land use distribution or land development projects it is vital to regularly check the long-term effect of such developments on the city environment.

Our project is to perform analysis on the land use changes in Regina, Saskatchewan - Canada over the time span of 2002 - 2017 and interpret the change in the distribution of the land cover types for the city. Moreover, based on these results calculate the spatial trends and transitional potentials of various land uses to predict a probabilistic model for the year 2032.

1.2 Proposed Solution

With the use of Geospatial Information System (GIS) and Remote Sensing (RS) analysis techniques analyze the land use changes in the City of Regina area over the past 15 years, and obtain various transitional factors for such changes. This understanding can be beneficial to project the future scenarios for land management systems and create more efficient development plans.

The use of GIS is vital for the proposed research analysis as GIS is the foundational platform on which the spatial relations and operations can be effectively performed to query or generate spatial trends. Along with this, the project makes use of another software IDRISI for performing the change predictions and generating the transitional potentials based on the classified images obtained from GIS.

A brief outline of the flow of the project is as follows:

Firstly, data accumulation and preparation for the analysis will follow the selection of the appropriate Landsat images of our study area for two different time periods (i.e. 2002 and 2017). To reduce data preprocessing and cleaning, the images will be filtered to have proper resolution and distinguishable properties with zero cloud cover. Following this, the obtained images will be classified using image classification techniques to generate land use covers which then will be reclassified into 5 types of land uses. This will provide a visual representation of the changes occurred between 2002 and 2017 for the city of Regina. These results will be taken as inputs for the IDRIS Land Change Modeler to calculate the change analysis and deduce the transitional probabilities for the time period. Lastly, these probabilities will be forwarded to be utilized in materializing the transitional models for the changes. Based on these models change prediction will be performed in order to create a predictive analysis of the year 2032.

To conclude, based on the change dynamics analyzed from the data of 2002 and 2017 a prediction following the obtained trend is to be created to provide a tentative view of the city development potential.

We discussed the introduction and the problem statement and how the problem can be solved. In section 2, the study area is discussed of Regina is discussed in detail. Section 3 discusses about the previous work done in the field and also provides integrated understanding of the methods used in other researches. In section 4, dataset and data preprocessing methods are shown. Section 5 contains the main methodology of solving the problem. Section 6 includes the custom models; these custom models are the automated tools to perform particular tasks. Section 7 shows the implementation of methodology shown in section 5. Section 8 is the discussion of the results achieved from the implementation. Section 9 discusses about the assumptions involved in the implementation and also the limitation of the implemented system is shown. Section 10 contains conclusion and discusses about the future scope of the system.

2. Study Area

The city of Regina, Saskatchewan is situated in South Central Saskatchewan on the Trans-Canada Highway. It is approximately midway between Calgary, Alberta and Winnipeg, Manitoba. Saskatchewan sits above the American states of North Dakota and Montana. Regina is the capital of Saskatchewan and the 16th largest city in Canada with a population of 215,000 (Learn about Regina, n.d.).

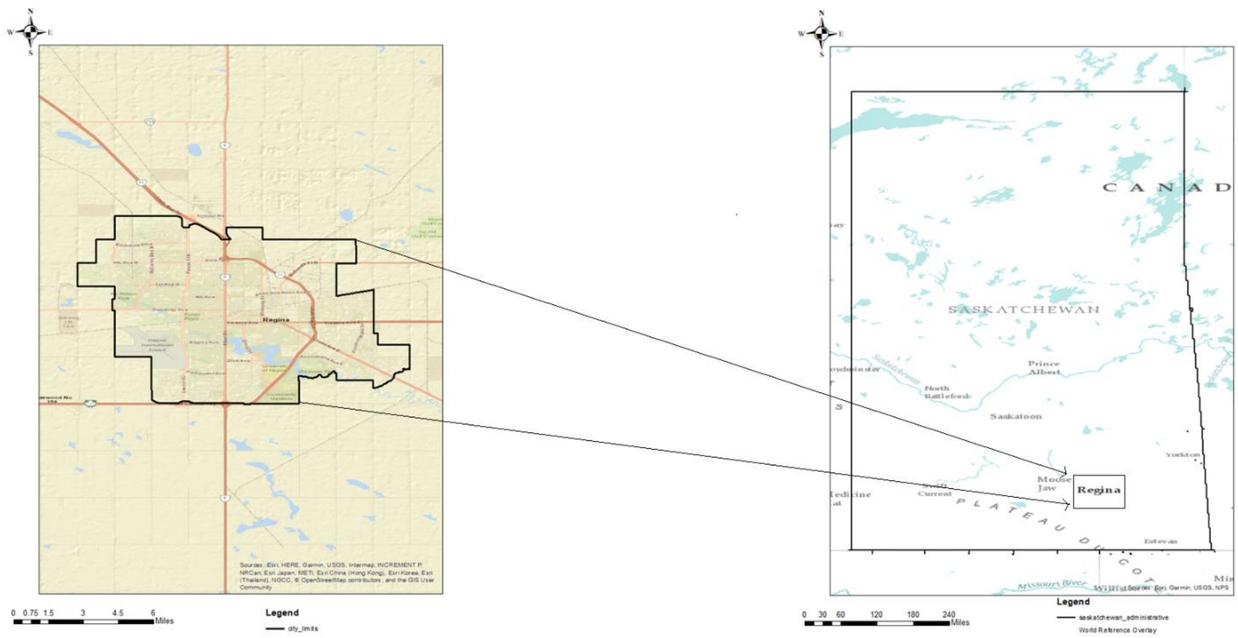


Figure 1 Study Area - City of Regina, Saskatchewan

3. Literature Review

Land use and cover change (LUCC) analysis is a vital aspect of Geographic Information System (GIS) application. With the rapid increment in the economy and population growth, there is a shifting focus towards the analysis of the suitability of land for certain uses. Considering the geographical aspect of the data under processing and its relevance to location-based criteria are some of the vital reasons for utilizing GIS. It is also necessary to monitor the developments in various resources and their direct/indirect implications on the overall resource stack. Now, understanding the factors affecting the rate of exploitation or development of certain resources can vary based on the criteria functions and the area of study respectively.

Moreover, one of the major factors influencing the development and change values for land utilization is a human impact. Considering the activities that act on the natural resources and environment which are performed by human have lasting implications on the various ecosystems in the environment. These changes have brought in changes to ecological processes and natural phenomenon. These changes not only work as promoting or limiting the human activities related to that location but also affect the natural environment (Gong, Zang, & Amuti, 2009). Gong, Zang, and Amuti in their research have displayed the use of 3S[1] and statistic combined with GIS to perform land use/land change analysis of Akesu Oasis for the time period of 1990 to 2002 (Gong, Zang, & Amuti, 2009). The data used here was Landsat TM data which was collected for May-1990 and August-2002, ArcGIS system was used to complete edge matching, editing, transformation, labeling, overlaying process and projection. ArcGIS is a software application developed for desktop mapping and spatial data analysis by Environmental Systems Research Institute (ESRI). Based on the data obtained and its classification the HAI (Human impact index) is calculated, furthermore, Delphi method[2] is utilized to confirm the parameters intensity. To understand in detail the characteristics such as gradient variation, land use type's spatial distribution, and directivity under man-made utilization and exploitation, geospatial analysis is used.

Another example of utilizing GIS is for calculating the land use suitability for a specific purpose. For any given type of land, the ability to support a specific use is labeled as Land suitability (Bagheri & Azmin, 2010). But a major problem in using only GIS for such task, despite being a tool powerful enough for spatial data handling, is that it itself is not capable to manage inconsistency related to the expert opinion referring to assigning and judging the relative importance of individual criteria suitable for the analysis (Bagheri & Azmin, 2010). To be specific allocating relative weights to different criteria involved in the decision-making process for the suitability of land mapping unit for a specific land use is the issue, thus to overcome such problem Analytical Hierarchy Process (AHP) can be used. AHP method is a mathematics and psychology based, structured technique for analyzing and organizing complex decisions, commonly used in decision-making for multi-criteria exercises. Bagheri and Azmin in their research have proposed a combination of AHP and GIS for land suitability analysis to generate solid results by taking an example of selecting best-suited land for building a hotel in the coastal area of Terengganu (Bagheri & Azmin, 2010). This research also uses Weighted linear combination analysis, one of the most popular procedures for multi-criteria evaluation. Multi Criteria Evaluation (MCE) is used in GIS to allocate land for

[1] Rule of Three: The test in which if there is an event of binomial distribution and after n trials it doesn't occur then the maximum chance of occurrence by the event is approximately 3/n

[2] Delphi method is a technique, which is a systematically and interactive forecasting method developed for a structured communication and relies on a panel of experts.

a specific purpose after some investigation which is based on various attributes of the selected area. Weighted linear combination analysis is an analytical method under MCE used for decision making where one or more attributes are taken into consideration. Every attribute which is considered is known as criterion and a particular weight is assigned to each criterion based on its importance. The results of the analysis are multi-attribute spatial features.

Coming back to the main objective, Land use and cover change (LUCC) is getting more attention due to the recent focus on environmental damages that have been incurred due to the growth in the rate of land use change. Remote Sensing (RS) analysis and Geospatial Information Systems (GIS) together is yet another combinational approach which is popular while discussing LUCC. Remote Sensing is a science which gathers the information of areas or objects using aircrafts or satellites. RS and GIS have been used by many researchers utilizing both of these technologies in deducing the rate of the land use change and calculating the major factors affecting such variations (Shi, et al., 2011) (Yanan, Lishu, Bo, & Hui, 2011). Considering the East River Valley in China as a base for the study, analysis of the rate and extent of LUCC as well as its reciprocal transformation between land types, can be used to display the latent discipline of the local land change in quantitative approach (Shi, et al., 2011).

The basic flow of the work for using RS and GIS techniques in the given studies follows the calculation of the land use by using the dynamic degree, which includes the Dynamic degree of single land-use type (certain time zone) and Dynamic degree of regional land-use (synthesized land-use). Using such information, it helps at understanding the transformation of land type in a certain region for a specific time period can indicate the direction of land-use developments. Another important index used for such analysis is the Landscape diversity index, which refers to the rich and complication of landscape patch. For this study specifically, Shannon-Weaver diversity index is used and this index is utilized by ArcGIS to make a comprehensive analysis of the data. (Shi, et al., 2011)

Similar to the previous study discussed, another study was conducted for LUCC specific for Shanghai, China. (Yanan, Lishu, Bo, & Hui, 2011) The data utilized in this research is taken from LANDSAT 7 ETM+ (remote sensing images and topographical maps), based on various information indexes. Decision tree classification method is used to extract relevant and accurate data from the images. ENVI4.2 and ERDAS IMAGINE8.7 are used to perform pre-processing on the images, from 1999 to 2005. This research was intentionally and only focused on calculating the recent change in the land-use division of the building land and other land covers.

Using remote sensing analysis on the images obtained from the satellites were pre-processed under the criteria of atmospheric and geometric correction, stitching (mosaicking), re-sampling, data projection transformation and masking the data (not required) out of the study area. Based on various key factors, 6s[3] model (tool provided by NASA) is used to pre-processing the atmospheric correction of the images, whereas with the use of vector topographic map of Shanghai, geometric correction is done by using the quadratic polynomial transformation model. A soil-adjusted vegetation index (SAVI[4]) was proposed to solve the unsatisfactory factor of extracting sparse vegetation which is sensitive to background noise. Other indexes calculated for the analysis are Normalised Difference Barren Index

[3] 6S: Second Simulation of the Satellite Signal in the Solar Spectrum is a Radiative Transfer Model used for atmospheric correction on satellite images.
[4] SAVI: Soil Adjusted Vegetation Index is the modification of NDVI, when the vegetation cover is low then the influence of soil brightness affects the result. It contains the soil brightness correction factor in the formula.

(NDBI)[5], Normalized Difference Bare Soil Index (NDBaI)[6] and Normal Difference Water Index (NDBI)[7]. (Yanan, Lishu, Bo, & Hui, 2011)

Another use of LANDSAT images as data for monitoring the urban expansion of the Greater Toronto Area from 1985 and 2013 (Wang, Wang, Li, & Li, 2014). The land use and Land cover change information for the GTA (Greater Toronto Area) is extracted with the help of Landsat-8 images and operational land imager (OLI). With this, a bi-temporal and multi-temporal with 6-year interval time-serial dynamic change detection method is applied on these images (Wang, Wang, Li, & Li, 2014).

Considering the present scenario, many change detection techniques such as Change Vector Analysis, Write Function Memory, and Principal Component Analysis have proved to be effective in producing the appropriate results. Whereas, this study focuses on the post-classification change detection methods are used for LUCC analysis. There are many supervised classification algorithms which have been prominent in the said field, such as Parallelepiped Method, Maximum Likelihood Classifier (MLC), and Minimum Distance Classifier (MDC). Considering these techniques with their respective pros and cons, this study applies a pixel-based supervised SVM[8] classification method (Wang, Wang, Li, & Li, 2014).

Performing the data pre-processing is only one task described in the research work, the other tasks include urban expansion analysis, change detection analysis, and image classification as shown in Figure 1. But for such methods and analysis to be performed after data pre-processing, there is a need for high classification accuracy which in turn promotes higher performance of the post-classification change detection algorithm's, thus this study implies the use of supervised support vector machine algorithm for each image (Wang, Wang, Li, & Li, 2014). Comparing the overall accuracy of the obtained results of SVM and MLC, the SVM was able to obtain good classification results.

In addition to this RS and GIS, Pre and Post Classification change detection methods can be used to assess the change (Haque & Basak, 2016). Pre-Classification methods analyze the change without classification of the image while Post Classification is based on detailed and categorized classification of land cover for evaluation of change in land cover. There are many methods to assess the change dynamics such as Change Vector Analysis (CVA)[9], Natural Difference Vegetation Index (NDVI)[10], Natural Difference Water Index (NDWI). Discrete Fourier Transform (DFT) is used during data preprocessing to reduce noise from the images. After preprocessing, classification is done using Supervised Maximum Likelihood method. This method uses means and variance out of the training data to estimate whether the pixel is a member of a class (Haque & Basak, 2016).

---

[5] NDBI is an indexes formula which is utilized in obtaining barren land (construction land) information from an image.

[6] NDBaI is an index formulation which can be used to obtain information about bare soil land in any image.

[7] NDWI is a formula to index information of water sources from a remote sensing image data.

[8] Support Vector Machine (SVM) is a supervised learning model that analysis data with use of associated learning algorithms for regression and classification analysis.

[9] Change Vector Analysis: It is a method to detect and characterize the land cover change. This method processes and analyses the change in multiple data layers.

[10] NDVI is a graphical indicator used for analyzing RS measurements to deduce if the specified location habitats live green vegetation or not.

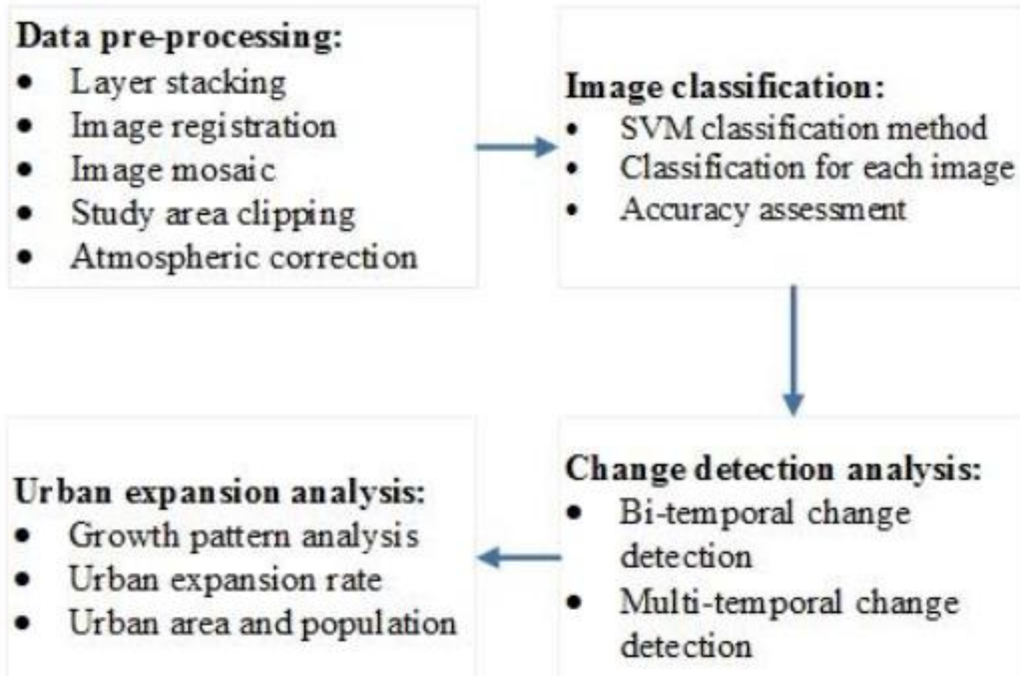


Figure 2 Workflow of the processing (Wang, Wang, Li, & Li, 2014)

Furthermore, quantitative change research is included in land use change analysis. Few mathematical models are used for spatial-temporal analysis of LUCC. Models such as land use dynamic degree model, land use degree, land use type transferring matrix model and spatial-temporal evolution model (Guobin & Lesheng, 2010). Spatial overlay analysis of ArcGIS can be used to gain the transition matrix of land use. Spatial Overlay Analysis is a collection of methodologies applied in suitable modeling or optimal site selection. Land use change could be denoted using land use dynamic degree model and thus land use change can be forecasted and can show land use change difference during different times. Certain types of land can be analyzed using Land use dynamic degree. For the forecasting of land use change, there are many models available, such as Markov chain model, Thünen model[11], system dynamics model, a statistical model and etc. (Guobin & Lesheng, 2010). Markov Chain Model (MCM) is a stochastic model used for describing the sequence of possible events where the probability of each event is dependent on the attained state from the previous event. Markov chain model can be used for forecasting land use change and for quantitative analysis.

Moreover, Maximum Likelihood classification can be applied on RS images to classify the study area. This method applies conditional probability density function as the discriminate function while using Bayes criterion as the discriminate method. For the analysis of changing land use, dynamic degree model is used. For developing land use trend Markov Chain formula is used which again uses transform probability matrix and obtained original matrix. Markov transform matrix model is important because it

[11] Thünen model shows how different locations can be used based on market processes.

can explain quantificational transform situation of land use types and to know spatial evolvement process of land use (Liang & Lilli, 2009).

Considering the research reviews performed as discussed above, we can see that many of the studies apply clipping as a method of deducting the unwanted data from the data source, this results in some outliner details being missed due to their relative position with respect to the study area, but these can sometimes be vital information in producing precise analysis. Another limitation that we can deduce from the researches is that GIS is a dedicated software which has complications in integrating with traditional maps. The major issue considering the change detection analysis in GIS is the effective weightage distribution of the criteria used in the analysis. One of the research papers, describes a relationship of human impact on the specified geographical area, but the human impact is not categorized but is taken in general (Gong, Zang, & Amuti, 2009). Thus, to obtain more in-depth relations between the human activities and the environmental effects there should be more categories. This is one of the retaining problems.

4. Dataset and Data Preprocessing

For the purpose of the research analysis the data required as input to the model to be generated are:

Index	Dataset Name	Type	Source
1	Landsat Image 2002	Tiff Image	USGS LandsatLook https://landsatlook.usgs.gov/viewer.html
2	Landsat Image 2017	Tiff Image	USGS LandsatLook https://landsatlook.usgs.gov/viewer.html
3	City Limits Regina	Polyline	Open Data by City of Regina http://open.regina.ca/dataset/city-limits
4	Digital Elevation Model Regina	Point	Open Data by City of Regina http://open.regina.ca/dataset/digital-elevation-model-dem

Table 1 Input Dataset for Project with source

Both Landsat images were obtained with a 0% cloud cover tolerance so that the cover of the land use could be accurately calculated for the analysis and additional correction would not be required. Each Landsat image covers a larger area than the required extent of the city of Regina. The Landsat images are projected in the Universal Transverse Mercator projection, UTM Zone 13N – WGS 1984, with the pixel resolution of 30 meters. While the City Limit data for Regina was projected in UTM Zone 13N – NAD 1983 projection. Thus, the TIFF Images were corrected geometrically to the UTM Zone 13N – NAD 1983 projection.

To correct the extent of the analysis and obtain the images relative to the study area, clipping was performed on the raster images with the use of the City Limits Regina, polyline shapefile. The clipped raster files were the modified inputs for our change analysis deductions.

Moreover, the metadata for the obtained images was not completely filled and had few missing fields, such as summary, description, tags, etc. these detailed were formulated and updated to the image files for later reference in future works. These adjustments are the preprocessing performed on the input files to generate appropriate input rasters.

4.1 Developing the geodatabase

Maintaining the raw input files and the processed input file in a single location is fruitful in locating and accessing all the files more easily. Thus, for the project work, a geodatabase named “Land Cover Analysis Regina” was created and maintained to store all the inputs/outputs, intermediate results and the final toolbox containing the one-click python script tool to perform the initial tasks for the analysis.

The geodatabase managed contains the original Landsat images (all the band images) for the two selected years, shapefiles of the City Limits of Regina and the Digital Elevation Model (DEM). Also, the intermediate files created as an output of various functions like clip, isocluster and reclassify will also be stored in this database.

5. Methodology

To perform the proposed analysis and obtain the efficient results the implementation and methodology of our project is a combination of two major software: ArcGIS and IDRISI TerrSet. The reason behind using two different software is to make use of the user-friendly environment provided by ArcGIS in performing the data preprocessing and land cover classifications for the prior and later images. IDRISI TerrSet brings the Land Change Modeler (LCM), which can help in performing accurate change analysis and trends using different driving variables.

ArcGIS also provides easy to use tools and methods to combine multispectral images into one single raster image for accurate classification of various land cover types. The main use of ArcGIS in our analysis work is to perform data preprocessing and generate the land cover classification for the input raster datasets. These classifications contain 5 categories: Water, Vegetation, Barren/Unused, Residential and Commercial. The classified images are generated using the Iso Clustering Unsupervised Method, using the user-specified number of classes or by default 25 classes for more accuracy, and are then reclassified using the Reclassify method into the discussed 5 categories.

The use of IDRISI TerrSet software platform is not only to access the Land Change Modeler (LCM) which is a model provided by IDRISI dedicated to performing the land change analysis and prediction. This is a high-end tool which takes inputs of the old and new classified images for a location to formulate the change analysis and trends for that time period. LCM also provides flexibility in setting various prediction values and can be tweaked to perform a specific type of prediction based on the provided criteria.

5.1 Major methods used in the project

The obtained Landsat images comprised multiple bands, each band representing a different spectral representation of the covered land. The main bands required to obtain an RGB organized image were the red band, green band, and the blue band images. Now, the analysis and classification cannot be performed accurately on these band images separately, thus there was a need of combing these three bands into a single raster image for the upcoming tasks. For performing this combination, the Composite Bands tool provided by ArcGIS was utilized. This resulted in a single raster image covering a larger area than the study area.

Following this, the next step was to extract the study area from the generated raster image. As discussed in section 2, the study area selected for the analysis is the City of Regina, so to extract the correct portion of the combined Landsat image the city limit shapefile was taken as reference. To perform such extraction from a raster dataset ArcGIS provides an efficient tool called, Clipping, which in layman's term simply cuts the specified portion (city limit extent) from the source image (Landsat image).

Performing this generates the output in the form of two images in the RGB combination but covering the extent specified by the city limits data file provided for the study area. Next phase goes into the classification of the various land cover types on the study area. There are two main categories of performing classification on raster images: Supervised and Unsupervised Classification. For this analysis, we have selected to use the Unsupervised Classification method to identify the land cover types.

Moreover, to perform this type of unsupervised classification the Iso Clustering Unsupervised Classification was performed, to be precise.

Iso Clustering Unsupervised Classification:

This method itself makes use of the Iso cluster and Maximum Likelihood Classification formulations, using which unsupervised classification is performed on the raster input bands to generate the output raster dataset. (Iso Cluster Unsupervised Classification, n.d.)

Iso Cluster is a method which makes use of an iterative optimized clustering procedure which is modified to handle the iterations. The algorithm initiates with the derivation of arbitrary means values for each cluster center, where the number of clusters is user-defined. The algorithm works as in each iteration the cell values are assigned to the closest mean cluster and in the next iteration, the mean values are recalculated based on the first iterations result. This process is repeated for the number of iterations specified by the user.

Maximum Likelihood Classification is an algorithm based on the following principles:

- The cells in each class sample in the multidimensional space being normally distributed
- Bayes' theorem of decision making

This algorithm considers both, covariance and variances, for the signature class file while assigning each cell to a specific class. An output confidence raster can be optionally produced while performing the maximum likelihood classification. The levels of confidence in the classification performed can be viewed in this file, the 14 levels are in direct relation to the valid reject fraction values number. The highest certainty is of the cell classified under the first level of confidence, i.e. the 1 confidence raster, as they have the smallest mean value to any given class value in the signature file. The next level of confidence will specify the cells with a reject fraction of 0.99 or less. Thus, the lowest level of confidence (14), would show the most likely cells to be misclassified, with a rejection fraction of 0.005 or more. (How Maximum Likelihood Classification works, n.d.)

Now, after performing the iso clustering we obtain a classified image of the study area, but this image contains 25 different classes. Each class represents a separate type of land cover, but for the intended analysis, only 5 major classifications (Water, Vegetation, Unused, Residential and Commercial) are required. So, for this, we need to reclassify the 25 classes into 5 classes. To achieve this the Reclassify tool present in the ArcGIS interface was used. The main function of this module is to take the input raster dataset which contains multiple raster values and reclassify these values into the user-specified values. Thus, the user will have to specify the observed values from the iso clustered images into the associated category. The tool will then generate a new raster dataset which will have only the newly specified class values and every similar value will be combined to generate a single class. (Reclassify, n.d.)

The end result of the reclassification module would produce a raster dataset. But for the prediction and the change analysis to be performed in the IDRISI Terrset, this data was needed to be in TIFF format and thus, for converting this into TIFF format the Raster to Other Format tool present in the ArcGIS was utilized. This tool is a simple tool which takes one or multiple raster datasets as input and creates a new file of any specified format, for our requirements the preferred output format was a .tiff image.

Predictive Analysis

Markov Chain Model

Markov chain model is a stochastic advancement which shows the probability of one state which can be altered to another state. Markov Chain creates the probability of change from one category or type (e.g. Barren/Unused Land) to another type (e.g. Urban or vegetation) using a key descriptive outcome. This is also called the transition probability matrix. (Jamal Jokar, Wolfgang, & Ali Jafar, 2011)

When there is no requirement of intermediate transition for the transition of one state to another state, the Markovian process is a first-order Markov process.

$$x^2 = \sum_{\mathrm{i}} \sum_{i} \left(\frac{\left(N_{ij} - M_{ij}\right)^2}{M_{ij}} \right)$$

Where, N is the matrix which shows the LUCC between 2-time assumption (e.g., between 2002 and 2017 or between 2017 and 2032)

M is the matrix which shows the values of expected change while assuming the independence hypotheses.

X^2 is the distance between the practical values of LUCC. (Jamal Jokar, Wolfgang, & Ali Jafar, 2011)

According to the Chapman–Kolmogorov equation, the transition probabilities from 2002 to 2032 can be calculated by multiplying the transition probability matrix of 2002 to 2017 and 2017 to 2032.

$$x^2 = \sum_{\mathrm{i}} \sum_{j} \left(\frac{\left(N_{ij} - O_{ij}\right)^2}{O_{ij}} \right)$$

CA Markov Model

CA Markov model is the integration of Cellular Automaton (CA) and Markov Chain model. By getting the transitional area matrix of the quantity of change from Markov Chain Model the CA Markov implements contiguity kernel which using CA function helps to grow out the land use map for the later time period. (Jamal Jokar, Wolfgang, & Ali Jafar, 2011)

As discussed in Section 3, the prior researches done in this field have shown promising results with the use of CA Markov model. The reliability and computational probability of the model have high strength statistically which is beneficial for the predictive work.

5.2 Custom Models

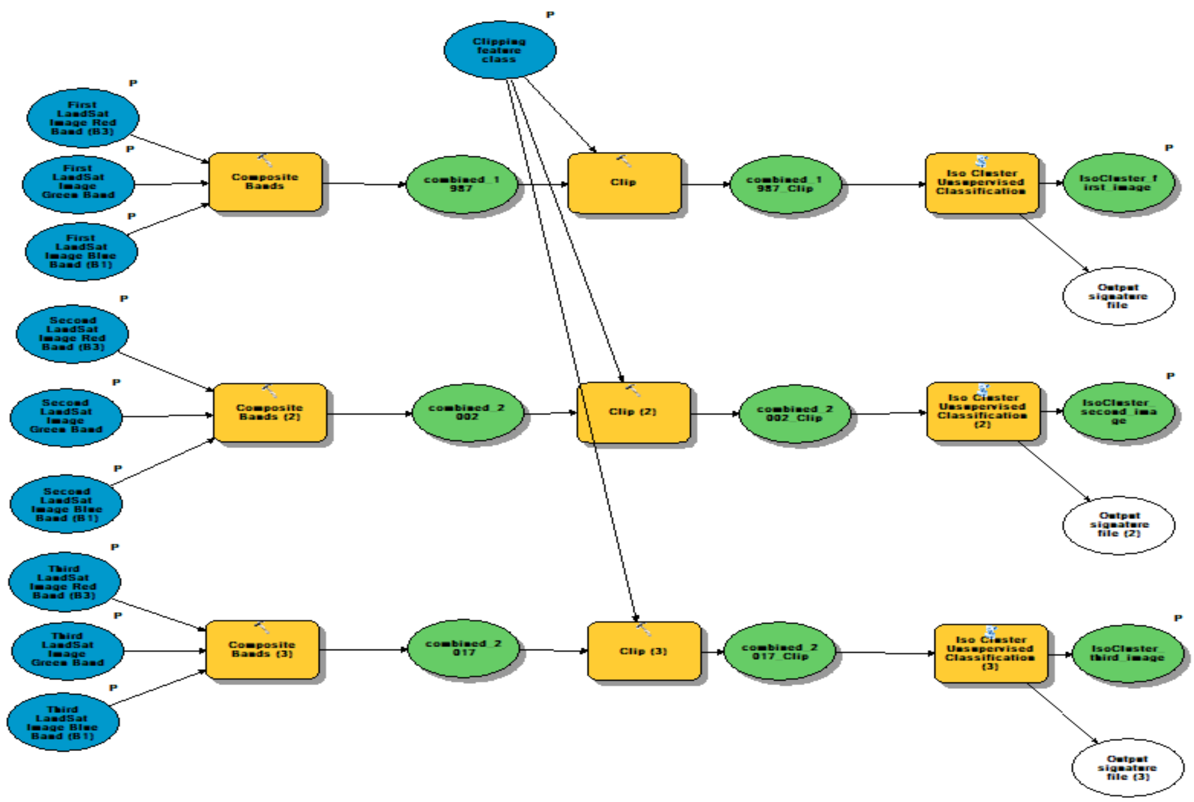


Figure 3 Model Generating Iso Clusters

As the model diagram displays the flow of the functions that are used in our custom python script, we can see that the Landsat Band Images will be parameters to our script, and the clipping feature class. The output and intermediate results will be stored into the specified workspace which will also be asked as a parameter.

Thus, considering this the tool will have in total 15 parameters to be passed from images to the output file names and the number of classes to be calculated for the iso cluster classification.

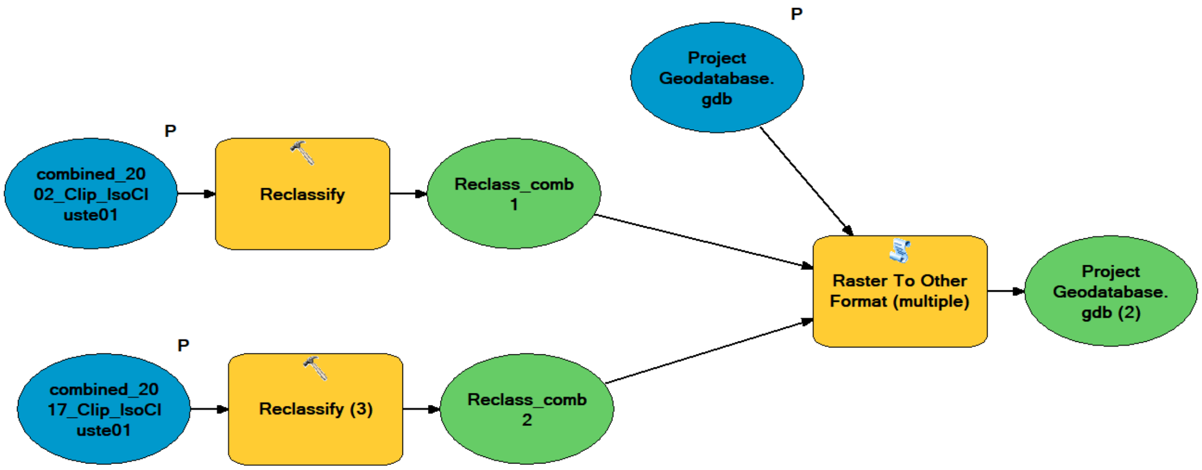


Figure 4 Model to Reclassify Clusters

This is the model for the second custom tool created for performing the reclassification and conversion of the raster dataset to the Tiff files. This will take the isocluster images as inputs and create the reclassified tiff images which can be imported to the IDRISI TerrSet more efficiently. This will make use of 3 parameters: the two classified images and the output location directory.

6. Implementation

The implementation of our analysis and prediction project work follows the flow depicted in Figure 5 & Figure 6.

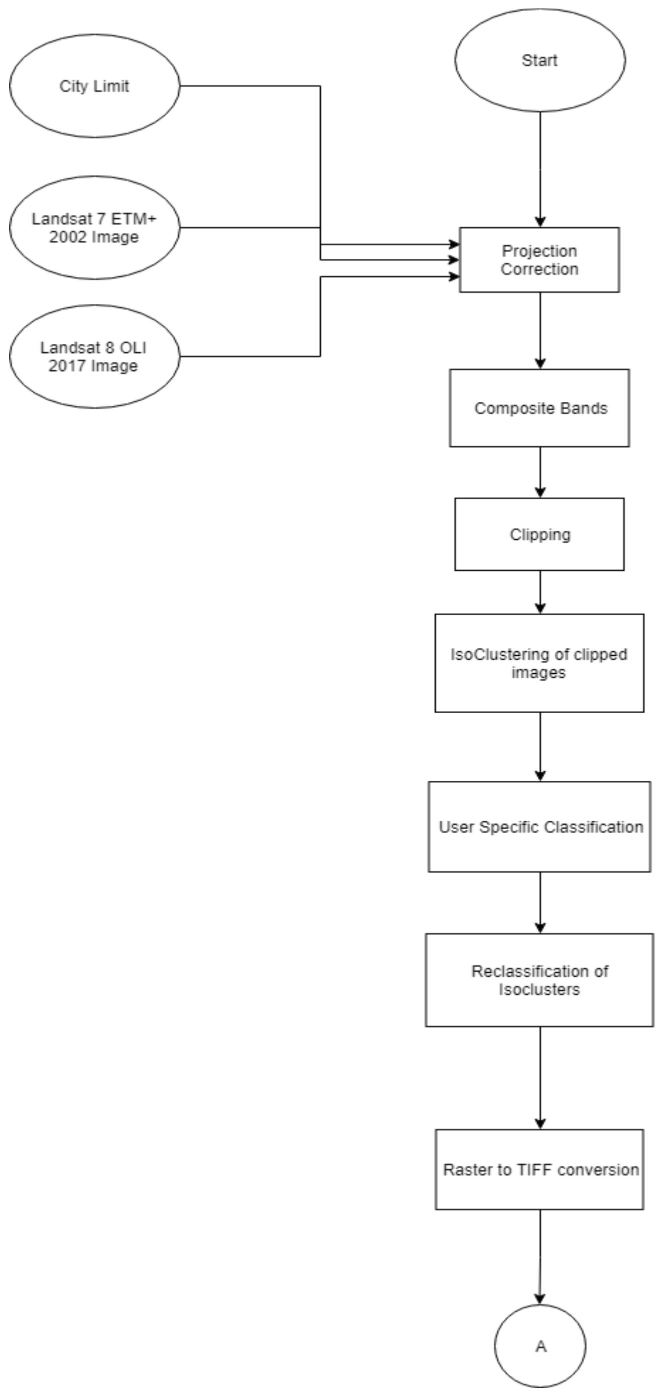


Figure 5 Flow diagram of the work in ArcMap

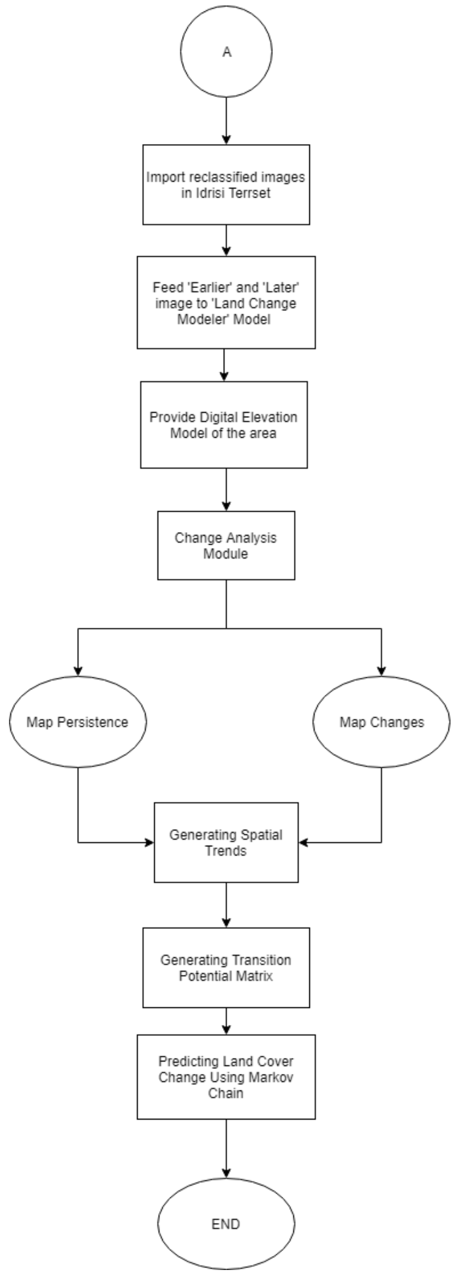


Figure 6 Flow diagram of the work in IDRISI TerrSet LCM

The first flow diagram is a representation of the workflow of the data preprocessing and classification of the refined (clipped) Landsat Images covering the area of the city of Regina. The user will provide the band images and the clipping feature shapefile as input to the custom tool created by us to perform the displayed tasked on a single click. However, the toolbox created contains a tool script tool: Generate Clusters and Classify Clusters. These tools will need to be utilized by the user.

The first step in our project is to correct the projections of the various input images to a single matching projection specification. And these corrected images will be passed through the clip function which will snip the area based on the extent of the provided clip feature class and generate the clipped images which will be covering the required study area. This will be passed to the iso cluster unsupervised method and the number of classes to generate will be taken from the user. This method will generate the iso cluster classified raster datasets. All of these intermediate results will be stored inside the created geodatabase or the workspace directory specified in the input of the custom tool.

Now the output of this will be displayed on the current map file as layers. The next step follows identifying each class defined by the unsupervised classification method into appropriate categories and these identifications will be given as input to the next tool, i.e. Classifying cluster. This tool is a combination of the reclassify method and the conversion method to generate .tiff images as outputs from the generated reclassification.

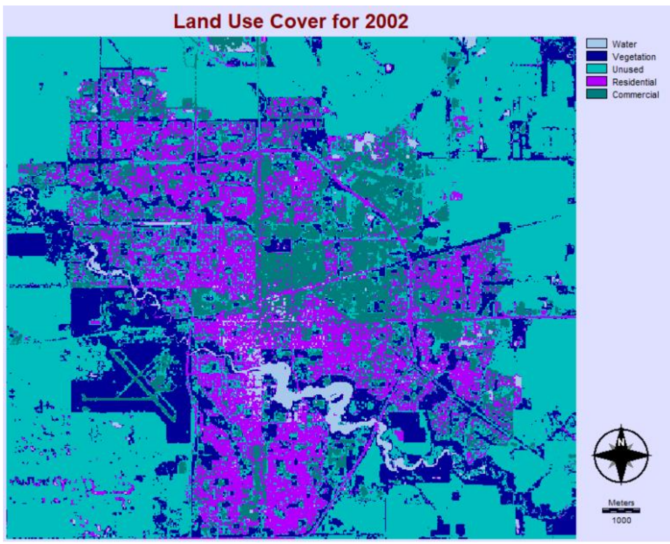


Figure 7 Land Cover of 2002

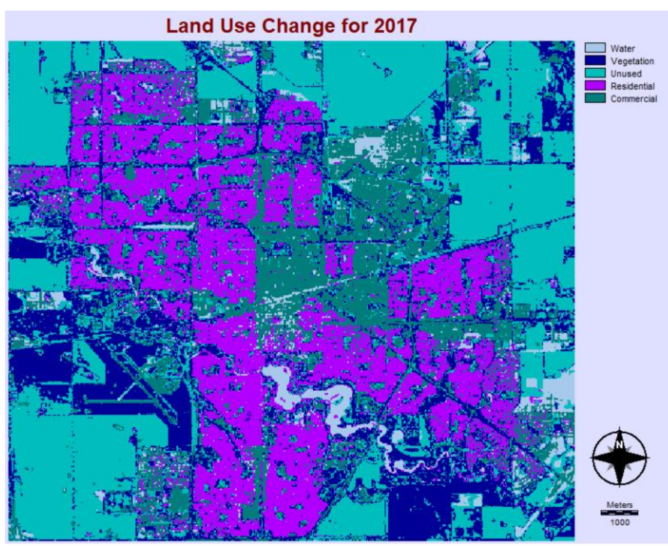


Figure 8 Land Cover of 2017

As you can observe the main categories taken for the analysis is Water, Vegetation, Unused, Residential and Commercial. As these are the main land uses for which we want to generate the spatial trends.

Thereafter, the workflow for the IDRISI TerrSet is used. The generated reclassified images are then imported into the IDRISI TerrSet platform in the form of .rst files. The Land Change Modeler in the TerrSet is used to perform the change analysis by taking the old (2002) reclassified image and the new (2017) reclassified image. For this analysis, the DEM file is provided as an additional factor to better understand the change dynamics.

The result of this is the MapPersistence and MapChange images provided below. The MapPersistence image depicts the unchanged cells in the given two images, while the MapChange displays the changes that occurred over the time period. Based on these images and values the next step is to generate the transition potential models for the change in potential dynamics for each category to another category.

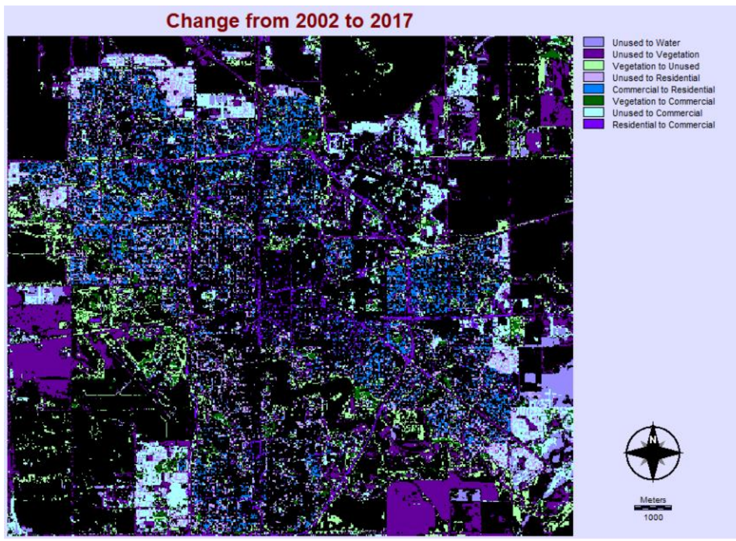


Figure 9 Change from 2002 to 2017

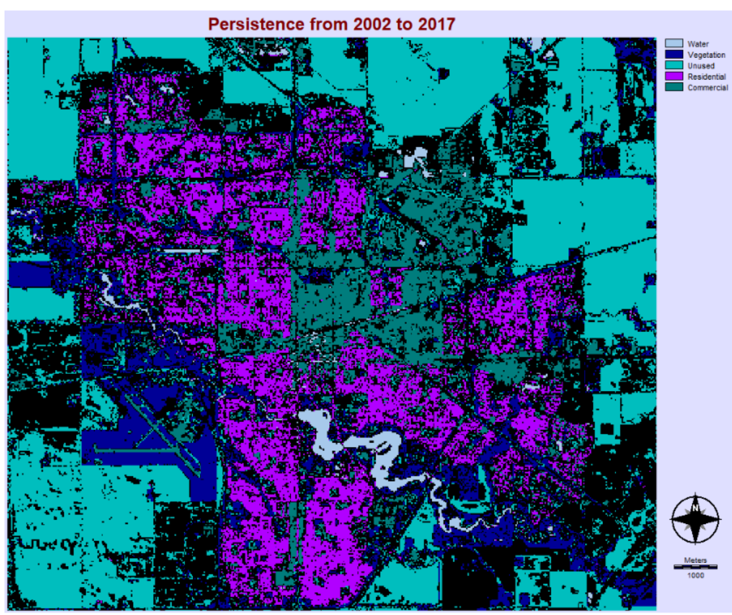


Figure 10 Persistence from 2002 to 2017

Following this, we move into the Transitional Potential Model of the LCM to generate the Transitional Potential Matrix. This will require the deriving variables to understand the statistics of generating the dynamic growth of one or more categories with respect to decrease in other one or more categories.

Based on the changes and persistence model generated in the change analysis section as discussed above, the spatial trends in various growth changes can be plotted and seen. These trends specify the potential of the dynamic pattern following which we want to generate the transitional potential for the categories.

The spatial trends deduced by our analysis and are vital to the transitional model are:

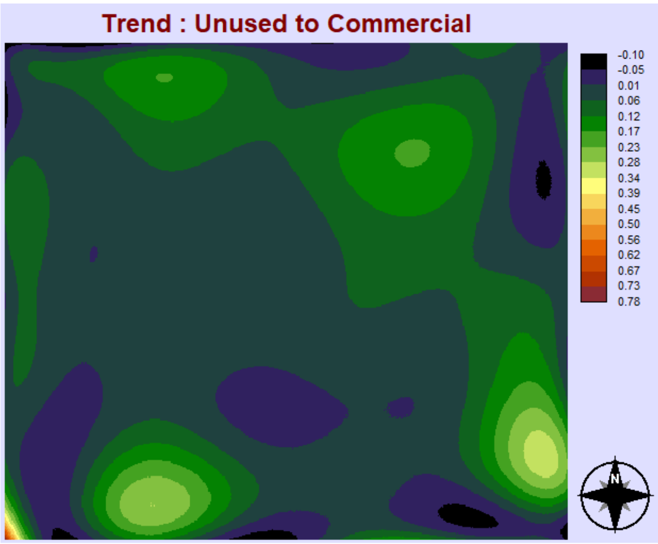


Figure 11 Trend Analysis of Unused to Commercial

The image on the left displays the trend analysis of the change in the unused land for commercial use.

The image on the right contains the trend recognized for conversion of unused land to residential use.

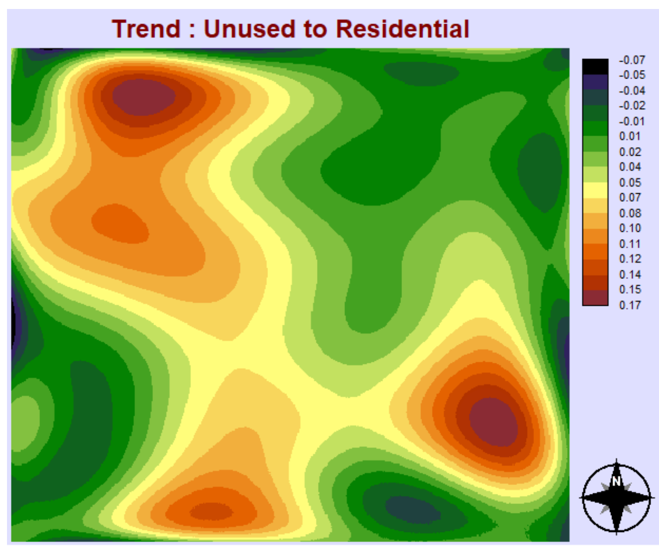


Figure 12 Trend Analysis of Unused to Residential

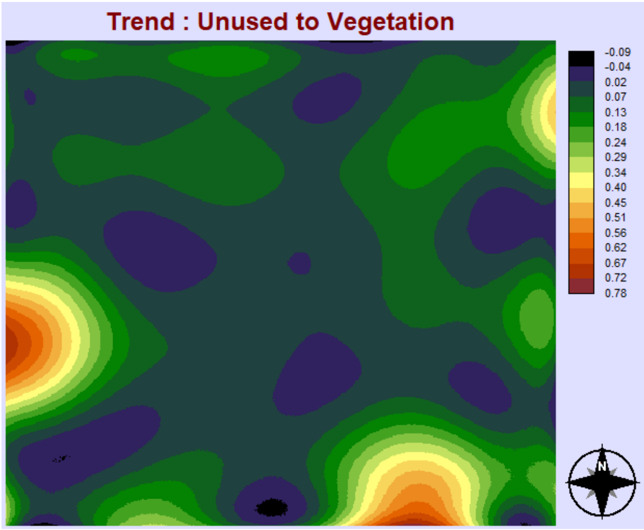


Figure 13 Trend Analysis of Unused to Vegetation

This trend analysis depicts the changes in the vegetation cover for the unused land over the study area. We can observe major changes in the West-Southwest direction of the city.

These trends depict the spatial relations between the change dynamics of one land use to another over the course of 15 years. Thus, these trends can be integral in understanding the transitional potentials for the change prediction which is our end goal.

Thus, with use of these obtained trends and its deductions, we generate the transitional potential models for the various transitions possible between the categories.

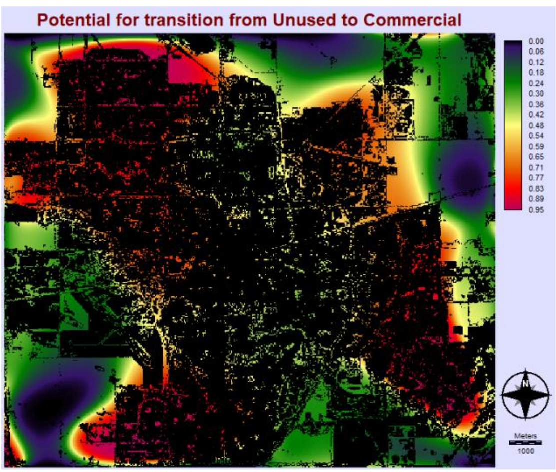


Figure 15 Transition potential from Unused to Commercial

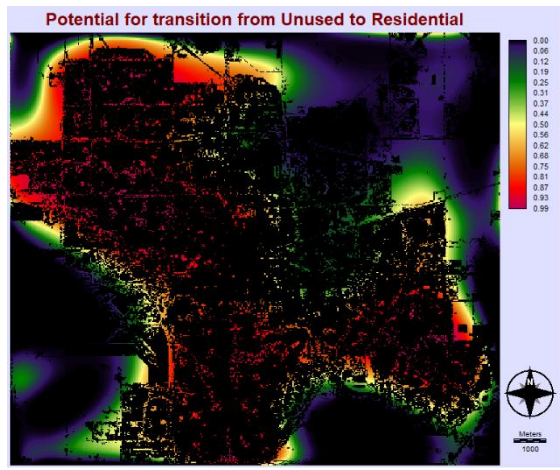


Figure 14 Transition potential from Unused to Residential

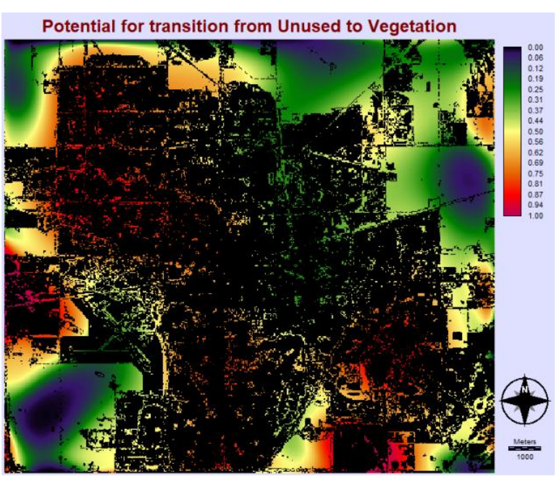


Figure 17 Transition potential from Unused to Vegetation

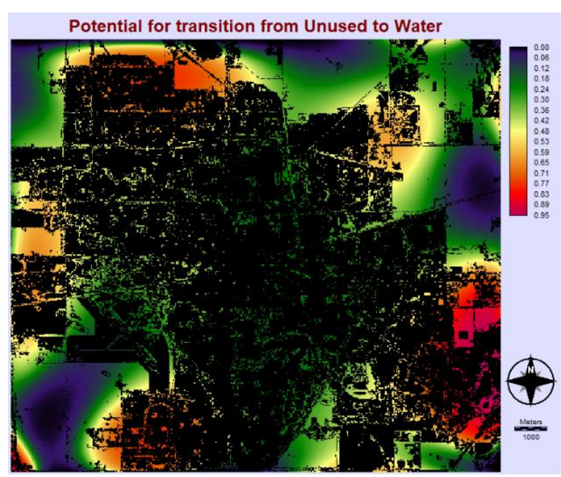


Figure 16 Transition potential from Unused to Water

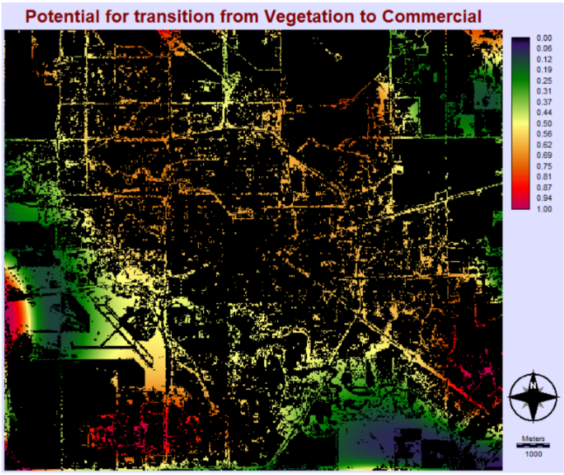


Figure 19 Transition potential from Vegetation to Commercial

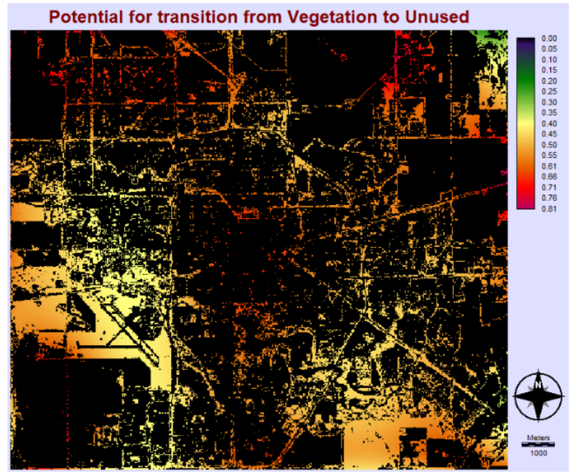


Figure 18 Transition potential from Vegetation to Unused

These obtained potential models of various transitions can be processed and understood to validate the transitional potential model accuracy. Using these transitional potential matrixes and models, the prediction for the year 2032 was performed. The LCM generated two prediction models: Soft Prediction and Hard Prediction.

The soft prediction models display the potential of every pixel value, in the specified image, to undergo a change in the selected time period. The hard prediction model converts the soft predictions into a hard map. The results for the prediction are discussed in the next section of the report.

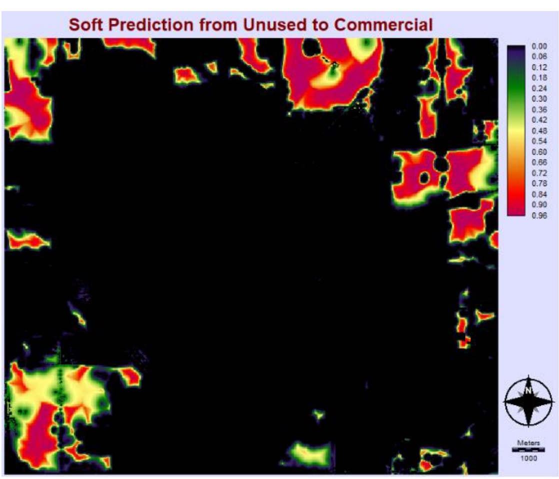


Figure 21 Soft prediction for Unused to Commercial

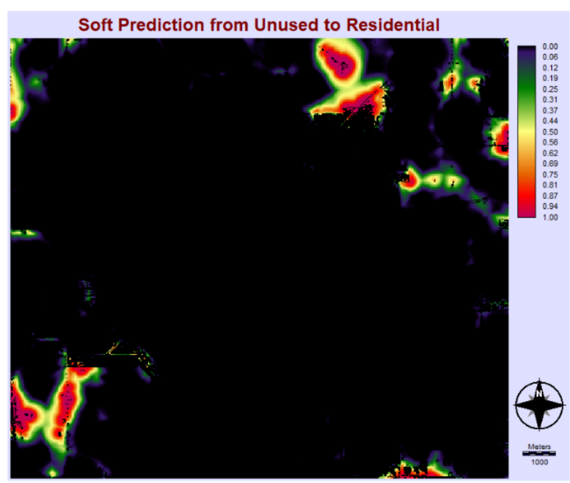


Figure 20 Soft prediction for Unused to Residential

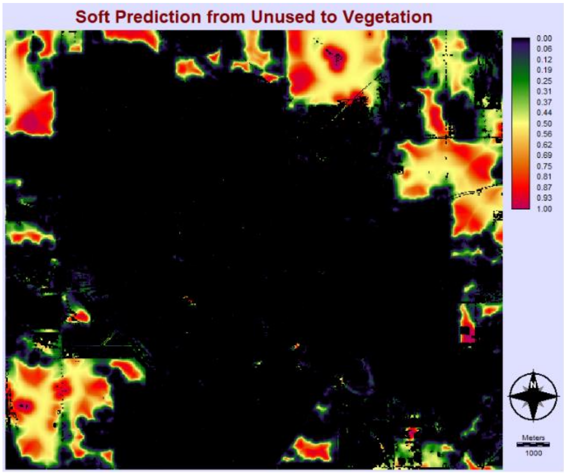


Figure 24 Soft prediction for Unused to Vegetation

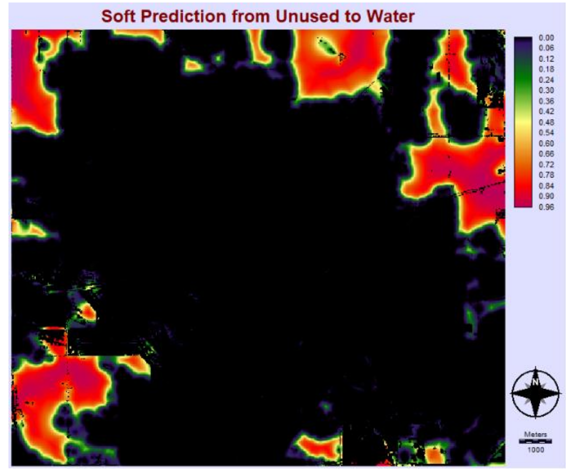


Figure 23 Soft prediction for Unused to Water

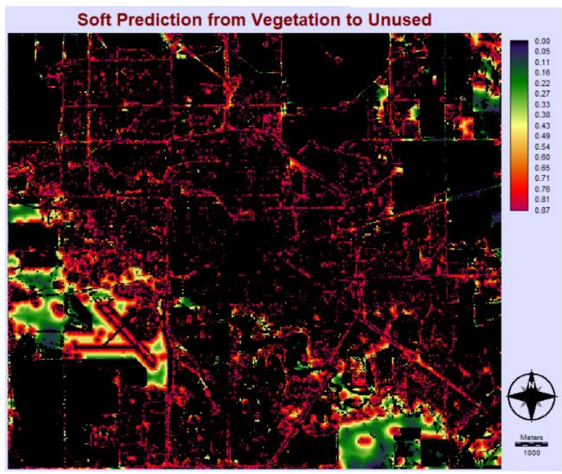


Figure 25 Soft prediction for Vegetation to Unused

7. Result and Discussion

Based on the change analysis performed for the 2002 and 2017 images, we can observe the gains and losses for each specified category as shown in the image below.

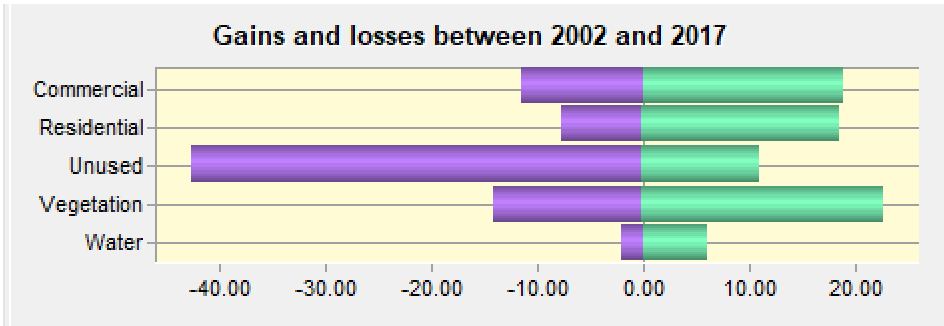


Figure 26 Gains and Losses between 2002 to 2017

As one can see, the unused land cover has seen the most negative change over the course of 15 years. Based on this we can state that the unused land in the year 2002 for the city of Regina, was converted or utilized for any one or more categories. Mainly looking at the reclassified images, we can further distinguish that the major transition has occurred for unused/barren land to vegetation and commercial sector of the city.

The end prediction generated results in the following tentative map of the city of Regina. Based on this we can see that the potential of vegetation cover growth is comparatively high and is the best user of the barren/unused land. We can also deduce that the expansion of the residential sector of the city could move more towards the North-East and South-West regions on the perimeter of the city. Moreover, the commercial sector growth is somewhat linked to the increase in water body coverage of the land. We can see that the North Eastern perimeter of the city is most suited for industrial development.

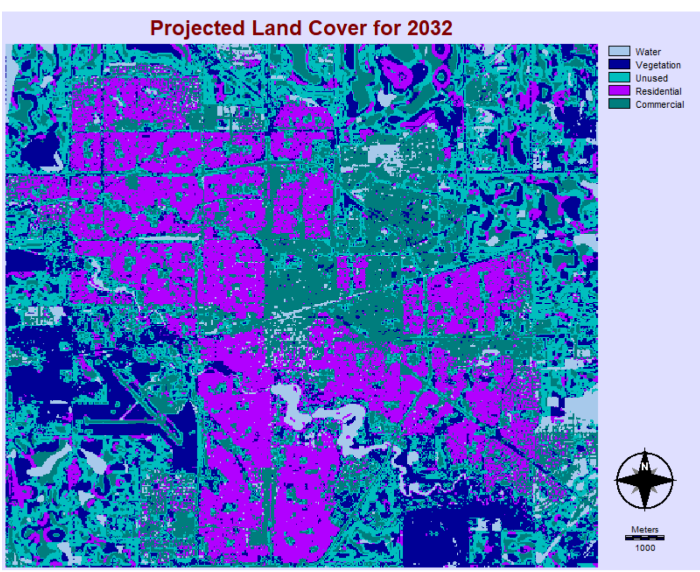


Figure 28 Projected Land Cover for 2032

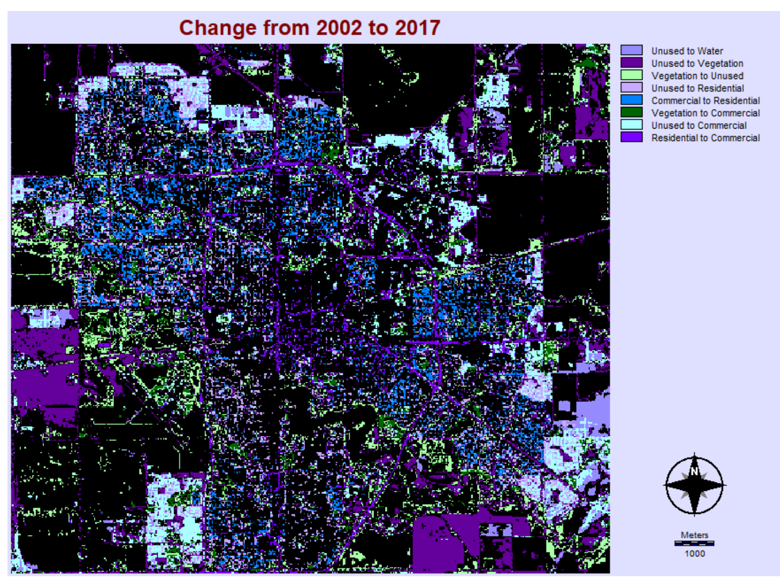


Figure 27 Changes from 2017 to 2032

Legend	Area 2002		Area 2017		Area 2032	
	Sq. KM.	%	Sq. KM.	%	Sq. KM.	%
Water	4.5396	2.377339	8.613	4.510534006	11.1735	5.8514399
Vegetation	30.1356	15.78168	38.9133	20.37847009	36.7263	19.233162
Unused	97.1325	50.86723	65.7	34.40637225	47.5605	24.906914
Residential	32.6187	17.08206	43.7121	22.89154923	49.4901	25.917425
Commercial	26.5266	13.89169	34.0146	17.81307442	46.0026	24.091059

The table above shows the numerical and percentage cover of the respective land cover category over the study area for the years 2002, 2017 and 2032. To better understand the changes in these land covers, we can generate a graph as shown below.

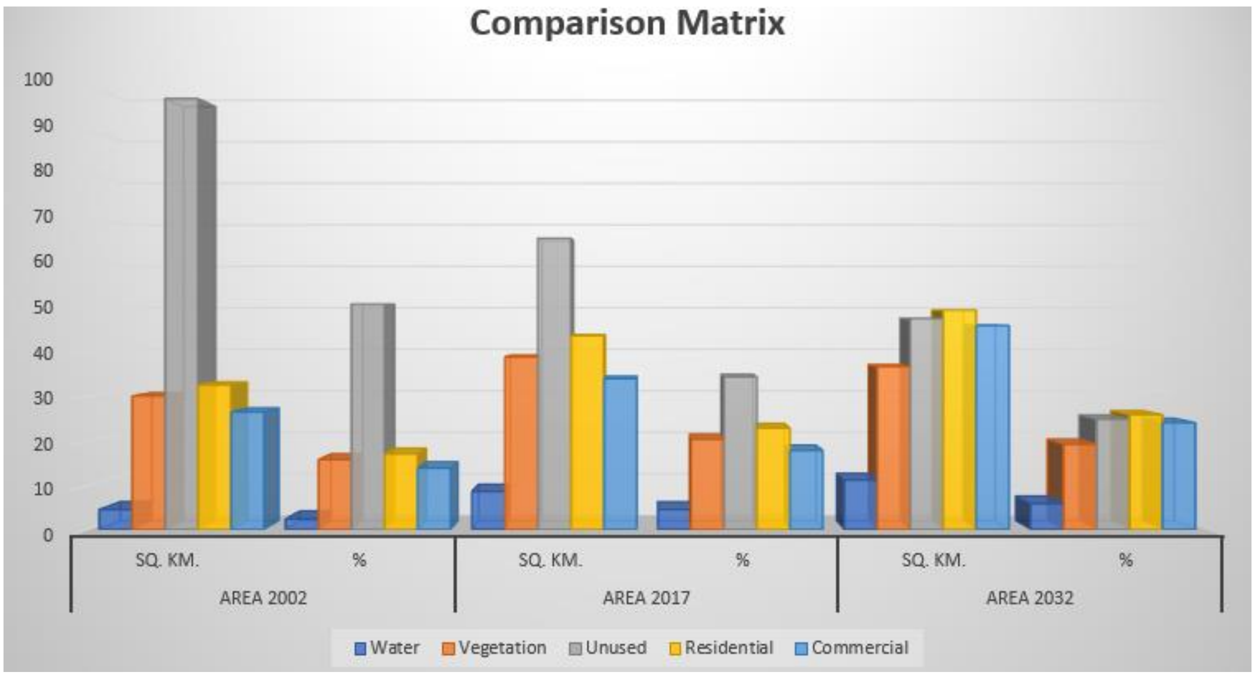


Figure 29 Comparison Matrix

We can see that for the year 2002, the unused land cover was covering almost 50% of the study area extent. But for the year 2017, it reduced to around 34% simultaneously we can observe growth in all the other categories while maintaining equal distribution factor. Whereas, the predicted coverage values show that the commercial growth of the city booms and we can see a growth of 7% between 2017 and 2032. This, in turn, hints the advancements in the economic growth of the city of Regina. But, one thing to notice is that between the years 2017 and 2032, we can see a 1% (minute) depletion in the vegetation cover over the city area. This is an important factor to focus on and prevention routes can be discussed.

8. Assumption and Limitation

The limitation to the prediction performed here is that it considers the spatial trends as the driving variables, which are strongly relevant to the prediction criteria. But the other predictive works performed in this field of analysis utilizes different driving variables.

Moreover, the accuracy of the transitional potential model developed for the prediction can be observed in the given image below.

3) Backwards Stepwise Constant Forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	85.72	0.7145
Step 1: var.[1] constant	[2,3]	85.72	0.7145
Step 2: var.[1,3] constant	[2]	85.14	0.7028

Figure 30 Variable accuracy and skill

Thus, we can consider a possibility of generating a more accurate model with the use of more detailed criteria for the prediction. Another important point to be noted is that the city limit extent taken for the analysis and prediction is kept same for all the years, but in real-time this extent changes and thus, the ratio of the covers will vary. This will have major effects on the prediction.

9. Conclusion and Future Work

The problem stated for this project was to understand the spatial trends of the developments in the categories of water, vegetation, commercial, residential and unused, for the city of Regina. Based on these trends and classification the prediction for the land covers for the year 2032 was to be generated and analyzed.

The result of the prediction and analysis shows positive growth for the city of Regina over the years 2002 and 2017. Moreover, the predicted changes and potential growth is steady and has all-around increments for each category (Water, Residential, Commercial and Vegetation). The unused land cover is not totally nullified and we can see some extent of the land cover to be still unused.

While, performing this analysis and generating the prediction of the land covers, we learned the fundaments concepts behind Image Classification using Supervised and Unsupervised learning methods, the use of ArcMap and IDRISI TerrSet software's for manipulating and performing the analysis. The driving variable selection and generation plus the spatial trend creation and comparison. This has created a more profound understanding within our selves about the complexity and importance of the minute details while working with geospatial analysis and prediction models.

For the future work of this project, we can move forward in validating the created model with the use of different images of other time periods. In addition to this, other driving factors can be obtained and analyses to produce an even more promising prediction. This method or process can be utilized to perform Land Use Cover Change analysis for other study areas.

Moreover, using the prediction values we can do the city planning. For example, we can use the most suitable location to build the residential area or commercial area outside the city so the city can expand. There are multiple parameters we can consider for doing this planning. Using GIS technologies, the method of multi-criteria decision making can be utilized for this. The process of selecting the appropriate location is known as site selection.

To perform the site selection, we need to use multiple attributes. For the selection of sites in Regina, we are planning to use attributes such as:

- City limits – for the purpose of knowing the city limits
- Water bodies- we cannot do an expansion on water bodies

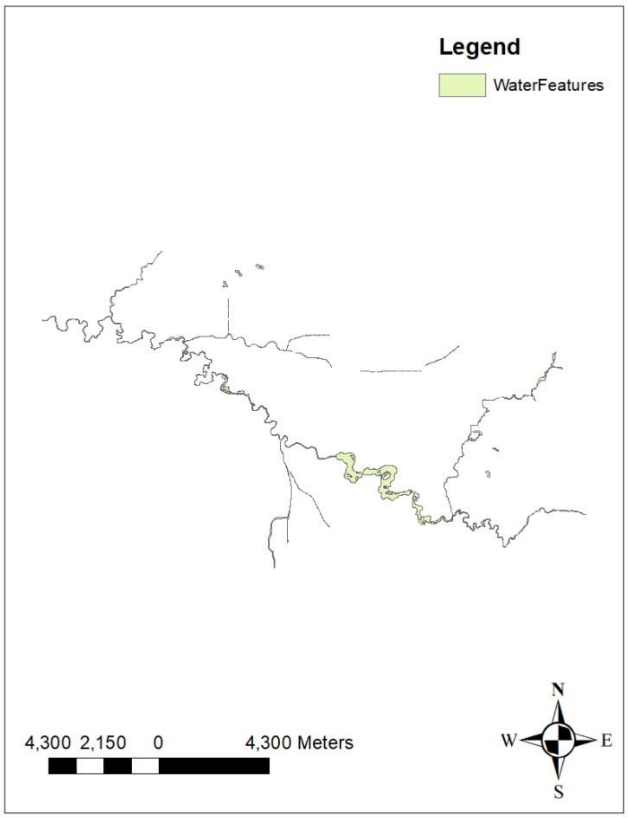


Figure 32 Water Feature Map

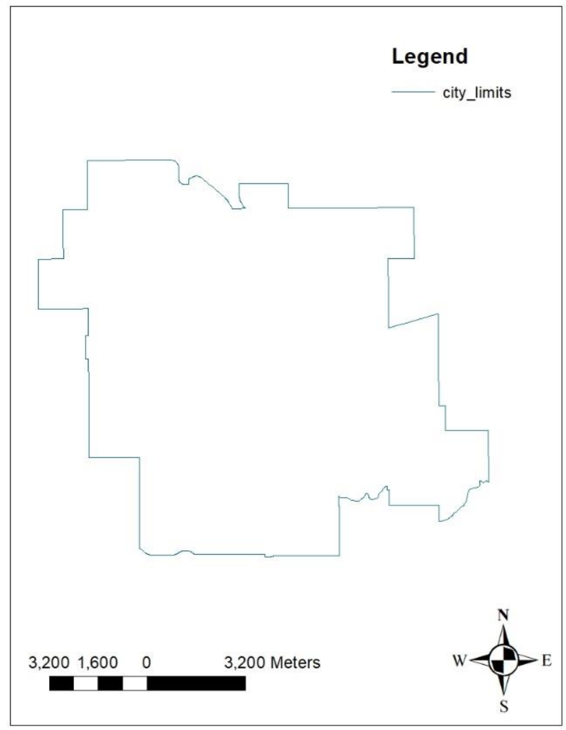


Figure 31 City Limit Map

- Road Network- road networks are essential for city development because they connect the city. So, to develop anything out of the city we need to consider the current road network of the city.
- Address point- these points are used to know the existing land utilized inside the city. We cannot develop anything on the existing infrastructure. Thus, with the help of this, we can exclude the internal city area from the analysis.

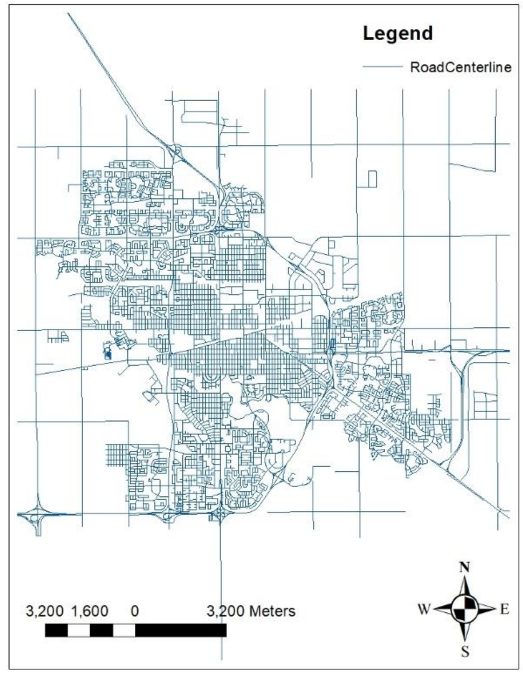


Figure 33 Road Network Map

Figure 34 Address Points Map

- Park locations over the city to find better locations with nearby parks to attract more suitors and visitors.

Figure 35 Park Locations Map

The basic step is to exclude the city build up area and water bodies inside the city. After that, with the help weighted overlay, we can select the areas near to roads network for the development of commercial markets.

10. References

Bagheri, M., & Azmin, W. N. (2010). Application of GIS and AHP Technique for Land-Use Suitability Analysis on Coastal Area in Terengganu. *2010 World Automation Congress.* Kobe.

Gong, L., Zang, H., & Amuti, A. (2009). Spatial Different Analysis of Land Use Change and Human Impact in Typical Oasis Based on GIS. *World Congress on Computer Science and Information Engineering*, 350-354.

Guobin, H., & Lesheng, L. (2010). Extracting Change Information of Land use Based on Landsat TM Image and GIS. *5th International Conference on Computer Science & Education.* Hefei.

Haque, M. I., & Basak, R. (2016). Land Cover Change Detection Using GIS and Remote Sensing Techniques. *ICISET.* Dhaka.

How Maximum Likelihood Classification works. (n.d.). Retrieved from http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/how-maximum-likelihood-classification-works.htm

Iso Cluster Unsupervised Classification. (n.d.). Retrieved from http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/iso-cluster-unsupervised-classification.htm

Jamal Jokar, A. a., Wolfgang, K. a., & Ali Jafar, M. (2011). Tracking dynamic land-use change using spatially explicit Markov Chain based on cellular automata: the case of Tehran. *International Journal of Image and Data Fusion*.

Learn about Regina. (n.d.). Retrieved 08 01, 2018, from https://www.regina.ca/residents/residents-regina-facts/about-regina/

Liang, P., & Lilli, W. (2009). The Analysis on LUCC and Its Drive Factors Based on RS and GIS. *Urban Remote Sensing Joint Event.* Shanghai.

Reclassify. (n.d.). Retrieved from http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/reclassify.htm

Shi, W., Wu, G., He, L., Chen, G., Jiang, C., & Wang, Y. (2011). An RS and GIS Analysis on Land-Use / Cover Change in East River Valley, China. *2011 19th International Conference on Geoinformatics.* Shanghai.

Wang, L., Wang, S., Li, W., & Li, J. (2014). Monitoring Urban Expansion of The Greater Toronto Area from 1985 to 2013 using LANDSAT Images. *IEEE.* Quebec City.

Yanan, X., Lishu, W., Bo, W., & Hui, G. (2011). A RS AND GIS ANALYSIS ON LAND-USE-COVER CHANGE OF SHANGHAI. *IET International Communication Conference on Wireless Mobile and Computing.* Shanghai.

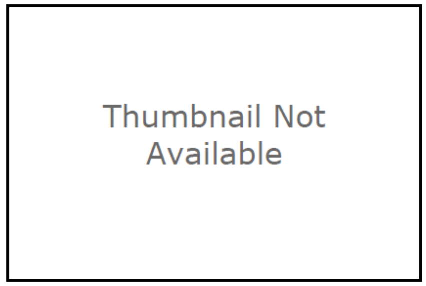
11. Appendix

11.1 Metadata

1. Metadata for Landsat Image of the year 2002

combined_2002

File Geodatabase Raster Dataset



Tags

2002, combined, rgb representation, Landsat 5 image, Saskatchewan, Regina

Summary

The combined image from the Red, Green and Blue band images from the Landsat 07 ETM+ multispectral image collection for use in land cover classification.

Description

It is a combined image of the RGB bands from the Landsat 5 image collection for the area covering the city of Regina.

Credits

Sagar Patel, Shirish Soni

Extent

West -107.037800 East -103.557028
North 51.300253 South 49.276091

Scale Range

Maximum (zoomed in) 1:5,000
Minimum (zoomed out) 1:150,000,000

ArcGIS Metadata

Topics and Keywords

* CONTENT TYPE Downloadable Data

EXPORT TO FGDC CSDGM XML FORMAT AS RESOURCE DESCRIPTION No

Citation

TITLE combined_2002

CREATION DATE 2018-08-01 00:00:00

PUBLICATION DATE 2018-08-10 00:00:00

REVISION DATE 2018-08-09 00:00:00

PRESENTATION FORMATS * digital table

Citation Contacts

RESPONSIBLE PARTY
INDIVIDUAL'S NAME Shirish Soni
CONTACT'S ROLE user

RESPONSIBLE PARTY
INDIVIDUAL'S NAME Sagar C. Patel
CONTACT'S ROLE user

Extents

EXTENT
GEOGRAPHIC EXTENT
BOUNDING RECTANGLE
EXTENT TYPE Extent used for searching
* WEST LONGITUDE -107.037800
* EAST LONGITUDE -103.557028
* NORTH LATITUDE 51.300253
* SOUTH LATITUDE 49.276091
* EXTENT CONTAINS THE RESOURCE Yes

EXTENT IN THE ITEM'S COORDINATE SYSTEM
* WEST LONGITUDE 357885.000000
* EAST LONGITUDE 600615.000000
* SOUTH LATITUDE 5459985.000000
* NORTH LATITUDE 5683215.000000
* EXTENT CONTAINS THE RESOURCE Yes

Spatial Reference

ARCGIS COORDINATE SYSTEM
* TYPE Projected
* GEOGRAPHIC COORDINATE REFERENCE GCS_WGS_1984
* PROJECTION WGS_1984_UTM_Zone_13N
* COORDINATE REFERENCE DETAILS
PROJECTED COORDINATE SYSTEM
WELL-KNOWN IDENTIFIER 32613
X ORIGIN -5120900
Y ORIGIN -9998100
XY SCALE 450445547.3910538
Z ORIGIN -100000
Z SCALE 10000
M ORIGIN -100000
M SCALE 10000
XY TOLERANCE 0.001
Z TOLERANCE 0.001
M TOLERANCE 0.001
HIGH PRECISION true
LATEST WELL-KNOWN IDENTIFIER 32613

REFERENCE SYSTEM IDENTIFIER
* VALUE 32613
* CODESPACE EPSG
* VERSION 2.1(3.0.1)

Distribution

Distribution format
* Name File Geodatabase Raster Dataset

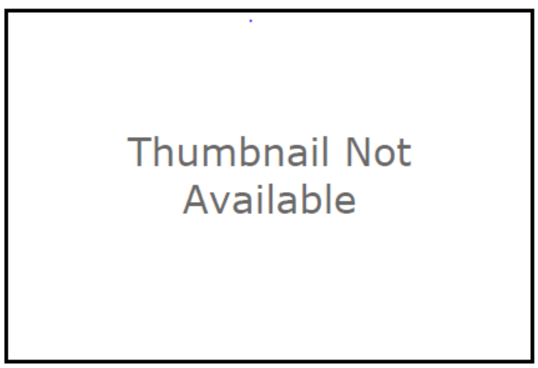
Metadata Details

* Metadata language English (CANADA)
Scope of the data described by the metadata * dataset
Scope name * dataset
* Last update 2018-08-17
ArcGIS metadata properties
Metadata format ArcGIS 1.0
Metadata style FGDC CSDGM Metadata
Standard or profile used to edit metadata FGDC
Created in ArcGIS for the item 2018-08-10 19:52:01
Last modified in ArcGIS for the item 2018-08-17 18:01:31
Automatic updates
Have been performed Yes
Last update 2018-08-17 18:01:31

2. Metadata for Landsat Image of the year 2017

combined_2017

File Geodatabase Raster Dataset



Tags

2017, combined, rgb representation, Landsat 8 image, Saskatchewan, Regina

Summary

The combined image from the Red, Green and Blue band images from the Landsat 08 multispectral image collection for use in land cover classification.

Description

It is a combined image of the RGB bands from the Landsat 5 image collection for the area covering the city of Regina.

Credits

Shirish Soni, Sagar Patel

Extent

West -105.343415 East -101.976404

North 51.351507 South 49.178148

Scale Range

Maximum (zoomed in) 1:5,000
Minimum (zoomed out) 1:150,000,000

ArcGIS Metadata

Topics and Keywords

* CONTENT TYPE Downloadable Data

Citation

* TITLE combined_2017

PRESENTATION FORMATS * digital table

Extents

EXTENT

GEOGRAPHIC EXTENT
BOUNDING RECTANGLE
EXTENT TYPE Extent used for searching
* WEST LONGITUDE -105.343415
* EAST LONGITUDE -101.976404
* NORTH LATITUDE 51.351507
* SOUTH LATITUDE 49.178148
* EXTENT CONTAINS THE RESOURCE Yes

EXTENT IN THE ITEM'S COORDINATE SYSTEM
* WEST LONGITUDE 476085.000000
* EAST LONGITUDE 710715.000000
* SOUTH LATITUDE 5451285.000000
* NORTH LATITUDE 5688915.000000
* EXTENT CONTAINS THE RESOURCE Yes

Spatial Reference

ARCGIS COORDINATE SYSTEM
* TYPE Projected
* GEOGRAPHIC COORDINATE REFERENCE GCS_WGS_1984
* PROJECTION WGS_1984_UTM_Zone_13N
* COORDINATE REFERENCE DETAILS

PROJECTED COORDINATE SYSTEM
WELL-KNOWN IDENTIFIER 32613
X ORIGIN -5120900
Y ORIGIN -9998100
XY SCALE 450445547.3910538
Z ORIGIN -100000
Z SCALE 10000
M ORIGIN -100000
M SCALE 10000
XY TOLERANCE 0.001
Z TOLERANCE 0.001
M TOLERANCE 0.001
HIGH PRECISION true
LATEST WELL-KNOWN IDENTIFIER 32613

REFERENCE SYSTEM IDENTIFIER
* VALUE 32613
* CODESPACE EPSG
* VERSION 2.1(3.0.1)

Distribution

DISTRIBUTION FORMAT
* NAME File Geodatabase Raster Dataset

Metadata Details

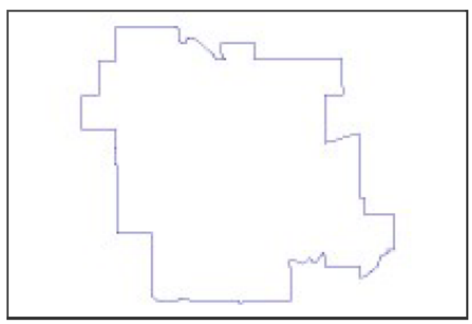
* METADATA LANGUAGE English (CANADA)
SCOPE OF THE DATA DESCRIBED BY THE METADATA * dataset
SCOPE NAME * dataset
* LAST UPDATE 2018-08-17
ARCGIS METADATA PROPERTIES
METADATA FORMAT ArcGIS 1.0

METADATA STYLE FGDC CSDGM Metadata
STANDARD OR PROFILE USED TO EDIT METADATA FGDC
CREATED IN ARCGIS FOR THE ITEM 2018-08-10 19:52:40
LAST MODIFIED IN ARCGIS FOR THE ITEM 2018-08-17 18:01:48
AUTOMATIC UPDATES
HAVE BEEN PERFORMED Yes
LAST UPDATE 2018-08-17 18:01:48

3. Metadata data for City Limit of Regina City

city_limits

File Geodatabase Feature Class



Tags

Limits, City Boundary, City Limits, Boundary, boundaries, planning cadaster, society

Summary

Developed as one of the Regina Base Map layers to be used with the ArcIMS Viewers

Description

Current Regina City Limits

Credits

Mario Valenzuela, Urban Planning

Extent

West -104.710507 East -104.502558
North 50.513399 South 50.396015

ArcGIS Metadata

Topics and Keywords

* CONTENT TYPE Downloadable Data

Citation

* TITLE city_limits
PRESENTATION FORMATS * digital map

Extents

EXTENT
GEOGRAPHIC EXTENT
BOUNDING RECTANGLE
EXTENT TYPE Extent used for searching
* WEST LONGITUDE -104.710507
* EAST LONGITUDE -104.502558
* NORTH LATITUDE 50.513399
* SOUTH LATITUDE 50.396015
* EXTENT CONTAINS THE RESOURCE Yes

EXTENT IN THE ITEM'S COORDINATE SYSTEM
* WEST LONGITUDE 520575.850013
* EAST LONGITUDE 535269.587876
* SOUTH LATITUDE 5582780.639995
* NORTH LATITUDE 5595755.451715
* EXTENT CONTAINS THE RESOURCE Yes

Spatial Reference

ARCGIS COORDINATE SYSTEM
* TYPE Projected
* GEOGRAPHIC COORDINATE REFERENCE GCS_North_American_1983
* PROJECTION NAD_1983_UTM_Zone_13N
* COORDINATE REFERENCE DETAILS

PROJECTED COORDINATE SYSTEM
WELL-KNOWN IDENTIFIER 26913
X ORIGIN -5120899.9999944558
Y ORIGIN -9998099.9999954589
XY SCALE 556760.31191091437
Z ORIGIN -100000
Z SCALE 8000
M ORIGIN -100000
M SCALE 8000
XY TOLERANCE 1.4368840287021136e-05
Z TOLERANCE 0.002
M TOLERANCE 0.002
HIGH PRECISION true
LATEST WELL-KNOWN IDENTIFIER 26913
REFERENCE SYSTEM IDENTIFIER
* VALUE 26913
* CODESPACE EPSG
* VERSION 6.13(3.0.1)

Spatial Data Properties

VECTOR

* LEVEL OF TOPOLOGY FOR THIS DATASET geometry only
GEOMETRIC OBJECTS
FEATURE CLASS NAME city_limits
* OBJECT TYPE composite
* OBJECT COUNT 1

ARCGIS FEATURE CLASS PROPERTIES
FEATURE CLASS NAME city_limits
* FEATURE TYPE Simple
* GEOMETRY TYPE Polyline
* HAS TOPOLOGY FALSE
* FEATURE COUNT 1
* SPATIAL INDEX TRUE
* LINEAR REFERENCING FALSE

Metadata Details

* METADATA LANGUAGE English (CANADA)
* METADATA CHARACTER SET utf8 - 8-bit UCS Transfer Format
* METADATA IDENTIFIER {22C20989-118B-4E5A-BB3E-3F9313047CBC}
SCOPE OF THE DATA DESCRIBED BY THE METADATA * dataset
SCOPE NAME * dataset
* LAST UPDATE 2018-08-17
ARCGIS METADATA PROPERTIES
METADATA FORMAT ArcGIS 1.0
METADATA STYLE FGDC CSDGM Metadata
CREATED IN ARCGIS FOR THE ITEM 2018-08-09 21:32:49
LAST MODIFIED IN ARCGIS FOR THE ITEM 2018-08-17 17:57:55
AUTOMATIC UPDATES
HAVE BEEN PERFORMED Yes
LAST UPDATE 2018-08-17 17:57:55
PUBLISHED TO AN ARCIMS METADATA SERVICE Published

11.2 Custom Scripts

11.2.1 Generate Clusters.py

```
# -*- coding: utf-8 -*-
# ---------------------------------------------------------------------------
# Generate Clusters.py
# ---------------------------------------------------------------------------

# Import arcpy module
import arcpy

# Set overwrite property true
arcpy.env.overwriteOutput = True

# Script arguments
# Obtain the Workspace
Workspace = arcpy.GetParameterAsText(0)
if Workspace == '#' or not Workspace:
    Workspace = "R:\\GIS Project"

# Band Images for the First Image
First_LandSat_Image_Red_Band__B3_ = arcpy.GetParameterAsText(1)
if First_LandSat_Image_Red_Band__B3_ == '#' or not First_LandSat_Image_Red_Band__B3_:
  First_LandSat_Image_Red_Band__B3_ = Workspace + "\\LT05_L1TP_035025_19870426_20170213_01_T1_B3.TIF" # provide a default value if unspecified

First_LandSat_Image_Green_Band__B2_ = arcpy.GetParameterAsText(2)
if First_LandSat_Image_Green_Band__B2_ == '#' or not First_LandSat_Image_Green_Band__B2_:
```

First_LandSat_Image_Green_Band__B2_ = Workspace + "\\LandSat07_1987\\LT05_L1TP_035025_19870426_20170213_01_T1_B2.TIF" # provide a default value if unspecified

First_LandSat_Image_Blue_Band__B1_ = arcpy.GetParameterAsText(3)

if First_LandSat_Image_Blue_Band__B1_ == '#' or not First_LandSat_Image_Blue_Band__B1_:

First_LandSat_Image_Blue_Band__B1_ = Workspace + "\\LandSat07_1987\\LT05_L1TP_035025_19870426_20170213_01_T1_B1.TIF" # provide a default value if unspecified

Band Images for the Second Image

Second_LandSat_Image_Red_Band__B3_ = arcpy.GetParameterAsText(4)

if Second_LandSat_Image_Red_Band__B3_ == '#' or not Second_LandSat_Image_Red_Band__B3_:

Second_LandSat_Image_Red_Band__B3_ = "R:\\GIS Project\\LandSat07_2002\\LE07_L1TP_036025_20020520_20170130_01_T1_B3.TIF" # provide a default value if unspecified

Second_LandSat_Image_Green_Band__B2_ = arcpy.GetParameterAsText(5)

if Second_LandSat_Image_Green_Band__B2_ == '#' or not Second_LandSat_Image_Green_Band__B2_:

Second_LandSat_Image_Green_Band__B2_ = "R:\\GIS Project\\LandSat07_2002\\LE07_L1TP_036025_20020520_20170130_01_T1_B2.TIF" # provide a default value if unspecified

Second_LandSat_Image_Blue_Band__B1_ = arcpy.GetParameterAsText(6)

if Second_LandSat_Image_Blue_Band__B1_ == '#' or not Second_LandSat_Image_Blue_Band__B1_:

Second_LandSat_Image_Blue_Band__B1_ = "R:\\GIS Project\\LandSat07_2002\\LE07_L1TP_036025_20020520_20170130_01_T1_B1.TIF" # provide a default value if unspecified

Band Images for the Third Image

Third_LandSat_Image_Red_Band__B3_ = arcpy.GetParameterAsText(7)

if Third_LandSat_Image_Red_Band__B3_ == '#' or not Third_LandSat_Image_Red_Band__B3_:

```
    Third_LandSat_Image_Red_Band__B3_ = "R:\\GIS Project\\LandSat07_2017\\LC08_L1TP_035025_20171005_20171014_01_T1_B3.TIF" # provide a default value if unspecified


Third_LandSat_Image_Green_Band__B2_ = arcpy.GetParameterAsText(8)

if Third_LandSat_Image_Green_Band__B2_ == '#' or not Third_LandSat_Image_Green_Band__B2_:

    Third_LandSat_Image_Green_Band__B2_ = "R:\\GIS Project\\LandSat07_2017\\LC08_L1TP_035025_20171005_20171014_01_T1_B2.TIF" # provide a default value if unspecified


Third_LandSat_Image_Blue_Band__B1_ = arcpy.GetParameterAsText(9)

if Third_LandSat_Image_Blue_Band__B1_ == '#' or not Third_LandSat_Image_Blue_Band__B1_:

    Third_LandSat_Image_Blue_Band__B1_ = "R:\\GIS Project\\LandSat07_2017\\LC08_L1TP_035025_20171005_20171014_01_T1_B1.TIF" # provide a default value if unspecified


# Clipping Feature value

Clipping_feature_class = arcpy.GetParameterAsText(10)

if Clipping_feature_class == '#' or not Clipping_feature_class:

    Clipping_feature_class = "city_limits" # provide a default value if unspecified


# Output Result File Names

IsoCluster_first_image = arcpy.GetParameterAsText(11)

if IsoCluster_first_image == '#' or not IsoCluster_first_image:

    IsoCluster_first_image = Workspace + "\\combined_1987_Clip_IsoCluste" # provide a default value if unspecified


IsoCluster_second_image = arcpy.GetParameterAsText(12)

if IsoCluster_second_image == '#' or not IsoCluster_second_image:

    IsoCluster_second_image = Workspace + "\\Project Geodatabase.gdb\\combined_2002_Clip_IsoCluste" # provide a default value if unspecified
```

```
IsoCluster_third_image = arcpy.GetParameterAsText(13)

if IsoCluster_third_image == '#' or not IsoCluster_third_image:

  IsoCluster_third_image = Workspace + "\\Project Geodatabase.gdb\\combined_2017_Clip_IsoCluste" # provide a default value if unspecified


# IsoCluster Classes variable

IsoCluster_Classes = arcpy.GetParameterAsText(14)

if IsoCluster_Classes == '#' or not IsoCluster_Classes:

    IsoCluster_Classes = 25



# Local variables:

combined_1987 = Workspace + "\\Project Geodatabase.gdb\\combined_1987"

combined_1987_Clip = Workspace + "\\Project Geodatabase.gdb\\combined_1987_Clip"

Output_signature_file = ""

combined_2002 = Workspace + "\\Project Geodatabase.gdb\\combined_2002"

combined_2002_Clip = Workspace + "\\Project Geodatabase.gdb\\combined_2002_Clip"

Output_signature_file__2_ = ""

combined_2017 = Workspace + "\\Project Geodatabase.gdb\\combined_2017"

combined_2017_Clip = Workspace + "\\Project Geodatabase.gdb\\combined_2017_Clip"

Output_signature_file__3_ = ""


# Band List Variables

rasterList01 = [First_LandSat_Image_Red_Band__B3_, First_LandSat_Image_Green_Band__B2_, First_LandSat_Image_Blue_Band__B1_]

rasterList02 = [Second_LandSat_Image_Red_Band__B3_, Second_LandSat_Image_Green_Band__B2_, Second_LandSat_Image_Blue_Band__B1_]

rasterList03 = [Third_LandSat_Image_Red_Band__B3_, Third_LandSat_Image_Green_Band__B2_, Third_LandSat_Image_Blue_Band__B1_]
```

```
# Calculate Clipping Extent

Description = arcpy.Describe(Clipping_feature_class)

MinX = Description.extent.XMin

MaxX = Description.extent.XMax

MinY = Description.extent.YMin

MaxY = Description.extent.YMax


Extent = str(MinX) + " " + str(MinY) + " " + str(MaxX) + " " + str(MaxY)


# Process: Composite Bands for First Image

#arcpy.CompositeBands_management("'R:\\GIS Project\\LandSat07_1987\\LT05_L1TP_035025_19870426_20170213_01_T1_B3.TIF';'R:\\GIS Project\\LandSat07_1987\\LT05_L1TP_035025_19870426_20170213_01_T1_B2.TIF';'R:\\GIS Project\\LandSat07_1987\\LT05_L1TP_035025_19870426_20170213_01_T1_B1.TIF'", combined_1987)

arcpy.CompositeBands_management(rasterList01, combined_1987)


# Process: Clip First Image

arcpy.Clip_management(combined_1987, Extent, combined_1987_Clip, Clipping_feature_class, "256", "NONE", "NO_MAINTAIN_EXTENT")


# Process: Iso Cluster Unsupervised Classification Firsta Image

arcpy.gp.IsoClusterUnsupervisedClassification_sa(combined_1987_Clip, IsoCluster_Classes, IsoCluster_first_image, "20", "10", Output_signature_file)


# Process: Composite Bands for Second Image

arcpy.CompositeBands_management(rasterList02, combined_2002)


# Process: Clip Second Image

arcpy.Clip_management(combined_2002, Extent, combined_2002_Clip, Clipping_feature_class, "256", "NONE", "NO_MAINTAIN_EXTENT")
```

```
# Process: Iso Cluster Unsupervised Classification Second Image

arcpy.gp.IsoClusterUnsupervisedClassification_sa(combined_2002_Clip, IsoCluster_Classes, IsoCluster_second_image, "20", "10", Output_signature_file__2_)


# Process: Composite Bands for Third Image

arcpy.CompositeBands_management(rasterList03, combined_2017)


# Process: Clip Third Image

arcpy.Clip_management(combined_2017, Extent, combined_2017_Clip, Clipping_feature_class, "65535", "NONE", "NO_MAINTAIN_EXTENT")


# Process: Iso Cluster Unsupervised Classification Third Image

arcpy.gp.IsoClusterUnsupervisedClassification_sa(combined_2017_Clip, IsoCluster_Classes, IsoCluster_third_image, "20", "10", Output_signature_file__3_)
```

11.2.2 Reclassify Cluster Script.py

```
# -*- coding: utf-8 -*-

# ---------------------------------------------------------------------------

# Reclassify Cluster Script.py

# Usage: Reclassify Cluster Script <combined_2002_Clip_IsoCluste01> <combined_2017_Clip_IsoCluste01> <Project_Geodatabase_gdb>

# ---------------------------------------------------------------------------


# Import arcpy module

import arcpy


# Set overwrite property true

arcpy.env.overwriteOutput = True
```

```
# Script arguments

combined_2002_Clip_IsoCluste01 = arcpy.GetParameterAsText(0)

if combined_2002_Clip_IsoCluste01 == '#' or not combined_2002_Clip_IsoCluste01:

    combined_2002_Clip_IsoCluste01 = "combined_2002_Clip_IsoCluste01" # provide a default value if unspecified


combined_2017_Clip_IsoCluste01 = arcpy.GetParameterAsText(1)

if combined_2017_Clip_IsoCluste01 == '#' or not combined_2017_Clip_IsoCluste01:

    combined_2017_Clip_IsoCluste01 = "combined_2017_Clip_IsoCluste01" # provide a default value if unspecified


Project_Geodatabase_gdb = arcpy.GetParameterAsText(2)

if Project_Geodatabase_gdb == '#' or not Project_Geodatabase_gdb:

    Project_Geodatabase_gdb = "R:\\GIS Project\\Project Geodatabase.gdb" # provide a default value if unspecified


# Local variables:

Reclass_comb1 = Project_Geodatabase_gdb + "\\Reclass_comb1"

Reclass_comb2 = Project_Geodatabase_gdb + "\\Reclass_comb2"

Project_Geodatabase_gdb__2_ = Project_Geodatabase_gdb

Input_reclass_images = Reclass_comb1 + ";" + Reclass_comb2


# Process: Reclassify

arcpy.gp.Reclassify_sa(combined_2002_Clip_IsoCluste01, "Value", "1 1;2 1;3 2;4 4;5 3;6 5;7 2;8 1;9 4;10 5;11 3;12 3;13 3;14 5;15 2;16 4;17 4;18 3;19 4;20 5;21 3;22 5;23 4", Reclass_comb1, "DATA")


# Process: Reclassify (3)

arcpy.gp.Reclassify_sa(combined_2017_Clip_IsoCluste01, "Value", "1 1;2 1;3 3;4 4;5 5;6 2;7 3;8 4;9 5;10 3;11 2;12 3;13 2;14 4;15 1;16 3;17 5;18 3;19 3;20 3;21 5;22 4;23 3;24 5", Reclass_comb2, "DATA")


# Process: Raster To Other Format (multiple)
```

```
arcpy.RasterToOtherFormat_conversion(Input_reclass_images, Project_Geodatabase_gdb, "TIFF")
```