Suitability Evaluation

NORTHEASTERN WASHTENAW COUNTY, MICHIGAN, USA

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SUITABILITY EVALUATION

I. Introduction

The Southeastern Michigan Council of Governments (SEMCOG) requested for a development plan maximizing land suitability and minimizing ecological impact in northeastern Washtenaw County. The 1995 land use data show that 4.67% of the plannable area is developed, 53.36% agricultural, 41.97% natural, and the remaining 30.75% unavailable for planning. The following are proposed changes from the 1995 levels: a decrease by 35% in agriculture, an increase by 30% in high-density development, and a decline by 24% in natural lands.

Our spatial analyst team created three suitability maps considering multiple criteria for each of agriculture, development, and nature using ArcGIS Model Builder. Next, we allocated the target proportions of land use after developing decision rules dependent on ArcGIS Highest Position Tool, and on a priority-based solution. This report presents the methods employed in our analysis process, and discusses the results.

TABLE 1 DATA FILES

File Name	Description	Source
neaa	Ann Arbor City Limits	Census Bureau TIGER File
neclayp	Percent clay in soils	USDA STATSGO soil database
nedem	Digital elevation model	USGS 7.5-Minute quads
nelu95	1995 land use*	SEMCOG
landuse_legend.dbf	Text descriptions of land use codes	SEMCOG MI Natural Features
nepreset	Presettlement vegetation*	Inventory
nepublic	Public land areas	Compiled by SEMCOG
neroads	Roads and Railroads*	MIRIS
nesandp	Percent sand in soils	USDA STATSGO soil database
nestream	Rivers, streams, lakes, and ponds*	MIRIS

** Legend explaining numeric codes is attached to the end of this document.*

The data for northeastern Washtenaw County originated from Dr. Daniel Brown at the School of Natural Resources and Environment, University of Michigan. We utilized all the data listed in Table 1, which are all in Arc Grid format at a 30-meter spatial resolution.

II. Methods

i. Creating Three Suitability Maps

Our team begin with producing three raster maps, where available lands are assigned suitability values (integers from 1 to 100) for development, agriculture, or nature. This section reviews how we identified and quantified the criteria, and how we built and improved our models in ArcGIS.

First, we identify and justify the criteria on land suitability (Table 2). Suitability increases as the values of positive (+) factors grow (for example, the more distant to wetlands, the more suitable for development), whereas inversely correlates to negative (-) factors (for example, the more distant to wetlands, the less necessary for preservation). Some factors exist in all the three types of land use; for example, slope is in the interest of construction in development, and soil erosion in agriculture and conservation. Such factors are not conflicting in the interests of the land use allocation; for example, greater distance to wetlands—another universal concern— is beneficial on the whole. Other factors are unique to one type of land use, such as clay content in agriculture, distance to major roads and Ann Arbor in development, and presettlement vegetation in preservation.

Second, we summarize thresholds from current literature on the effects of slope, and distance to the studied land use types (Table 2). These thresholds are later used as the parameters in the Slice Tool and Fuzzy Membership Tool. Due to limited time and resources, we set the missing thresholds based on the available research. Take agriculture for example, distance to 1995 development referred to the thresholds for

	CRITERION	*JUSTIFICATION*	*THRESHOLDS*	*SOURCES*
AGRICULTURE	Clay content (- Factor)	Soil capacity and infiltration	Good below 15%; poor above 20%	Stiegler (1998)
	Land Use in 1995 (constraint)	The existing agricultural lands		
	Slope (- Factor)	Soil erosion	Low under 3 degrees; high above 15 degrees	Manyevere, Muchaonyerwa, Mnkeni, & Laker (2016)
	Distance to 1995 development (+ Factor)	Transport of produce		
	Distance to lakes and streams (+Factor) and wetlands (+Factor)	Water quality degradation		
DEVELOPMENT	Distance to major roads (-Factor), public lands (-Factor), Ann Arbor (-Factor), and 1995 development (-Factor)	Minimize distance to urban services	500m and 2000m from cities; 300m and 1500m from major roads	Ullah & Mansourian (2016)
	Slope (-Factor)	Construction suitability	0.3-2.0 degrees best; over 25 degrees inappropriate	Liu, Zhang, Zhang & Borthwick (2014)
	Distance to lakes and streams (+Factor) and wetlands (+Factor)	Geological structure	300m and 1000m to wetlands; 100m and 500m to streams	Liu, Zhang, Zhang & Borthwick (2014)
NATURE	Slope (+Factor)	Soil erosion and plant growth		Auslander, Nevo, & Inbar (2003)
	Distance to 1995 wetlands (-Factor), and to lakes and streams (-Factor)	Water quality and vegetated buffers	A 4km impact on wetlands; Buffers: above 30m to wetlands and above 7m to streams	Meadows (2005); National Research Council (2000)
	Presettlement vegetation	Biodiversity and habitats		Bonnicksen & Stone (1982)

TABLE 2 SUITABILITY CRITERIA

distance to cities (500m and 2000m), with additional consideration of the effects of distance decay. For development, we consider thresholds for distance to 1995 development obtains the same as those for distance to Ann Arbor. However, no thresholds are set to particular criteria. Slope for nature, for example, cannot be associated with a value above which nature suitability remains the same. We assign 50, 75, and 100 to different types of presettlement vegetation according to their relative importance.

Third, we calculate the weights of the criteria in each land use group using Thomas L. Saaty's Analytical Hierarchy Process (AHP), and produce the three maps using ArcGIS Model Builder. The importance of each criterion in a group is determined through AHP matrix in Excel (Figure 1), where we input pair-wise comparison marks (integers between 1 to 9) to generate priority vectors (to be used as weights). Acceptable consistency ratio (CR) should be no greater than 0.10 to control inconsistency in personal judgement (Teknomo, 2006). The resulting priority vectors are shown in Table 3. Please refer to the reports for Assignment 1a for the detailed model buidling.

Table 3 AHP weighting results

	Criterion	Weight
Agriculture	Clay content	0.18
	Land Use in 1995 (constraint)	N/A
	Slope	0.44
	Distance to 1995 development	0.15
	Distance to lakes and	0.11
	Distance to wetlands	0.11
Development	Distance to major roads	0.21
	Distance to public lands	0.34
	Distance to Ann Arbor	0.18
	Distance to 1995 development	0.13
	Slope	0.03
	Distance to lakes and streams	0.06
	Distance to wetlands	0.05
Nature	Slope	0.08
	Distance to 1995 wetlands	0.64
	Distance to lakes and streams	0.21
	Presettlement vegetation	0.07

FIGURE 1 AHP WEIGHTING FOR NATURE CRITERIA

Extreme favors	Very Strong favors	Strongly favors	Slightly favors	Equal	Slightly favors	Strongly favors	Very Strong favors	Extreme favors
9	7	5	3	1	3	5	7	9

RECIPROCAL MATRIX						
Criteria	A	B	C	D		
A	1	0.14	0.5	1		
B	7	1	5	7	Criteria	
C	2	0.2	1	5	A	Slope
D	1	0.14285714	0.2	1	B	Distance to 1995 wetlands
Sum	11	1.48571429	6.7	14	C	Distance to lakes and streams
					D	Presettlement vegetation
NORMALIZED MATRIX					Sum	Priority Vector
	0.091	0.096	0.075	0.071	0.333	0.08
	0.636	0.673	0.746	0.500	2.556	0.64
	0.182	0.135	0.149	0.357	0.823	0.21
	0.091	0.096	0.030	0.071	0.288	0.07
Sum	1.000	1.000	1.000	1.000	4.000	1.00
	Lambda max		4.2528		n =	4
	Consistency Index (CI)		0.08			
	Consistency Ratio (CR)		0.09			

Finally, we exchange ideas on our models and improve our approaches. We choose Fuzzy Membership Tool over Slice when reclassifying the criteria and determining their scores. As for the negative factors, we realize that we can inverse the maximum and minimum values Fuzzy Membership Tool, as an alternative to the Minus Tool. Besides, we unify the reclasssification of the available lands.

ii. Making an Inclusive Decision

This section reports how we integrated the three raster into the final map. We first performed a statistical analysis and a sensitivity analysis of the three maps. Next

Table

correlation

#	STATISTICS of INDIVIDUAL LAYERS				
#	Layer	MIN	MAX	MEAN	STD
#	------------------------------------				
	1	1.0000	100.0000	45.1341	34.8479
	2	1.0000	100.0000	30.9369	39.6172
	3	1.0000	100.0000	45.1186	34.8472
#	====================================				
#	COVARIANCE MATRIX				
#	Layer	1	2	3	
#	------------------------------------				
	1	1216.76547	524.79734	825.01794	
	2	524.79734	1576.77700	579.29821	
	3	825.01794	579.29821	1210.57811	
#	====================================				
#	CORRELATION MATRIX				
#	Layer	1	2	3	
#	------------------------------------				
	1	1.00000	0.37888	0.67977	
	2	0.37888	1.00000	0.41930	
	3	0.67977	0.41930	1.00000	
#	====================================				

FIGURE 2 STATISTICS OF RASTER MAPS

Before combining the three maps, we use Band Collection Statistics to obtain the statistical information about each raster dataset (suiDev, suiAg, and suiNat). In Figure 2, Layer 1 is the suitability map for development, Layer 2 for agriculture, and Layer 3 for nature. The mean values of development and nature are almost the same (45), while the mean of agriculture is about 31. However, the variances of development (1216.8) and nature (1210.6) are less than that of agriculture (1576.8), which means the scores of cells in agriculture are general instead of clustered. Moreover, there is a strong correlation (0.68) between development and nature. After visually examining the two suitable maps, we believe that is because some rural roads are near to the streams and wetlands, where natural preservation is most necessary. In addition, the plannable areas must be confined in the existing agricultural areas, so the correlation between agriculture and development or natural preservation is low.

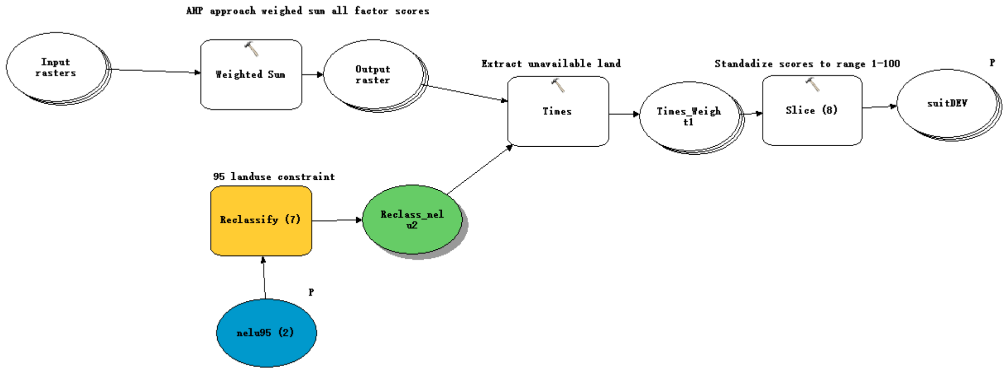


FIGURE 3 SENSITIVITY ANALYSIS

Another consideration before combining the three maps is sensitivity analysis, which examines the impacts of different criteria weighting on the final suitability map (Figure 3). We try more weighting schemes for the development raster map, and find the results change significantly with different schemes. We manage to identify an optimal weighting scheme for later steps.

Now, we use Python to integrate our previous models into the final model, which allocates land use with multiple decision rules. In order to apply the same models to different scenarios, we utilize a python script (like a package or an encapsulated class) because it can offer the interfaces for required inputs and run all the submodel processes at once. Using python script is faster than dragging separate submodels when combing each model to allocate the final land use. In order to make each submodel compatible, we set the relative path, and the intermediates in every process as managed. Then we export the three python scripts and add them to the new scripts into the toolbox. The parameters and outputs should be set as the same data type (Raster Dataset) with the submodels.

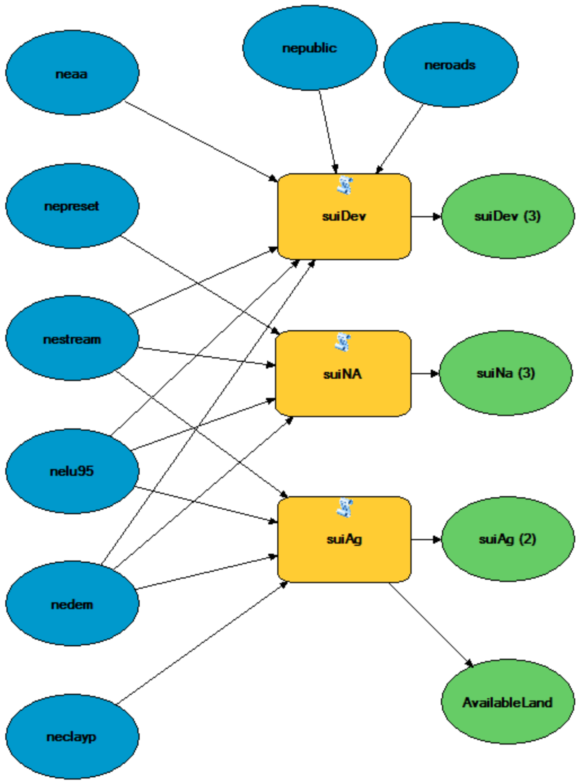


FIGURE 4 COMBINED PYTHON SCRIPTS

Figure 4 shows the python scripts in the final model, where the parameters match the raw data, and all processes in submodels are encapsulated. To avoid repeating the reclassification process, we output AvailableLand from agriculture script for later use. To save the running time in the two approaches we take, only Highest Position uses the python scripts; another solution directly use the outputs data from each submodel.

The first approach is Highest Position—a simple decision rule, but it does not constrain the users' choice. In this approach, we combine the three submodels directly, and the whole procedure is shown in Figure 5.

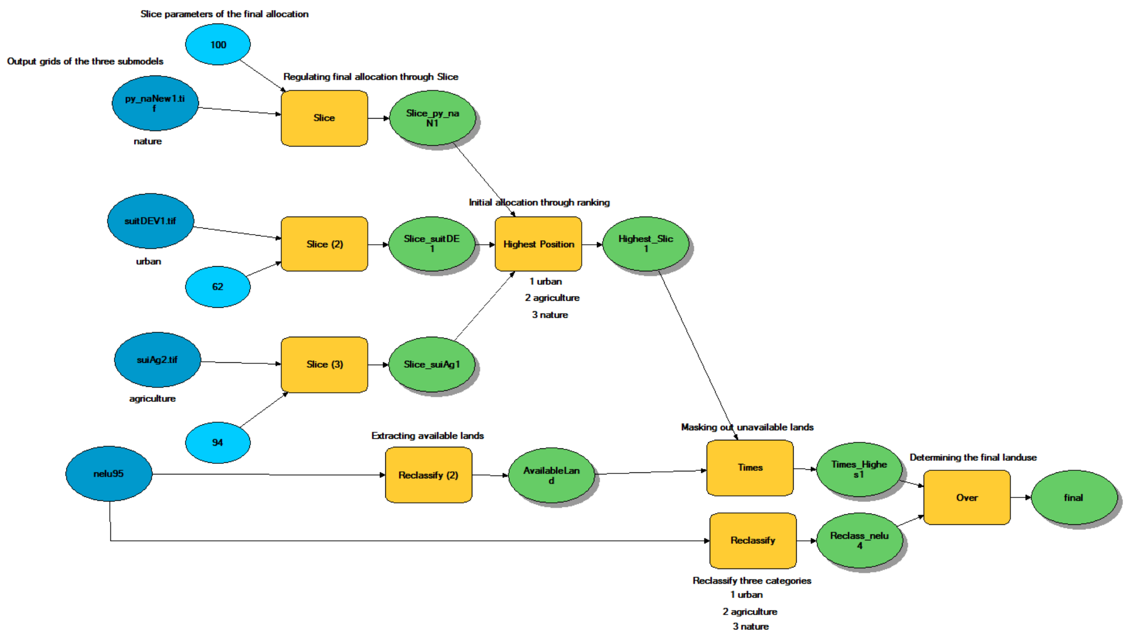
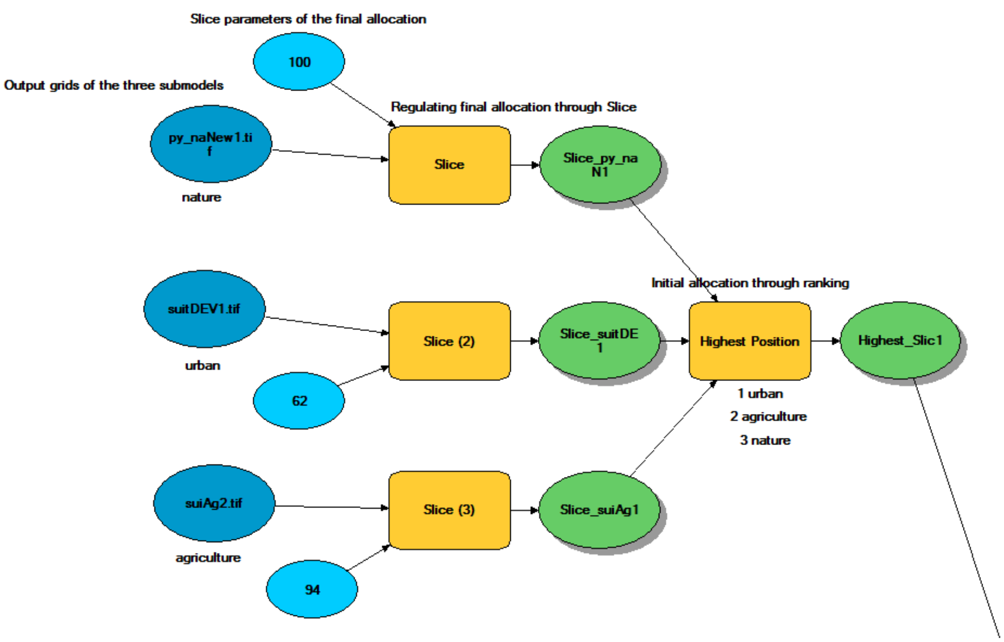


FIGURE 5 HIGHEST POSITION MODEL

In Figure 6, in the three parellell flows we slice the three output data for further regulation of the parameters. The input parameters (100) of the three Slices are the number of output cells; therefore, the sliced results are the same as the input submodels. Then we process the three outputs with the Highest Position Tool. The tool examines the parallel cell in three grids, and codes the output cell as the value that indicates in which grid the value is highest. In this instance, we set urban as value 1, agriculture as 2 and natural as 3 (based on the order set).

In the second branch (Figure 7), we firstly reclassify the nelu95 grid to acquire the grid of available lands; then we multiply the Highest Position result with available land grid with (available lands coded 1 and unavailable coded 0) using

TABLE 6 THE FIRST BRANCH



the TIMES Tool, to mask out the areas that are not available. We secondly reclassify the 1995 landuse grid to three categories (the urban land uses is coded 1, the agriculture land uses 2, and the natural 3—the same coding scheme as the allocation result). Thirdly, to acquire the final result, we use the OVER Tool to combine our allocation grid with the reclassified 1995 landuse map, and output the future landuse map.

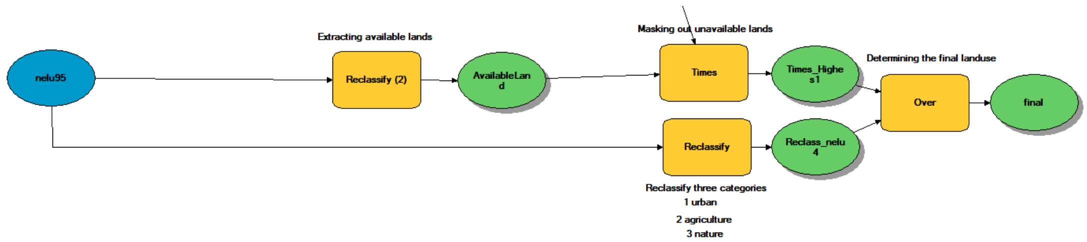


FIGURE 7 THE SECOND BRANCH

In this instance, the OVER Tool makes cell values of the first input raster (allocated highest position result) cover the cell values of the second input raster (reclassified 1995 landuse).If the cell value of the first raster is 0, the final value of this cell will be the value of this cell in the second raster. As a result, the unavailable cells coded 0 in the allocation grid are again reclassified into the three categories (1, 2 and 3) based on the original landuse records in 1995. The values of available landuse cells remain as we allocated; then we obtain the final suitability map which shows the future land uses that we expected based on our former calculation and allocation.

The target is to allocate the available land area as follows: 10% developed, 36% agriculture and 54% natural. From the attribute table of available land we know that there are 299545 available land cells; based on the given proportion, the target cell numbers in available land uses is showed in Table 4. However, the final grid also includes the cells in the unavailable area. Through the reclassification of unavailable landuse raster, we find that there are around 101504 urban development cells in unavailable landuse area, so the target cell number of urban in the final raster should be 130409. Similar to urban development cells, the final targets of other two rasters are calculated, the results are shown in the Table 4. It should be noted that agricultural lands are all in available land.

TABLE 4 TARGET OF LAND USES

	sum	1- developed	2- agriculture	3- natural
available target	289052	28905.2	104058.72	156088.08
unavaliable	136403	101504	0	34899
final target	425455	130409.2	104058.72	190987.08

Table 5 is attribute table of the initial output suitability map. The cell counts are largely different from the target, so we have to decrease the maximum value in the final Slice operation to make the result approach to the target as mentioned above. This step reallocates the weights of three land uses suitability map to approximate target. After at least 6 attempts, we finally acquire the best result with similar allocation to the target. The Slice maximum values are: 100 natural, 62 urban and 94 agriculture. The attribute table of the final allocated map is shown as Table 6.

TABLE 5 ATTRIBUTE TABLE OF INITIAL SUITABILITY MAP

(1- URBAN/DEVELOPMENT, 2- AGRICULTURE, 3- NATURAL PRESERVE)

OBJECTID *	Value	Count
1	1	197850
2	2	98361
3	3	129244

TABLE 6 ATTRIBUTE TABLE OF FINAL SUITABILITY MAP

(1- URBAN/DEVELOPMENT, 2- AGRICULTURE, 3- NATURAL PRESERVE)

OBJECTID *	Value	Count
1	1	131562
2	2	104628
3	3	189265

The second approach is the Priority-based approach. Based on SEMCOG's targets, a priority-based solution is an optimized approach to make decisions. It allocates the target amounts of each land use type reasonably. In our analysis, we attach greatest importance to development and least importance to natural preservation. All the target amounts of each land-use type are reached in this solution.

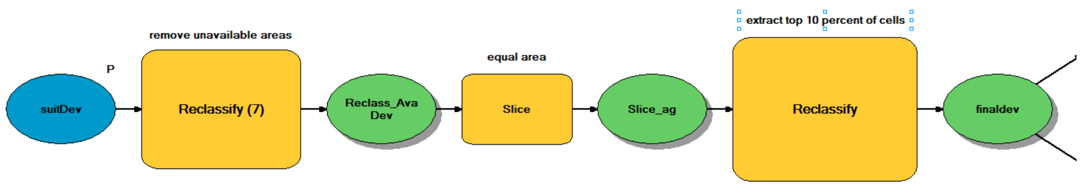


FIGURE 8 EXTRACTING DEVELOPMENT

Firstly (Figure 8), we slice the plannable areas of development with the equal area option to make the distribution more reasonable. Then the top 10 percent of cells are extracted as the final planning areas. The cells representing development are assigned to 1 and others 0.

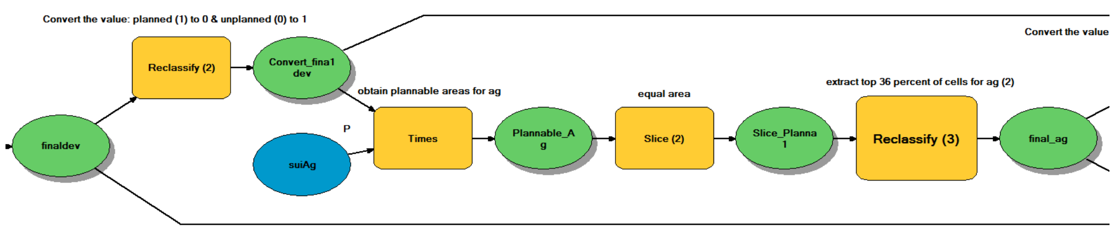


FIGURE 9 EXTRACTING AGRICULTURE

Secondly, we convert the values of the development map; the cells representing agriculture in the left unplanned areas are obtained by using TIMES (Figure 9). The plannable areas are also sliced with the same option, and then extracted the top 36 percent of cells. The cells representing agriculture are set as 2 and others 0.

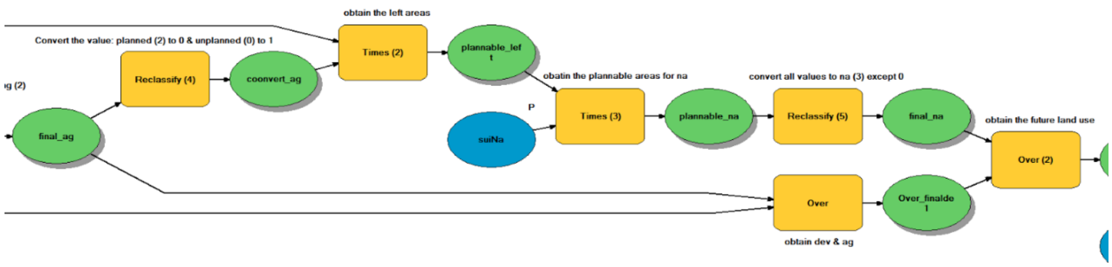


FIGURE 10 EXTRACTING NATURAL PRESERVATION

Thirdly (Figure 10), the left unplanned areas are obtained by multiplying the converted maps, which are the Cartesian product and only areas with value 1 are plannable. Then the cells representing natural preservation are assigned value 3. The future land use map is combined by using OVER twice.

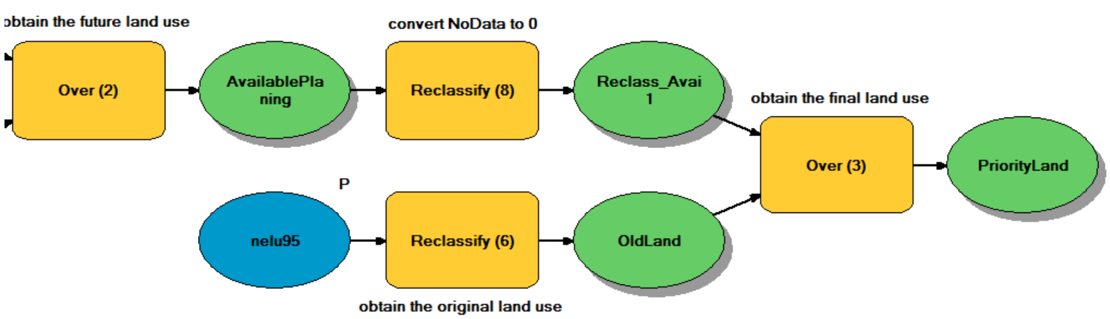


FIGURE 11 COMBINING RESULTS FROM DECISION RULES

Finally (Figure 11), the information about the old land use is incorporated into the future planning areas. We assign 0 to the cells which are no data, and then use OVER to combine the old reclassified data into the result.

FIGURE12 MODEL OF PRIORITY-BASED SOLUTION

In Figure 12, the input parameters are three suitable land use, and the raw data nelu95 is used to incorporate the original land-use information into the new land-use map.

III. Results and Discussion

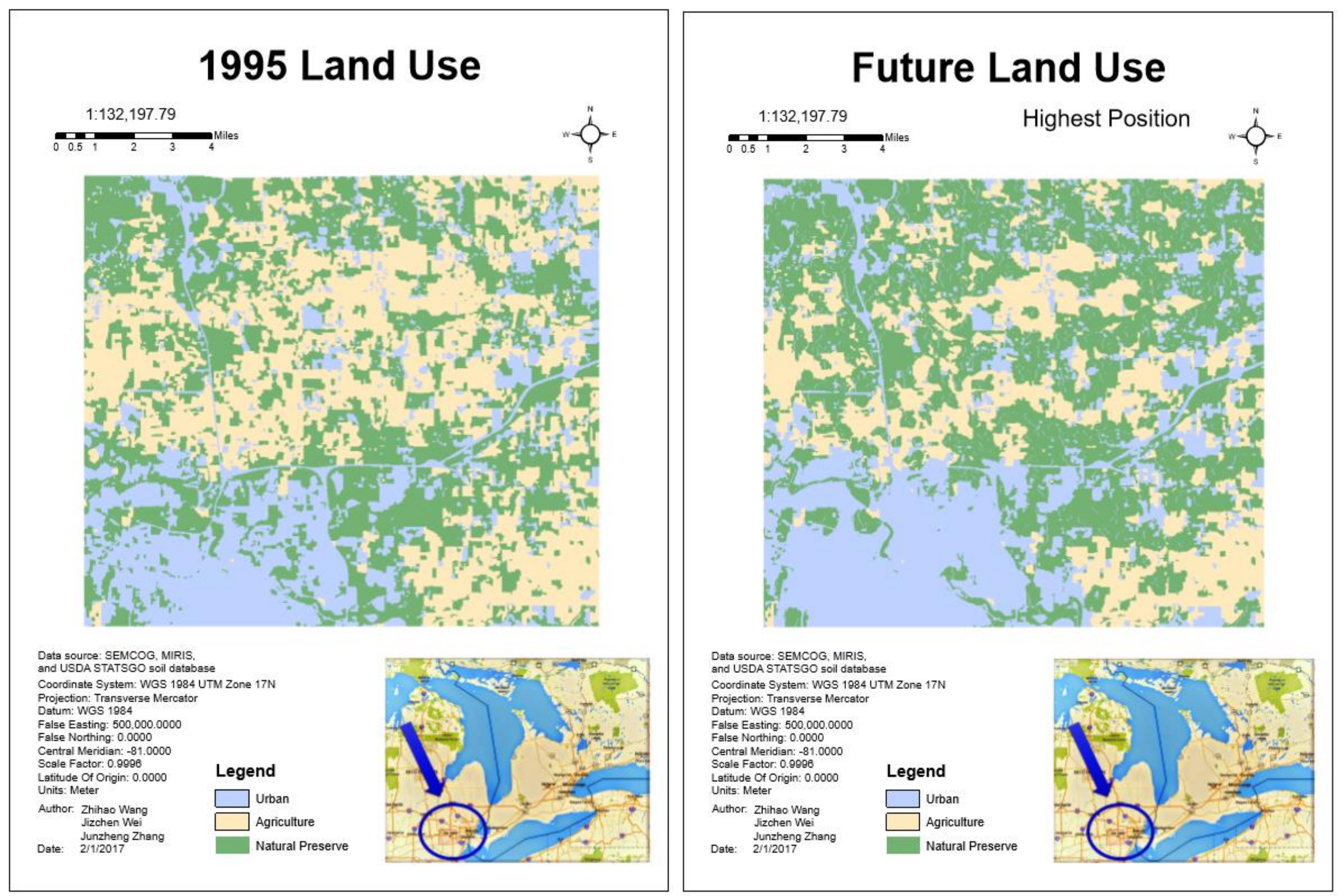


FIGURE13 1995 VS HIGHEST POSITION

This section presents the results from the two decision rules, compares the two results with the 1995 land use in response to the SEMCOG's targets, and discusses the strengths and limitations throughout each approach.

Figure 13 compares Highest Position map with 1995 land uses map. Our result meets the target percentages of future land use. The spatial patterns of the final map meet our expectation: the urban area will develop along the areas that are developed, roads and public lands; agricultural land use will decline be replaced by natural preserve lands. The values in the attribute tables of the two maps (Table 7) also confirm that development and nature will increase, while agriculture will decline.

OBJECTID *	Count
1	104991
2	159910
3	167687

OBJECTID *	Value	Count
1	1	131562
2	2	104628
3	3	189265

TABLE 7 COMPARISON OF 1995 LAND USES MAP AND FUTURE LAND USES MAP -- ATTRIBUTE TABLES (1- URBAN/DEVELOPMENT, 2- AGRICULTURE, 3- NATURAL PRESERVE)

The limitation of Highest Position is significant. Firstly, this approach determines the final land use of a cell by assigning the highest value to the cell. It does not consider the situation of a location, nor assigns weights to different land use suitability. From Figure 13 (right) we are surprised to see many isolated strips in urban land use, due to the limitation mentioned above or the impact of distance to major roads. Secondly, the parameter in the Slice Tool is set subjectively and baselessly, and we need to experiment with the parameters in numerous attempts before producing the optimal outcome. Even if the result meet our target, the parameters may not make any practical sense.

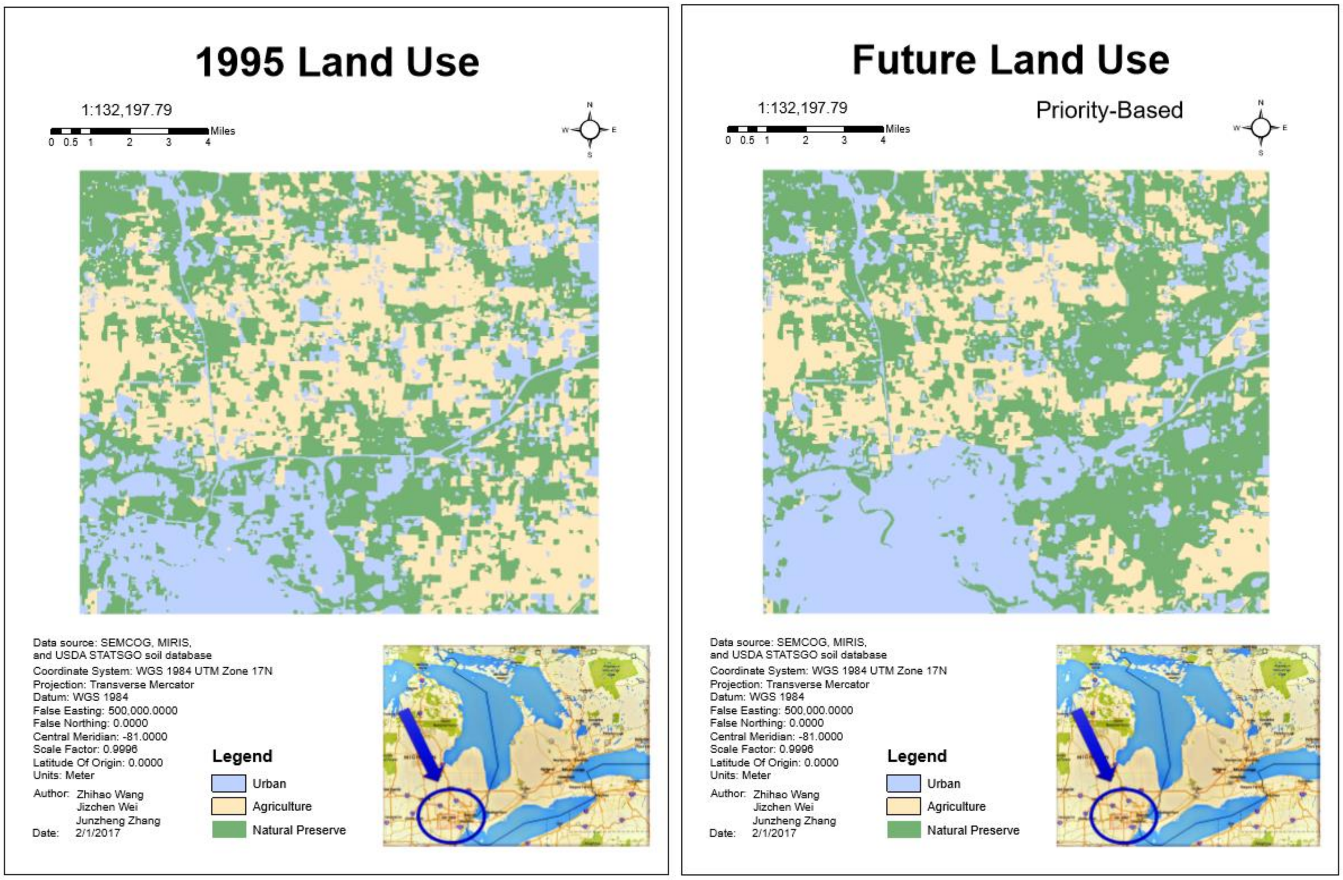


FIGURE1 4 1995 VS PRIORITY-BASED

By contrast, Priority-based solution is better than Highest Position approach. Because of the spatial autocorrelation, the cells with the same land-use type are often clustered, and their suitability scores are approximately equal within small regions. Therefore, the priority-based approach can efficiently extract the homogeneous cells, most of which are also interconnected. The result—the future land use plan—shows blurred boundaries between different land use types. Compared with the 1995 land use (Figure 14), the number of isolated cells is reduced, so the result is more reasonable. Moreover, the initial target amount of each land-use type is accomplished without repetitive work. This decision rule is indeed better than the simple Highest Position approach.

Table

PriorityLand

VAT_PriorityLand.OBJECTID *	VAT_PriorityLand.Value	Future_landuse	Original_Landuse
1	1	129745	104991
2	2	109610	159910
3	3	186101	167687

FIGURE 15 STATISTICAL COMPARION OF LAND USE

Figure 15 compares different land use types in 1995 and the future map from a statistical perspective. The object with value 1 represents development, and it slightly increases from original 104991 to 129745. The object with value 2 represents agriculture dramatically decreasing from 159910 to 109610. The last one with value 3 represents natural preservation slightly increasing from 167587 to 186101. The statistics prove that the target is accomplished.

In addition, we would remind SEMCOG of other pitfalls in our spatial analysis. Firstly, the data sets are at a spatial resolution of 30 m, and each cell only represents one type of land use. It implies great uncertainties in the cells on the boundaries between two land types in the real world. In order to restrict this effect, higher resolution data are welcome. Secondly, spatial autocorrelation is especially important when doing spatial analysis (Caparros, 2015). The criteria and the weights calculated using AHP are dependent and subjective to some extent. Besides, the real world involves many interacting factors (e.g. second order variation), and many specific scenarios. More criteria should be considered to perform the model.

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