Interactions between urban development and spatial distributions of specialty and commodity crops in Southeast Michigan, 1992-2001

Karly A. P. Wentzloff

A thesis submitted as partial fulfillment of
the requirements for the degree of
Master of Science
Environmental Informatics

School of Natural Resources and Environment
University of Michigan
October, 2010

Thesis Committee:
Professor Daniel G. Brown
Associate Professor William S. Currie

Acknowledgements

I owe many debts to those who helped with the completion of this project.

I would like to thank my advisor Dr. Daniel Brown for his continued support, feedback and patience during the completion of this project. There are few people that know so much, and even fewer who can teach it to others. I must also stress that my master's degree was only possible because of the financial support that Professor Brown and the School of Natural Resources and Environment provided me. Additionally, I would like to thank Dr. William Currie for his support and feedback on this project. Many thanks to Shannon Brines for his technical help and ongoing encouragement. I would also like to thank my ESA lab mates, namely Kyle Kwaiser.

I also could not have made it this far without the lifelong support of my family and friends. I must thank my husband, Tim, for his patience and occasional tough love. I would also like to thank my parents, David and Kathy Pence, for providing me with a world of opportunity as I was growing up.

Table of Contents

List of Figures

List of Tables

Abstract

Agriculture is being displaced by development throughout the United States. Because agricultural activities vary among crop types and farm operations, and because agricultural competes for space with urban land uses at the urban-rural fringe, it is important that we understand the spatial dynamics of agriculture in this area, where conversion to development is most acute. In particular specialized crops, such as fruits and vegetables, are important because they promote biodiversity and provide more diverse food products than commodity crops. I developed a model to test the idea, from the von Thünen model of agricultural land rents, that specialty crops are more likely to be located lost the process of urbanization than commodity crops. Because historical data on the locations of farms by crop type do not exist at a resolution finer than counties, I used dasymetric mapping to estimate locations of specialized crops in 1992 and then analyze their loss by 2001. The study area for this analysis was the ten-county region of Southeast Michigan. A regression analysis showed that specialized crops were significantly more likely to be located where there was less development and more agriculture in an area, higher population density and nearer distance to water. These relationships were then used to create a suitability surface for specialty agriculture in 1992. Specialized and Commodity designations, for which land areas were available at the county level, were then allocated to agricultural areas identified in a land-cover data product, and those that were lost between 1992 and 2001 were identified. The tabulated results showed that the entire region experienced a higher rate of loss specialized crops compared with commodity crops, with the loss happening more rapidly in the urban-rural fringe than in exurban areas. This application of dasymetric mapping could be used as a model to investigate agricultural dynamics of other urban areas.

1. Introduction

In 2007 just over 40% of the land area in the United States was farmland, according to the United States Census of Agriculture (U.S. Department of Agriculture 2007). With agriculture occupying such a large percentage of area, it is essential that we understand its dynamics, including not only nominal trends in agriculture such as farm size, plantings and yields, but also where these changes are happening on the landscape. Agriculture is undergoing changes, notably an increase in the area planted in commodity crops (from 126 million acres to 140 million acres between 1992 and 2002) and the availability of processed foods, while decreasing the area planted in specialized crops (from 3.8 million acres to 3.7 million acres in the 1990s), namely fruits and vegetables (Fields, 2004; USDA, 2002).

My aims with this project were to analyze agricultural land dynamics in Southeastern Michigan to address two primary objectives. My first aim was to better understand the past and present diversity of agriculture in the region, and identify locations where there is change in the agricultural diversity of the landscape. For this analysis agricultural diversity is assumed to be increased by the presence of specialty crops. These patterns can be analyzed to identify areas where diversity is suppressed by agriculture, which might be ideal for agricultural conservation practices or habitat restoration (Rayburn and Schulte, 2009). I pursued this objective with dasymetric mapping of specialized and commodity, or non-specialized, crops. My second aim was to examine the dynamics of specialty and commodity crops across the landscape in comparison to relevant spatial theories and models, notably the von Thünen model of agricultural land rents. A key research question here is, as agricultural land is lost to development, is there a disparity between the proportion of commodity and specialty crops that are being lost? If there are more specialty crops near the urban-rural fringe, as the von Thünen model would suggest, then we might expect to be losing specialty crops at a higher rate in the urban-rural fringe than in the exurban regions.

It is important that this analysis look not only at the land cover in the suburban and exurban regions, but also crop types. In this case study, the data on crop types comes from the Cropland Data Layer (CDL), which identifies the type of crops grown within the agricultural land. Here, I categorized crops as commodity crops and specialized crops. Commodity crops, referred to in the analysis as non-specialized, are row crops that are often processed after harvest to produce shelf-stable goods. Conversely, there are specialized crops, which can also be row crops; however they are often produced on a smaller scale and can be sold directly as sustenance (Fields, 2004).

Specialized crops are a component of agriculture that needs to be understood for two reasons. First, they provide nutritious foods that do not need to be highly processed (USDA, 2010, Wallinga, 2010). This is important when considering that our current farming system where commodity crops are incentivized. Therefore markets are replete with inexpensive processed foods. Meanwhile, policy makers and farmers have not aimed to produce more and lower the cost of fresh fruits and vegetables (Fields, 2004; Kimmons et. al., 2009, Wallinga, 2010). Commodity crops are often processed into less healthful foods including sweeteners and hydrogenated fats (Fields, 2004). The sweeteners refined from commodity crops have even been linked to the increase in type-2 diabetes and the obesity epidemic (Gross et. al., 2004). Identifying a greater loss of specialty crops could provide support for changes in agricultural legislation that currently subsidizes commodity production (Fields, 2004). Secondly, specialty crops only account for 0.4% of the agriculture in Southeastern Michigan, but research has shown that diversified cropping systems help promote sustainability and increase biodiversity on the landscape (Hendrickson et.al, 2008, Perfecto and Vandermeer, 2010). Commodity crops are often grown as large monocultures, decreasing the ecological quality of an area and making crops susceptible to pests and disease (Fields, 2004). Knowing where this biodiversity is, or has been, will be an important tool in allocation of land for agricultural and habitat conservation and restoration (Rayburn and Schulte, 2009; Freemark et.al, 2002). If we can understand the spatial dynamics of specialized crops, then we can provide insight for policy and planning.

This work is premised on the idea that not all agricultural land serves the same functions, economically or ecologically, an idea that is difficult to investigate spatially, because of limited data availability. Since little spatial data exists identifying crop types, used a spatial estimation procedure known as dasymetric mapping (Holloway et. al, 1999). Dasymetric mapping uses identified spatial relationships between a phenomenon and related variables to generate fine-scale estimates of where that phenomenon occurs based on aggregate (e.g., county-level) information about how much is there. This technique combines historical high resolution land-cover data with county-level information on crop mix to identify where specialized or commodity crops are located. Increasing spatial resolution in this way is an important technique, because it allows spatial patterns to be analyzed over time, even if there are gaps in available data. This will help us to understand the past conditions and drivers of change to use as a foundation for future planning (Rayburn and Schulte, 2009).

In order to address these questions, I first identified the statistical relationships between specialty cropland, identified in the USDA Cropland Data Layer (CDL; USDA, 2001), and spatial factors, such as distance from roads and rivers, population, soils or slope. Second, in order to analyze agricultural land dynamics, I used these relationships to estimate likelihoods that crop lands, identified in 1992 and 2001 National Land Cover Data (NLCD; Vogelmann et. al., 2001; Homer et. al. 2004; Fry et. al., 2009), were in specialty crops. Using Census of Agriculture data (US Census of Agriculture, 1992, 1997, 2002), I then allocated the appropriate amount of cropland area in each county to specialty crops based on the suitability ratings. Finally, I examined where the loss of specialty cropland occurred across the region and the dynamics of that loss.

Agriculture is affected by climate, soil, population and economic and technological change (Waisanen and Bliss, 2002). The agricultural dynamics resulting from each of these factors can be examined over time and space, but availability of data limits our ability to do so (Petit, 2009). During the last half century, the United States has seen exceptional expansion of suburban and exurban areas and at the same time loss of agriculture due to conversion or abandonment (Theobald, 2001; Hansen and Brown, 2005). These significant changes in land use have negative implications for the economic and ecological functioning of the affected areas, and identifying these implications can help identify areas in need of habitat restoration (Rayburn and Schulte, 2009; Brown et. al., 2005). There is some research on the land-use dynamics at the urban-rural interface, but there is little understanding about the consequences for the agricultural system (Theobald, 2001). It is therefore important that we understand agricultural land-use change at the urban-rural fringe and in the surrounding exurban developments (Theobald, 2001 and 2005).

Residential growth during that latter part of the 20th century has been concentrated primarily around urban centers. Southeastern Michigan experienced several hotspots of housing growth that primarily displaced agricultural land, and Chicago, Indianapolis and Minneapolis- St. Paul experienced similar patterns of development (Lepczyk et. al. 2007). Developing a method to understand these changes in Southeast Michigan could provide a model for investigating other metropolitan areas.

In the early 19th century, the von Thünen model of agricultural land rents suggested that when transportation costs are a primary determinant in the pattern of agricultural land use, that agriculture becomes more intense (i.e. specialized) closer to urban centers, or markets (Sinclair, 1967). It has been suggested that the increasing ease of transportation changed the patterning of agricultural land, and that land rent is a clearer determinant of where specialized crops are located (Sinclair, 1967). If either of these models hold true it would be assumed that the spatial distribution of specialized crops relates to distance from urban centers. An alternative to this scenario would be a random distribution of specialized and non-specialized agriculture on the landscape. Looking at the specialized and non-specialized crops on the landscape will give us insight into which model holds true for the region, and offer some insight into the present application of the von Thünen model.

2. Study Region

I focused on the ten-county region of southeast Michigan, including Genesee, Lapeer, Lenawee, Livingston, Macomb, Monroe, Oakland, St. Clair, Washtenaw and Wayne counties (Figure 1). The region is ideal for examining the dynamics of crop loss at the urban-rural fringe for two reasons. First, land cover in the region is primarily developed or agricultural (Table 1), so expansion of developed land at the urban-rural fringe has mostly displaced agricultural land. In fact, the NLCD change product (Fry et. al. 2009) shows that 60% of agriculture lost between 1992 and 2001 was converted to urban land (Table 2). Second, the area has exhibited a large suburban expansion beginning in the 1970's and continuing through the turn of the century. The expansion occurred primarily around Detroit (SEMCOG, 2002). Ann Arbor and Flint also experienced exurban development as well as transportation corridors in areas such as Livingston County (SEMCOG, 2001).

Michigan is also the second most agriculturally diverse state, behind California, commercially growing over 120 different crops (Michigan Department of Agriculture, 2009). This is important for this analysis, because one would expect this diversity to be reflected in remotely sensed crop data sets, such as the CDL. Therefore, the comparison of specialized and commodity crops is possible, whereas it may not be possible in other locations, such as Iowa, where the agricultural system is less diverse overall.

3 Methods

The approach for this analysis was to first separate the crops identified by the National Agricultural Statistics Service's Cropland Data Layer (CDL) into commodity and specialized crops. This was done by identifying the crop types from the classification table and creating a raster data set consisting of two categories, commodity and specialized. I then mapped several variables that I hypothesized would predict the locations of specialty crops, compared to commodity crops (Figure 3-10). These maps were then used as independent variables in a regression analysis. The regression model was evaluated for the significance and direction of the relationship between each predictor variable and crop types. Then, the regression model was used to create a raster surface, based on maps of the predictor variables, describing the probability that an agricultural land area would be in specialized crop in 1992. The agricultural cells that had the highest probability of being specialty crops were then allocated to that type in proportions consistent with specialty crop percentages reported in the agricultural census data at the county level. For instance, if a county has nine percent specialized cropland in 1992, the highest nine percent of cells identified as agricultural in the NLCD layer were allocated as specialized cropland for that time.

I then identified areas where agriculture was lost between 1992 and 2001 from the NLCD retrofit change product (Fry et. al, 2008). Those areas that were lost were compared to the dasymetrically mapped estimates of specialized and non-specialized cropland in 1992 to identify if the lost cropland was specialized or non-specialized cropland. I then looked at what proportion of the loss was specialized versus commodity in the whole region, in the urban rural fringe and the exurban areas. The null hypothesis was that there was no difference between the percentages of cropland loss in specialty crops in the urban-rural fringe versus the exurban areas.

3.1 Data and Variable Creation

The United States Census of Agriculture has provided data on United States agricultural lands since its inception in 1840, with a more robust examination of agriculture after its current configuration came into existence in 1997 (Craig, 2010). It was at this time the Census of Agriculture moved to the United States Department of Agriculture's (USDA) newly created National Agricultural Statistics Service (NASS) from the United States Census Bureau. These data allow for an examination of trends, such as annual production of soybeans by county, however, because of the way in which the data are reported, it does not allow for insight into the spatial dynamics of these changes at resolutions finer than the county level.

To understand finer-scale spatial dynamics we need spatially explicit data such as aerial photographs or satellite images. For the last two decades the National Land Cover Dataset (NLCD) has provided land-cover data for the conterminous United States. These remotely sensed images help us understand where land covers, including agriculture, are on the landscape. This is useful to analyze the spatial dynamics of agriculture, but it is limited by its ability to only identify the presence or absence of agriculture, and not different types of agriculture.

This limitation was addressed in 1997, when the Cropland Data Layer (CDL) was piloted in Arkansas and North Dakota. The CDL is a comprehensive dataset that is based on the NLCD land-cover types, but utilizes the spectral response curves of different crop types to distinguish between them in the data set. This information has been and will be useful in analyzing the spatial dynamics of crop types, however cannot be used to investigate historic spatial-temporal trends in agriculture. Therefore to fully utilize these data a historic spatial data set with more agricultural information needs to be created.

Data were gathered from the Michigan Geographic Data Library (MiGDL, Michigan Department of Technology, Management and Budget, 2010), NLCD (Vogelmann et. al., 2001; Homer et. al. 2004; Fry et. al., 2009), CDL (U.S. Department of Agriculture, 2001) and USGS SSURGO (Soil Survey Staff, 2000). All data were projected into World Geodetic System UTM Zone 16 North with a 56 meter cell size to match the CDL. There were eight predictor variables extracted from the raw data (Table 4) with five static variables and three that changed between the early 1990s and 2000.

The variables, described below, were all based on a hypothesized relationship that they had with specialized agriculture. The null hypothesis for each variable was that no significant difference between the variables and the presence of specialized cropland exists. The hypotheses were tested using a generalized linear model, described in section 3.3.

The predictor variables *developed in vicinity* (Figure 3) and *agriculture in vicinity* (Figure 4) were calculated using focal statistics to determine how many cells within 280 meters of each location were developed or agricultural land, respectively. This distance, equal to five cells, was chosen to identify the area in the immediate vicinity of the farm. By looking at the landscape immediately surrounding each cell, these variables can be used to identify the relationship between the surrounding land cover and the type of agriculture being grown in a particular location. I hypothesized that there was a different amount of developed and agriculture land cover in the vicinity of specialized and commodity agriculture. The *population density* (Figure 5) of a cell was calculated as the number of people in the census block group in which that cell fell, divided by the area of that block group in square kilometers. I used population density to test the hypothesis that there were significantly different densities of people around specialized crops versus commodity crops. If the von Thünen model holds true, specialty crops would consistently be located in areas of denser population.

I used a digital elevation model to calculate *slope* in degrees (Figure 6). The *soil* variable is based on the drainage attribute from the SSURGO soils data. It is a raster file with values from 1-5 depending on the drainage capacity of the soil (Figure 7); very poorly drained is indicated by a 1, and excessively drained by a 5 (Soil Survey Staff, 2010). I hypothesized that specialty crops will be allocated to better land, i.e., those with lower slopes and better drainage.

Indicators based on the *distance* of a given cell of agriculture to *water* (Figure 8), *roads* (Figure 9) and *railways* (Figure 10) are based on the hypothesis that the land with better access to water and transportation would be more ideal for growing specialty crops.

3.2 Sample Design and Data Extraction

A stratified systematic sampling was used to select an even number of points for each category in the dependent variable, i.e., specialized (total n = 5578) and non-specialized (n = 139,442) crops. This approach creates a more manageable dataset and a model that equally addresses both presence and absence of specialty crops. Using a general rule of thumb that a regression should have a number of sample points (*n*) >= *30v*, where *v* is the number of predictor variables, I set a target sample size of 240 data points. To achieve this quantity of sample points the specialized and non-specialized data were resampled to a coarser resolution, thus ensuring a systematic sample of different densities within each type. Using trial and error of multiples of 56 m, sample spacings of 280 m and 4,200 m were chosen to sample specialized and non-specialized crops, respectively, producing 240 specialized cells and 244 non-specialized cells.

The ArcGIS sample tool was used to sample the independent variable values at each selected sample point location. The resulting table contained the values of the dependent and independent variables at each sample location.

3.3 Determining Statistical Relationships using a GLM

A generalized linear model (GLM) was used to analyze the relationships between the presence of specialized agriculture and the predictor variables. This approach allowed the inclusion of predictor variables with categorical or continuous values. Because the response variable was binary, I used the GLM with a binomial distribution and the logistic link function. The reference category in the response variable is 0, which is non-specialized crop, so 1 refers to specialized crops.

I evaluated the GLM results by examining the direction and strength of relationship between each of the independent variables and the dependent variable, using the coefficient and associated p-value, respectively. The overall fit and predictive ability of the model were evaluated using the likelihood chi-square ratio and associated p-value, and calculating a pseudo-R2 value. This provided information about how well the model could predict the status of an agricultural area as specialty vs. non-specialty crops.

3.4 Dasymetric Mapping and Allocation

After identifying the relationship between specialized cropland and the independent variables, the likelihood that a given cell of cropland was in specialized crops was calculated and then used to allocate agricultural cells (see ArcGIS workflow in Figure 11). Having identified the relationship between specialty cropland and the significant variables ($p < 0.1$), I created a suitability surface based on the values of those variables in 1992.

I then multiplied each county's suitability by a binary mask of agriculture, agriculture being 1, to identify the suitability for only cells that were known to be agriculture. The suitability was then sliced into 1,000 equal-area classes, which provides a ranking of cells by suitability level. These classes were then reclassified as specialized or commodity crops according to the percent of agriculture reported as specialized for each county in the 1992 Agricultural Census (Table 6). For example, Washtenaw County reported 1.61% of agriculture as specialized, so the 16 suitability levels with the highest suitability were reclassified as specialized (Figure 16).

Once the cells were allocated as specialized and commodity (Figure 17) for the 1992 time frame, the agriculture lost from 1992 to 2001 was identified by creating a mask of agricultural areas lost to development with data from the NLCD Change Product (Fry et. al., 2008). With the areas of specialized and commodity crops lost to development identified (Figure 18); I then needed to distinguish the loss that occurred in the urban-rural fringe from those that happened in exurban areas. Using a distance grid I reclassified all areas within 1.5 kilometers of development as the urban-rural fringe and all areas beyond that as exurban (Figure 19). This value was chosen visually because it gave the best proportion of urban-rural fringe and exurban regions, any greater distance would encompass too great of the region as the urban-rural fringe. The specialized and non-specialized crop lost within the urban-rural and exurban regions were then identified and tabulated as results.

4. Results

4.1 Model results and variable relationships

The likelihood chi-square for the generalized linear model returned a p-value of <0.001 with 10 degrees of freedom. This indicates that the model outperforms a random assignment of cells to specialized and non-specialized. Also, the goodness of fit statistics were notable, the deviance and Pearson Chi-Square divided by the degrees of freedom were 1.336 and 1.015 respectively. With values over and near one it shows that fitting the model is reasonable. A contingency table shows that the model can predict specialized cropland better than chance, with a kappa of .149 (Table 10). Additionally a pseudo-R2 vaue of .048 was calculated. This suggests that the model describes little of the variance within the model.

Using p<0.1 as the threshold for significance of factors, the significant factors are *developed in vicinity* (Figure 12), *agriculture in vicinity* (Figure 13), *distance to water* (Figure 14), and *population density* (Figure 15). *Developed in vicinity* and *distance to water* were inversely related to the presence of specialized agriculture, while *agriculture in vicinity* and *population density* were positively related (Table 5). The coefficients for these variables were then used in the following equation to calculate the likelihood of cropland being specialized:

*Exp ((-0.480 - 0.031 * [devarea1992] + 0.016 * [agriarea1992] - 0.241 * [hydrodiv1000] + 0.003 * [popdenraster])) / (1 + Exp ((-0.480 - 0.031 * [devarea1992] + 0.016 * [agriarea1992] - 0.241* [hydrodiv1000] + 0.003 * [popdenraster])))*

4.2 Agricultural Loss in the Urban-Rural Fringe

The region experienced a greater area (Table 8) and higher rate of specialized crop loss, at 4.69 percent between 1992 and 2001, than commodity crop loss, at 1.06 percent (Table 9). There were also a greater proportion of specialized crops lost than commodity crops in both the urban-rural fringe and the exurban region. Additionally, every county showed a higher proportion of specialized crop lost in the urban-rural fringe than in the exurban region, except Wayne County.

5. Discussion

The GLM suggests a positive relationship between population density and presence of specialized agriculture. Therefore, by allocating specialty crops to their most likely locations within each of the counties in the study region on the basis of that model, I estimated that there was more specialized agriculture in the urban-rural fringe in 1992, 7,006 square kilometers, than in the exurban region, with 963 square kilometers (Table 7). This is consistent with the Von Thünen model, which suggests that specialized crops are located closer to the markets.

Based on the model results, I was able to that the region lost proportionally more specialized agriculture than commodity agriculture between 1992 and 2001. The rate of specialty crop loss was the highest in the urban-rural fringe, where the rate of urban development was also highest.

The only county where the loss of specialty crops was higher in the exurban region than in the urban-rural fringe was Wayne County, probably due to the fact that it did not have much area defined as exurban.

Knowing that specialty cropland is being lost at a greater rate is important for several reasons. First, agricultural diversity is important to the economic sustainability of an agricultural area.

Additionally, with declining specialty crops there is a decrease in landscape biodiversity. Because of the benefits that specialty crops can have on biodiversity, health and the economy, it is important to understand this loss and recognize the need to protect existing specialty cropland and establish additional specialty cropland through government programs and incentives.

Though it is impossible to attribute causation on the basis of this analysis, the higher rate of specialty crop loss may result from current agriculture and land-use policies that support an increase in commodity crops at the expense of specialty cropland. Because there is more specialty crop being lost in the urban-rural fringe, and it is being lost to urbanization, we may conclude that urbanization is an important contributor to specialty crop loss.

This analysis combines spatial data analysis with dasymetric mapping to investigate spatial trends on a finer scale than the original data would allow. The method could provide a framework for investigations into other land-use studies. Now that data gathering is more robust, it could be possible to utilize dasymetric mapping to recognize trends, in agriculture or other land uses, which we would otherwise have to wait for future data collection. It would be possible to apply a similar method to understand other land use dynamics on a finer scale than previously available.

This method could help identify how the regional food system has evolved over time. Better information about agricultural land dynamics will help identify if specialized crops are becoming more isolated, closer or further from the major markets, and even identify possible spatial scenarios that lead to rapid loss of specialized crops.

These results are limited by the model itself. The model indicators were very low. The predictive capability was low, as indicated by the kappa of .149. Additionally, the model had little power in explaining variance, given the low pseudo-R2 of .048. Therefore the predictive power of the model itself is weak.

The model includes development in vicinity and population density as spatial predictors of where specialized crops are located within a county. The model reports that specialized agriculture is negatively related to development in vicinity and positively related to population density (Table 5). Therefore when factoring this into the suitability index we created a preferential effect for specialized agriculture to be in areas settled at higher densities, but with lower amounts of development nearby. To the degree that these two variables are also related to urbanization, there is some potential for over-estimation of the loss of specialty agriculture. Therefore, the relationship between specialty agriculture and development is important in both allocating specialized crops, based on where they are found in 2001, and in determining the effect of development on them. It is precisely because specialized crops occur in higher population density areas that they are most susceptible to conversion. This model demonstrates that relationship, but also relies on estimates of locations of specialty crops in 1992 rather than actual observations. So, the general pattern is realistic, but the actual quantitative results are difficult to confirm.

The model also has errors that extend from the use of the data. With this analysis the NLCD, CDL and Agricultural Census are all used to describe agriculture. There is, however, great disparity with the amount of agriculture that these data report. Most notably is the difference between the USDA Agricultural Census and the NLCD, where for some counties the NLCD reports 2-5 times as much agricultural area as the agricultural census (Table 6). This is a poignant reminder that all data are created with some uncertainty, and it is difficult to know whether these additional areas of cropland in NLCD, which I allocated to specialized or non-specialized crops, are in locations that might bias the analysis of relative amounts of loss.

With this analysis, another point of consideration is that specialized and commodity agricultures were chosen in a relatively ad hoc manner. More research could be done to identify how different crops are planted (Table 3). For example, sugar beets are considered a specialized crop; however they are planted in large plantings and refined for their sugar and could be classified as a commodity crop. They were not chosen as such, however, because they are not one of the commonly identified commodity crops. Similarly, some of the grains that were included as commodity crops could be classified alternatively as specialized, because they are processed and contribute to a whole grain diet.

The model could be considered more reliable if two further analyses were complete. First, the analysis could be repeated without the developed-in-vicinity variable to see if the results are replicable. Second, additional information about the predictive accuracy of should be obtained in any future analysis. For this purpose, the ability of the model to predict presence of specialty crops with the data set used to build the model could be described using the receiver operating characteristics (ROC). More tellingly, the model could be applied to an alternate time frame, possibly when future data are released, to validate the model. These future directions would help refine the dasymetric mapping process to gain further insight into agricultural dynamics.

Figure 1- Ten county study region of Southeast Michigan (Michigan 2010)

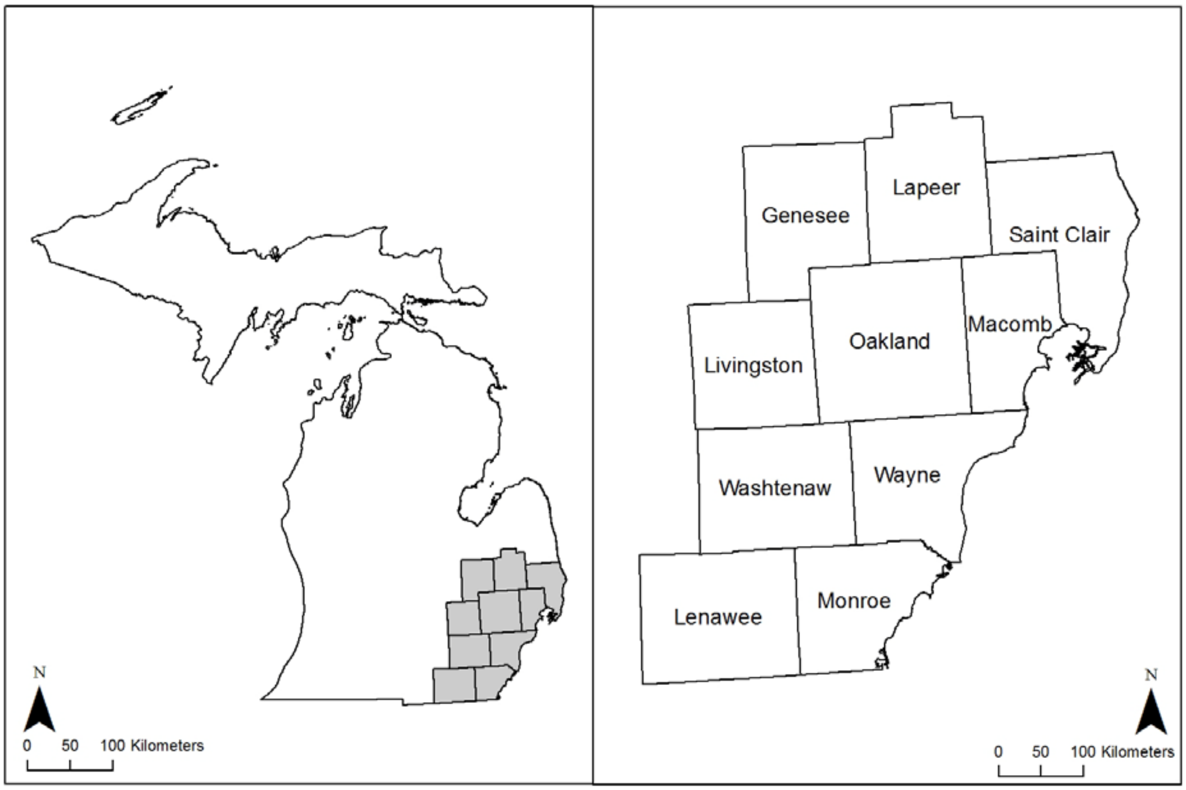

Figure 2- Snapshot of ArcGIS Model Builder flow of variable compilation, sample design and extraction used in data creation

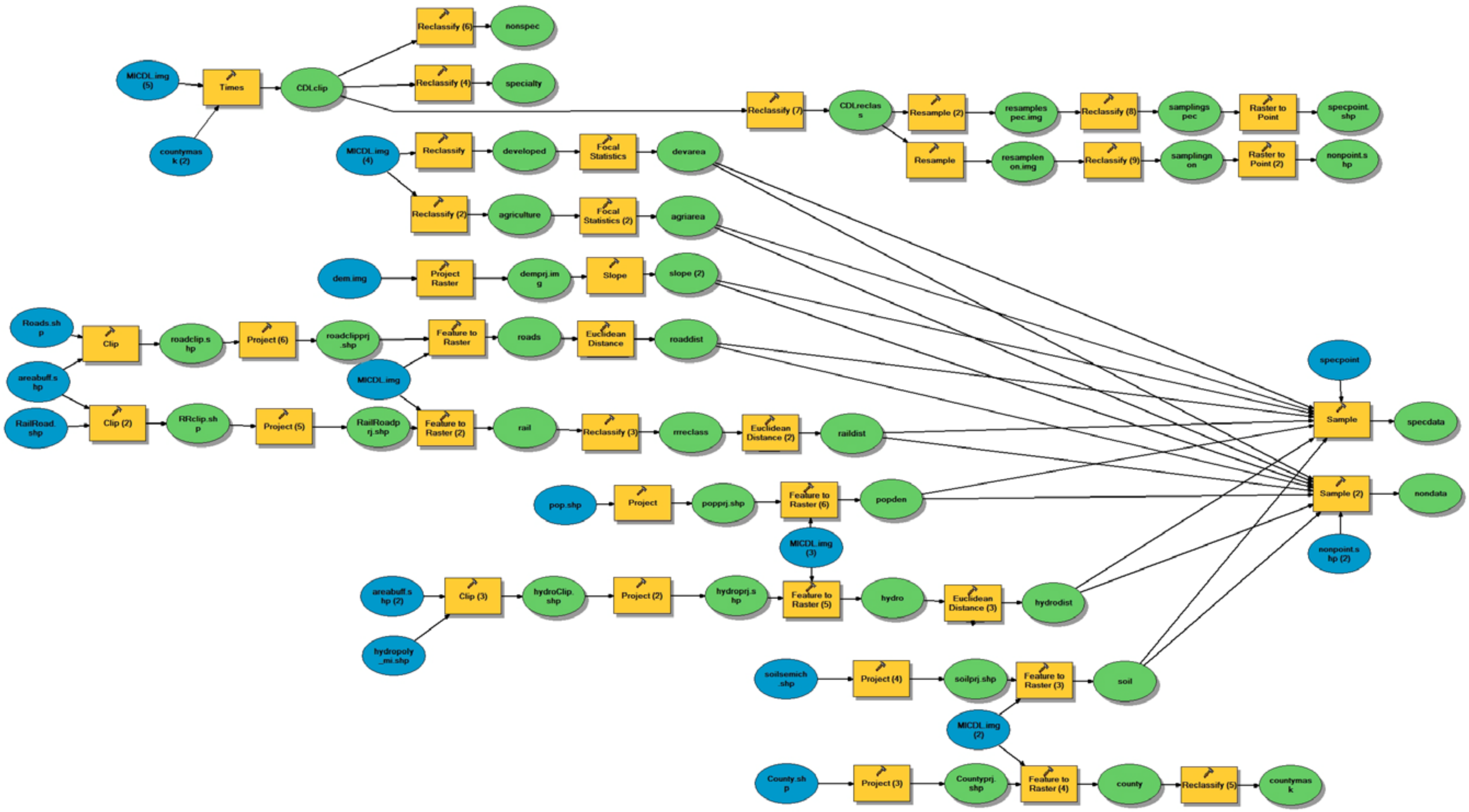

Figure 3- Developed in vicinity, 2001 (NLCD)

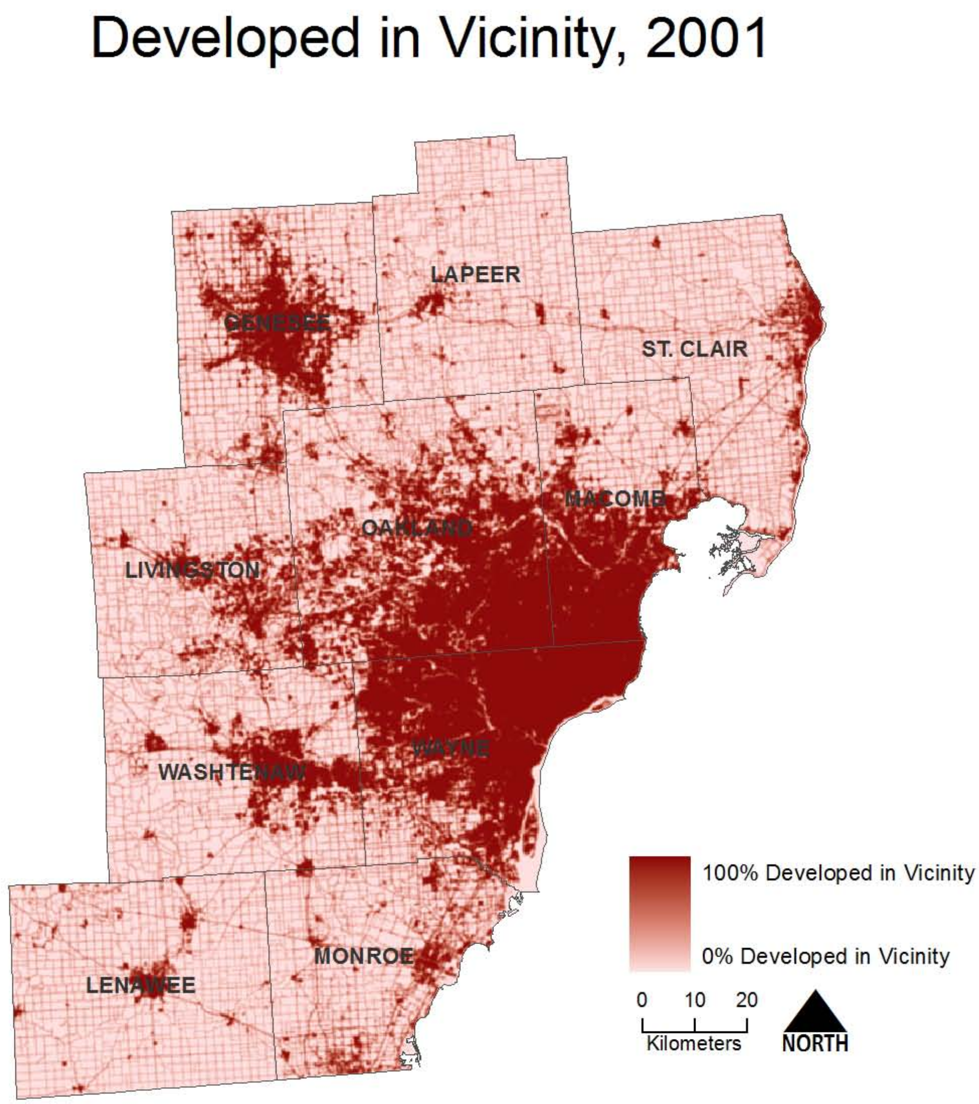

Figure 4- Agriculture in Vicinity, 2001 (NLCD)

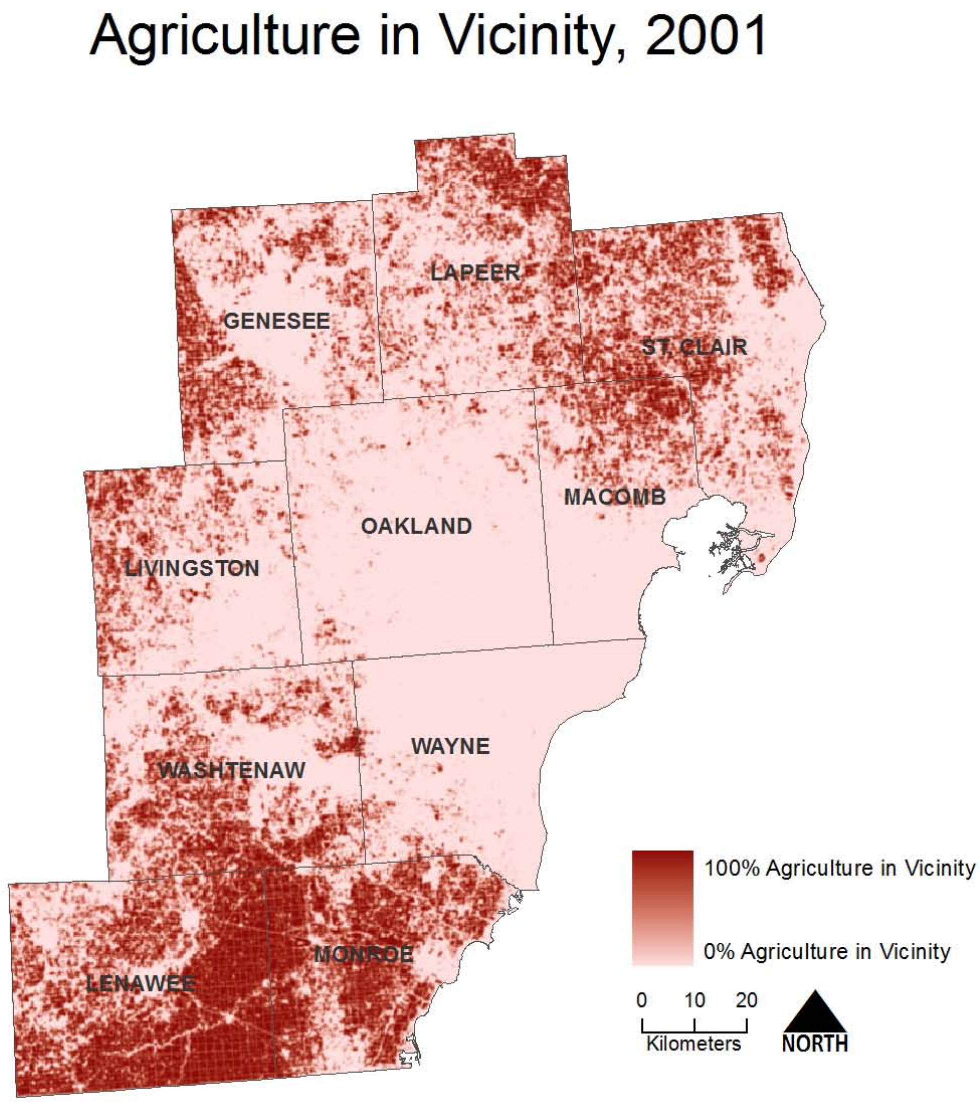

Figure 5- Population Density, 2000 (Census)

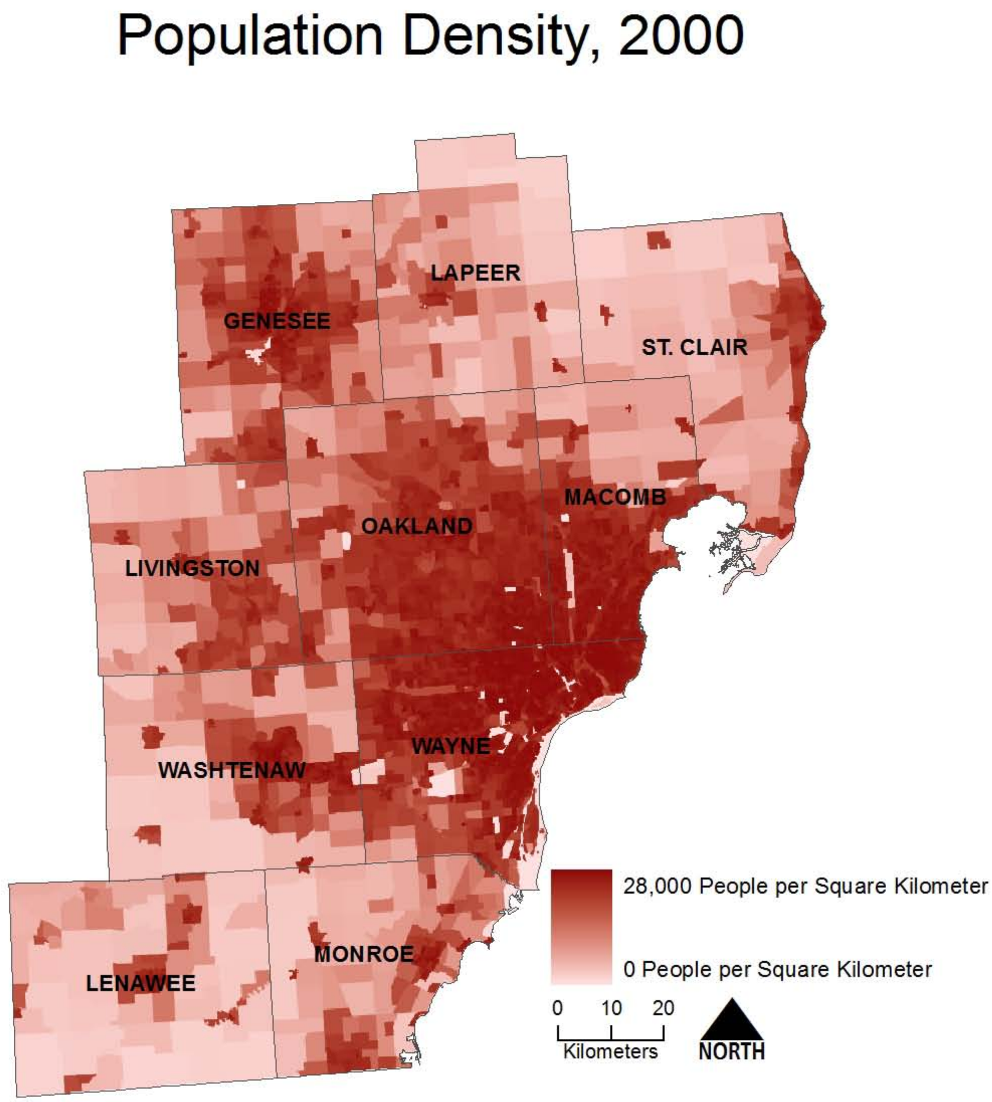

Figure 6- Slope in degrees (MiGDL DEM)

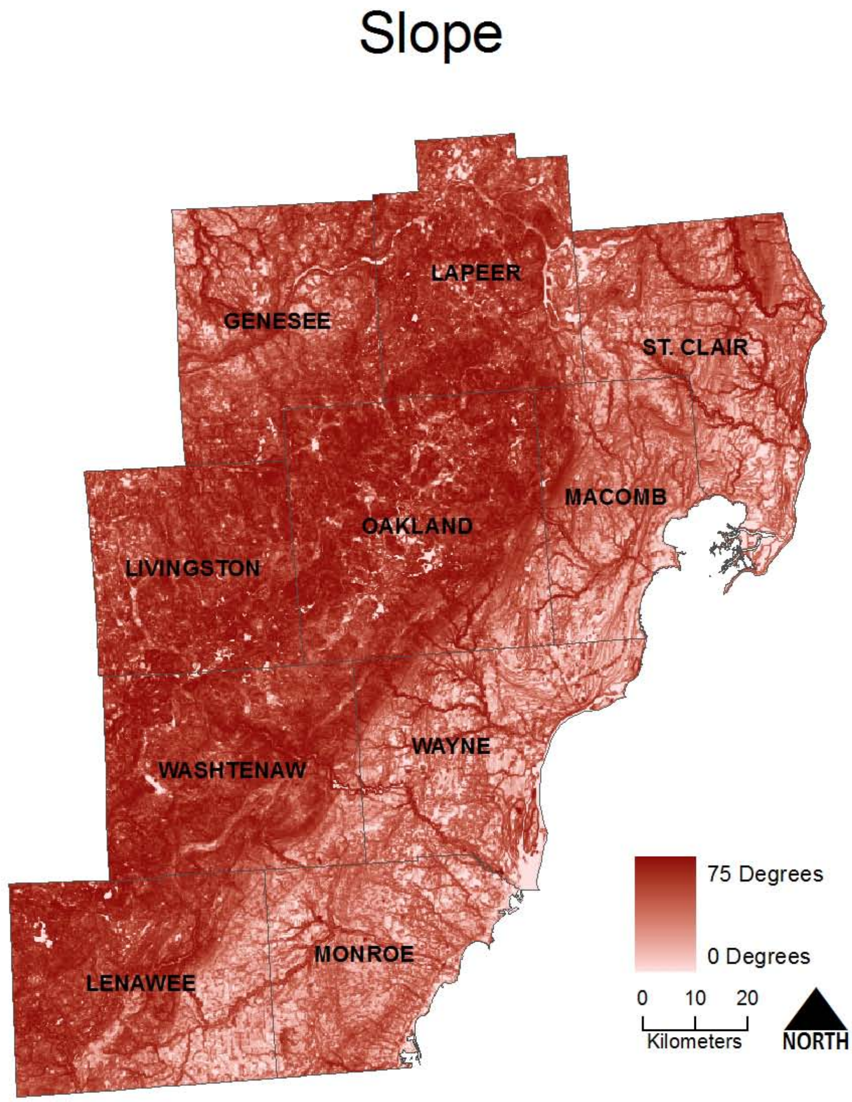

Figure 7- Soil suitability (SSURGO)

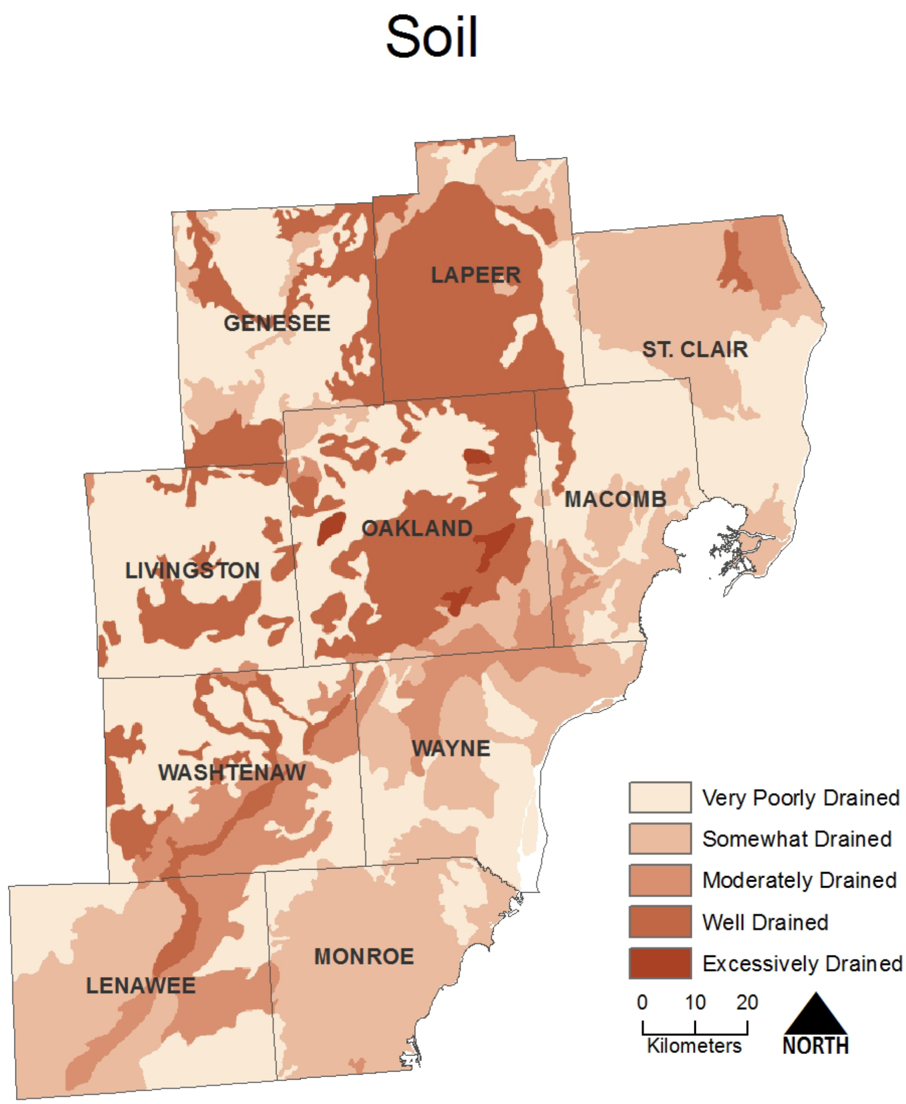

Figure 8- Distance to water (MiGDL)

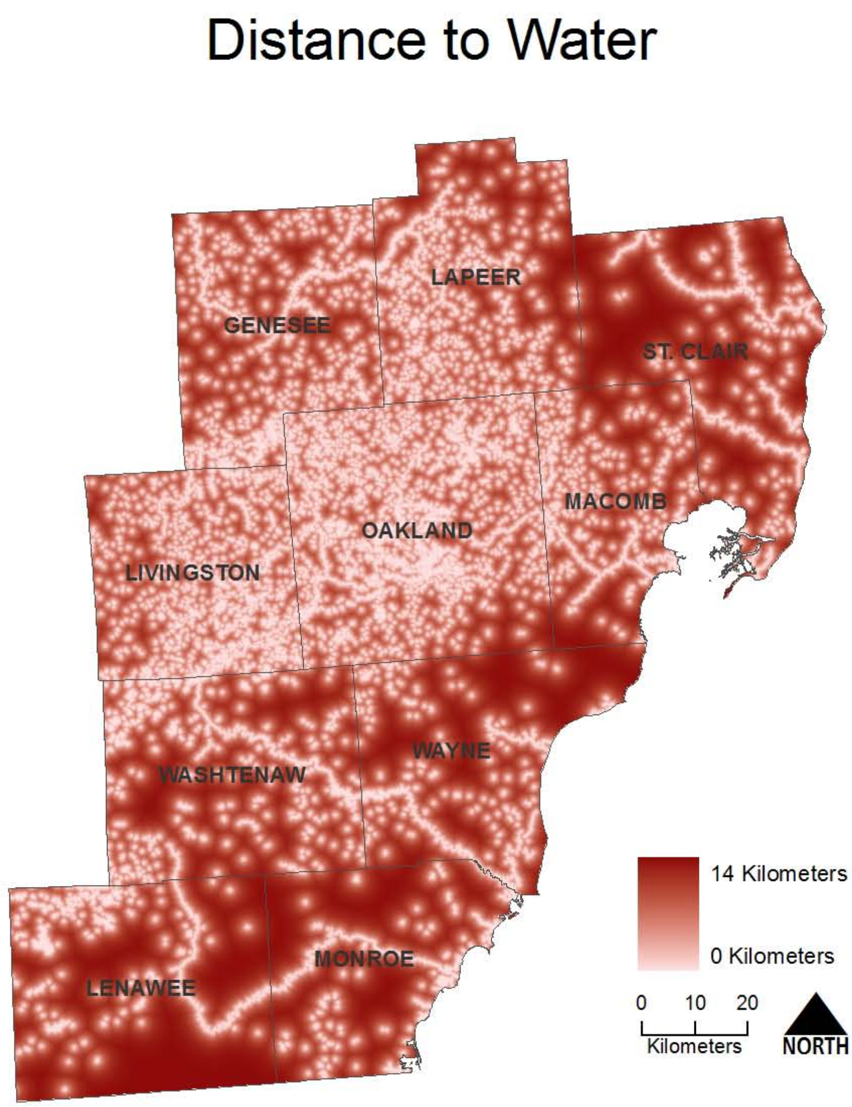

Figure 9- Distance to roads (MiGDL)

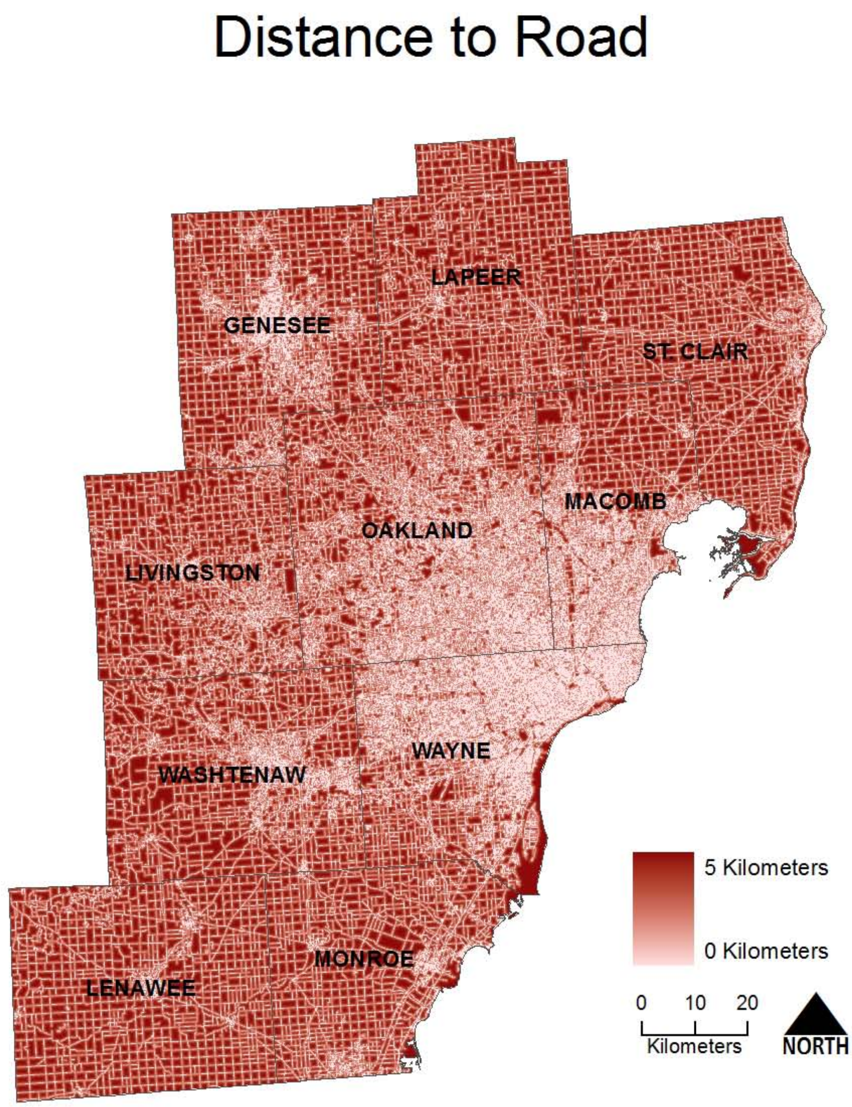

Figure 10- Distance to railroads (MiGDL)

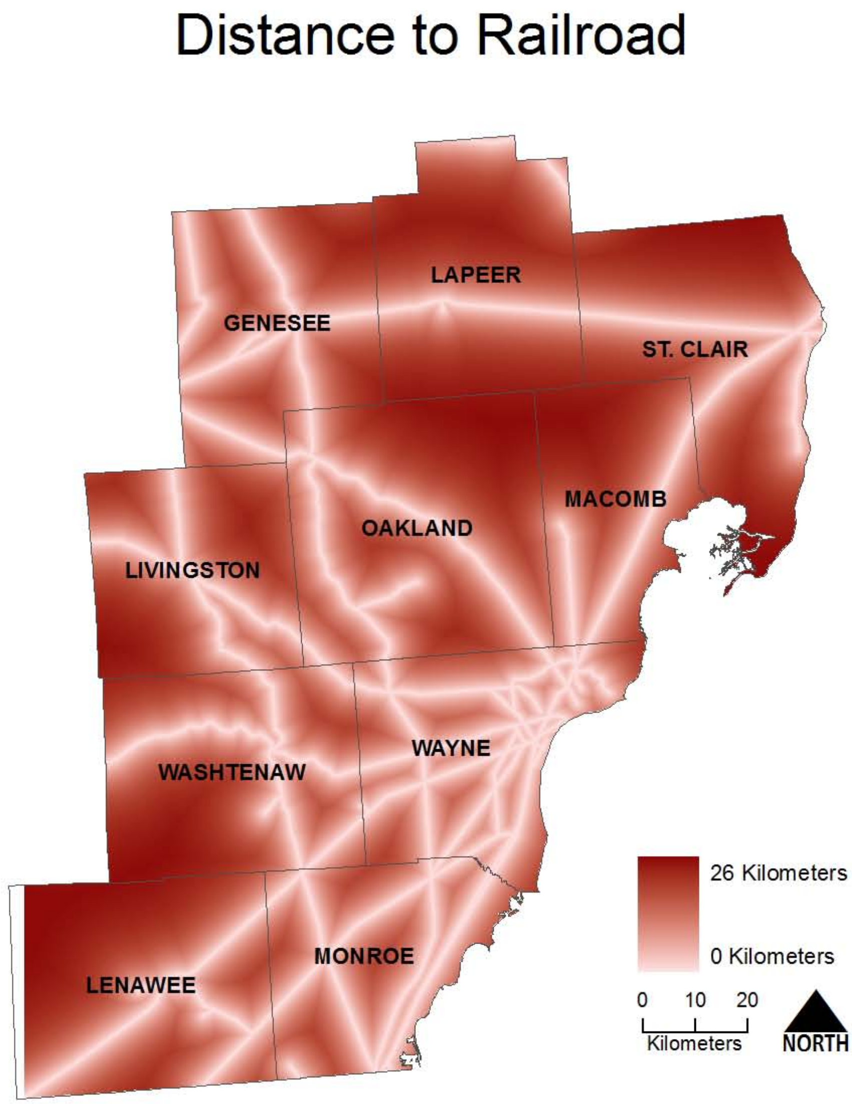

Figure 11- Snapshot of ArcGIS Model Builder model of suitability creation and agriculture allocation

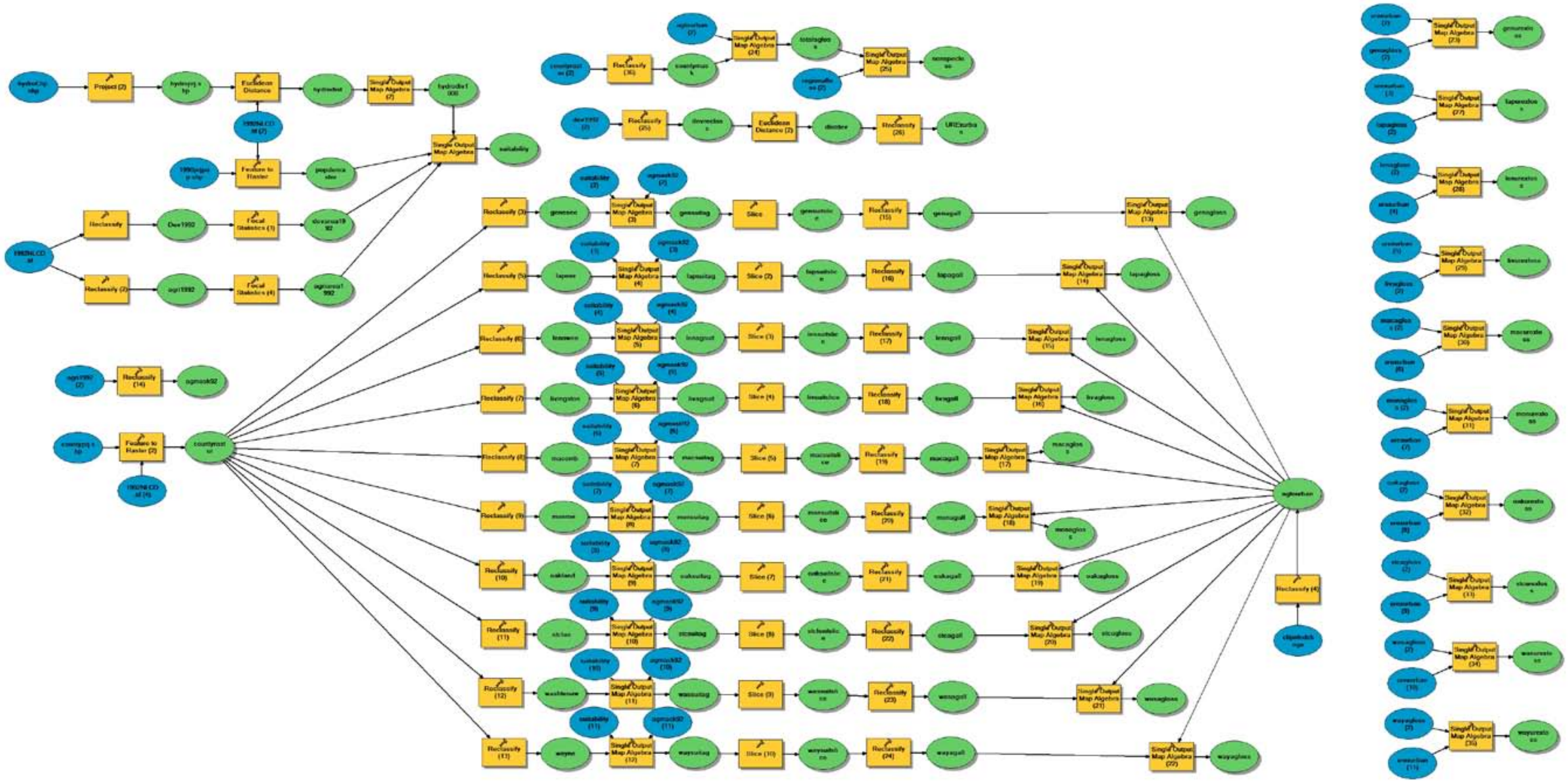

Figure 12- Developed in vicinity, 1992 (NLCD)

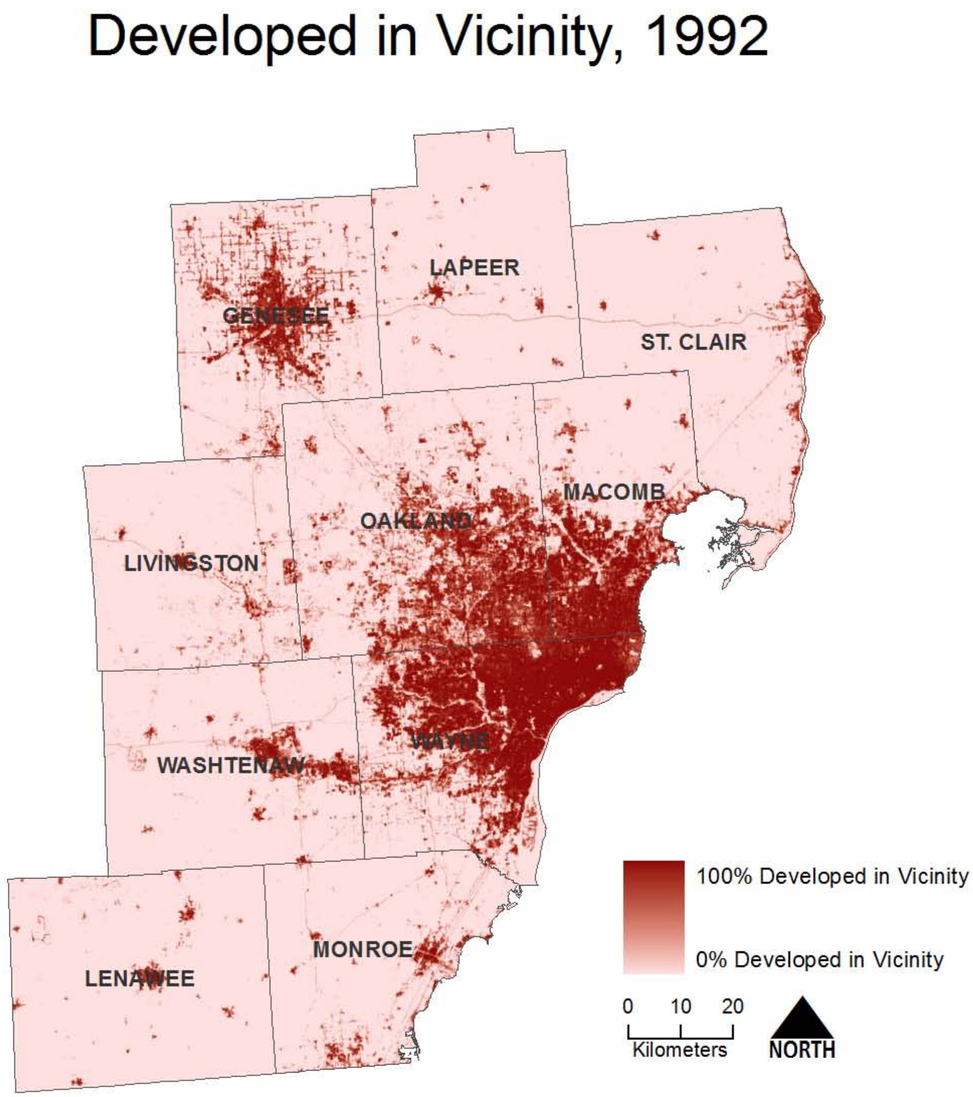

Figure 13- Agriculture in vicinity, 1992 (NLCD)

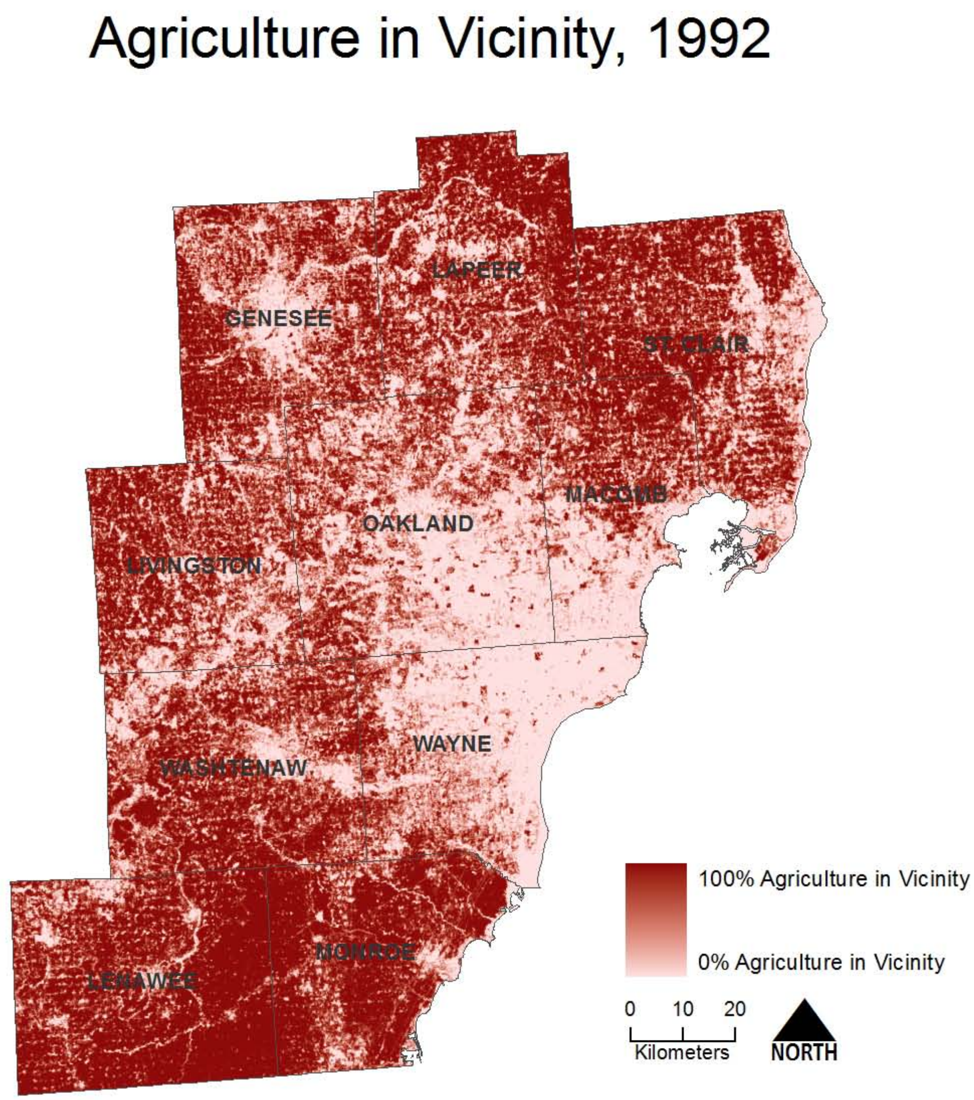

Figure 14- Population density, 1990 (U.S. Census)

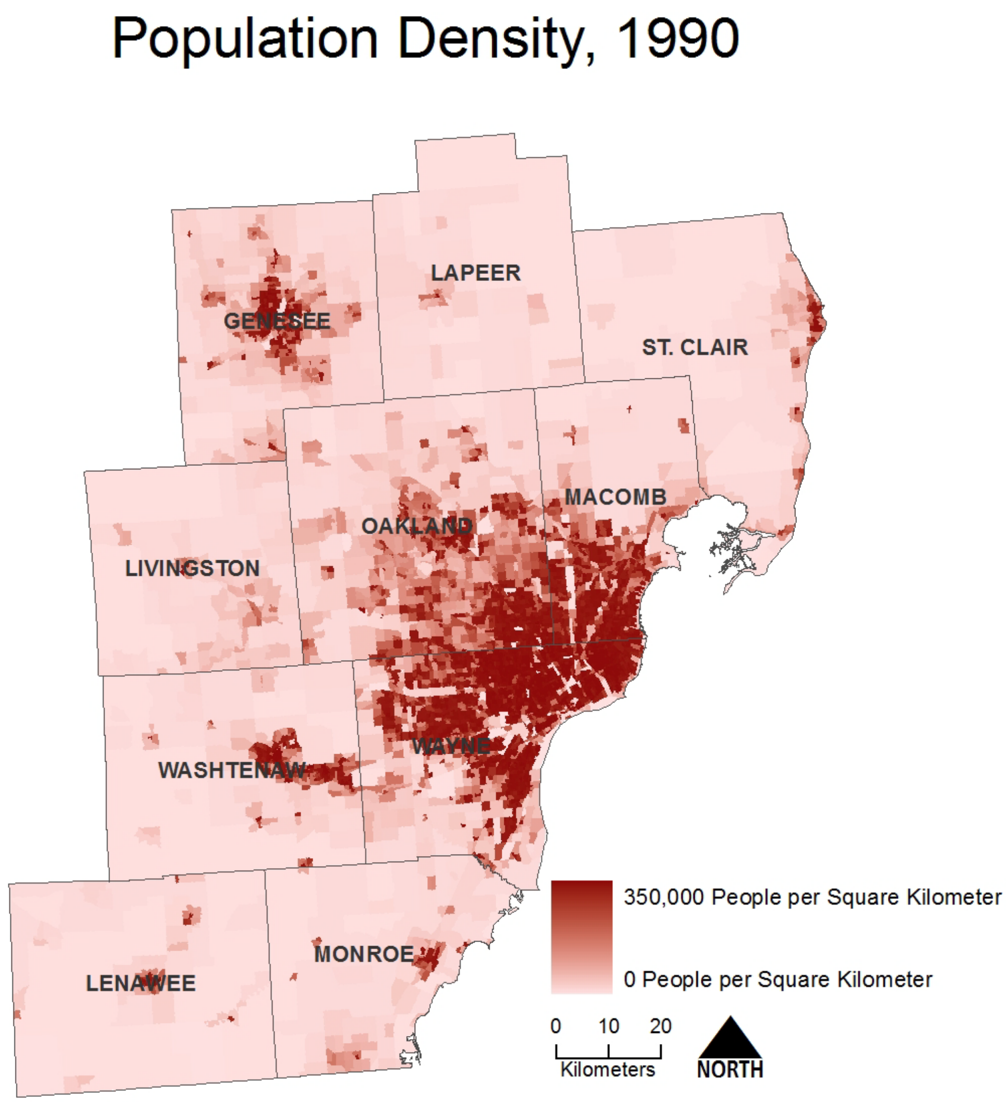

Figure 15- County Agriculture Allocation Process: Livingston is a binary mask of Livingston county, suitability is the suitability surface or specialized crops, agmask92 is a binary mask of area in agriculture in 1992, livagsuit is the area of agriculture in Livingston county and the cells value is defined as the suitability as specialized agriculture, livsuitslice is the sliced suitability in 1,000 pieces, livagall is the allocated specialized and non-specialized agriculture in Livingston county and the livagloss are the areas of all agriculture that were lost between 1992 and 2001

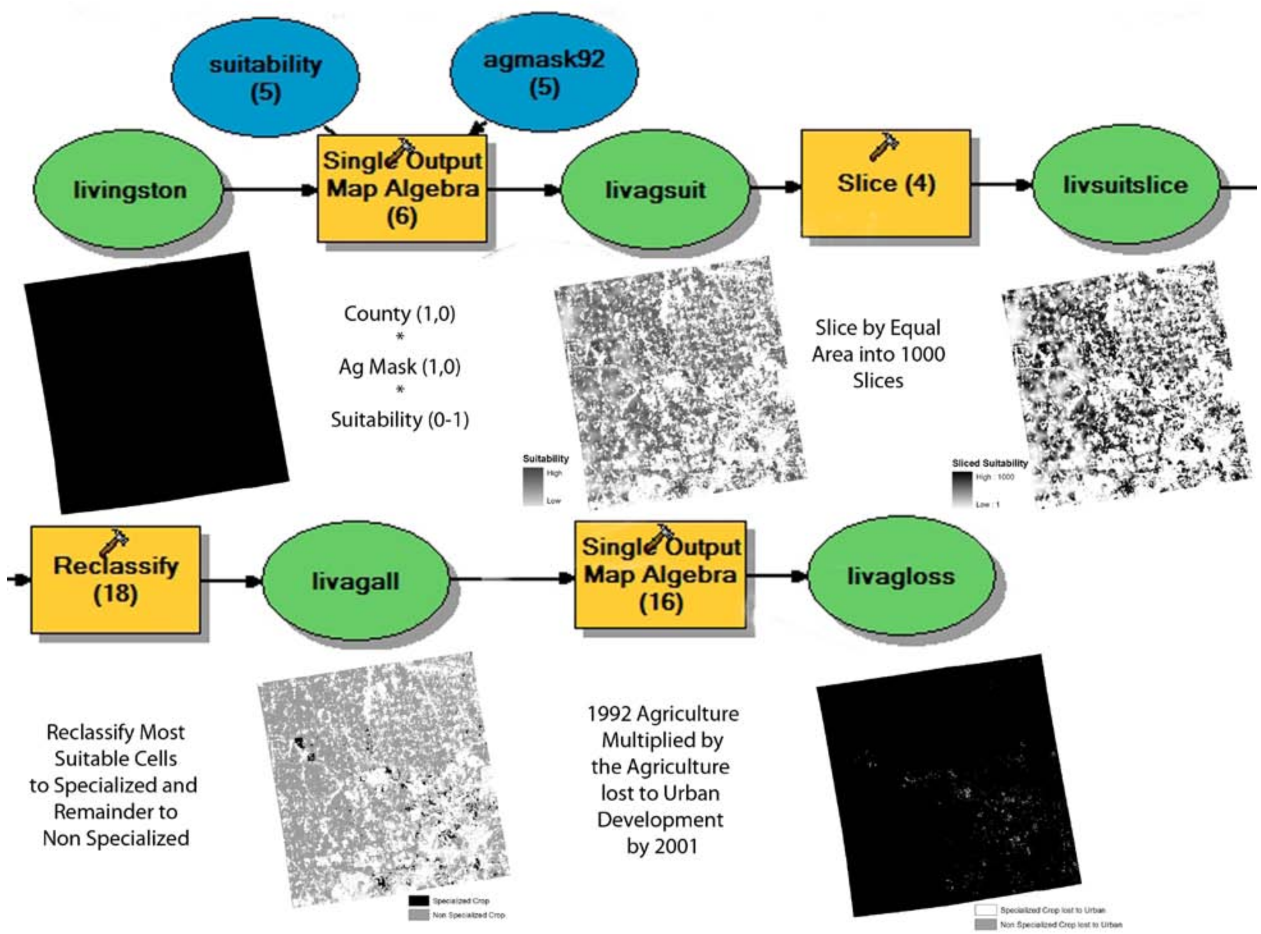

Figure 16- Allocated specialized and non-specialized agricultural land, 1992

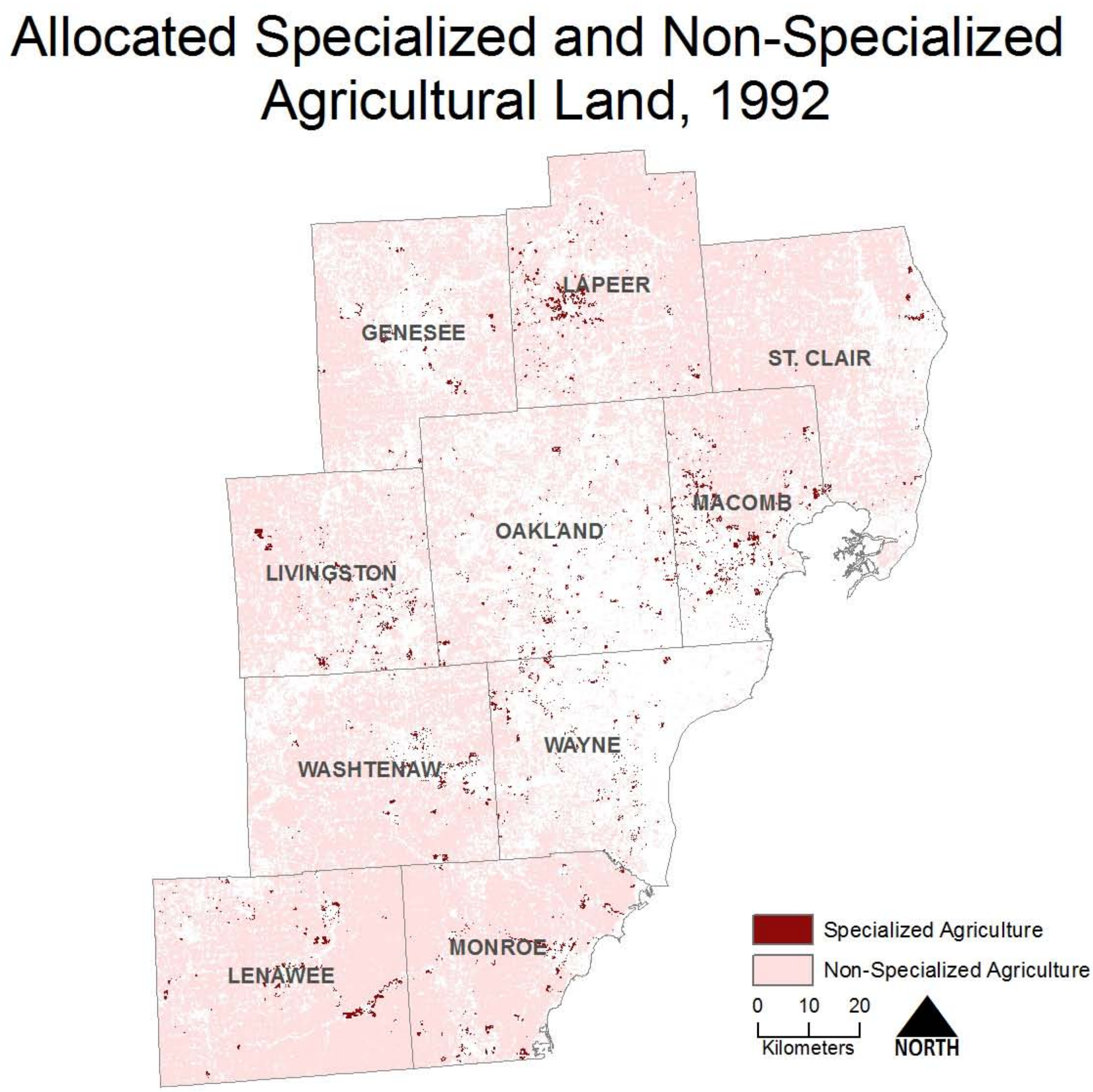

Figure 17- Agriculture lost to urban development, 1992-2001

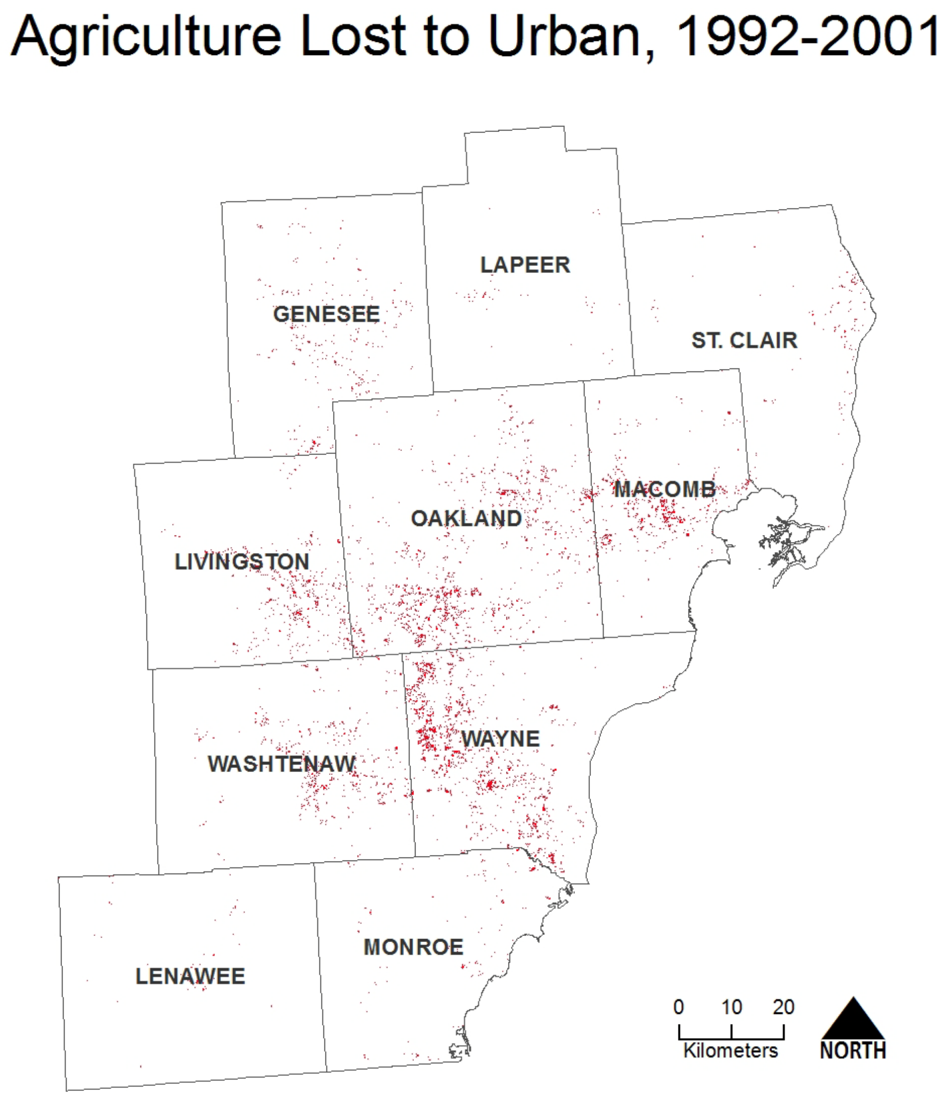

Figure 18- Urban, urban-rural and exurban regions, 1992

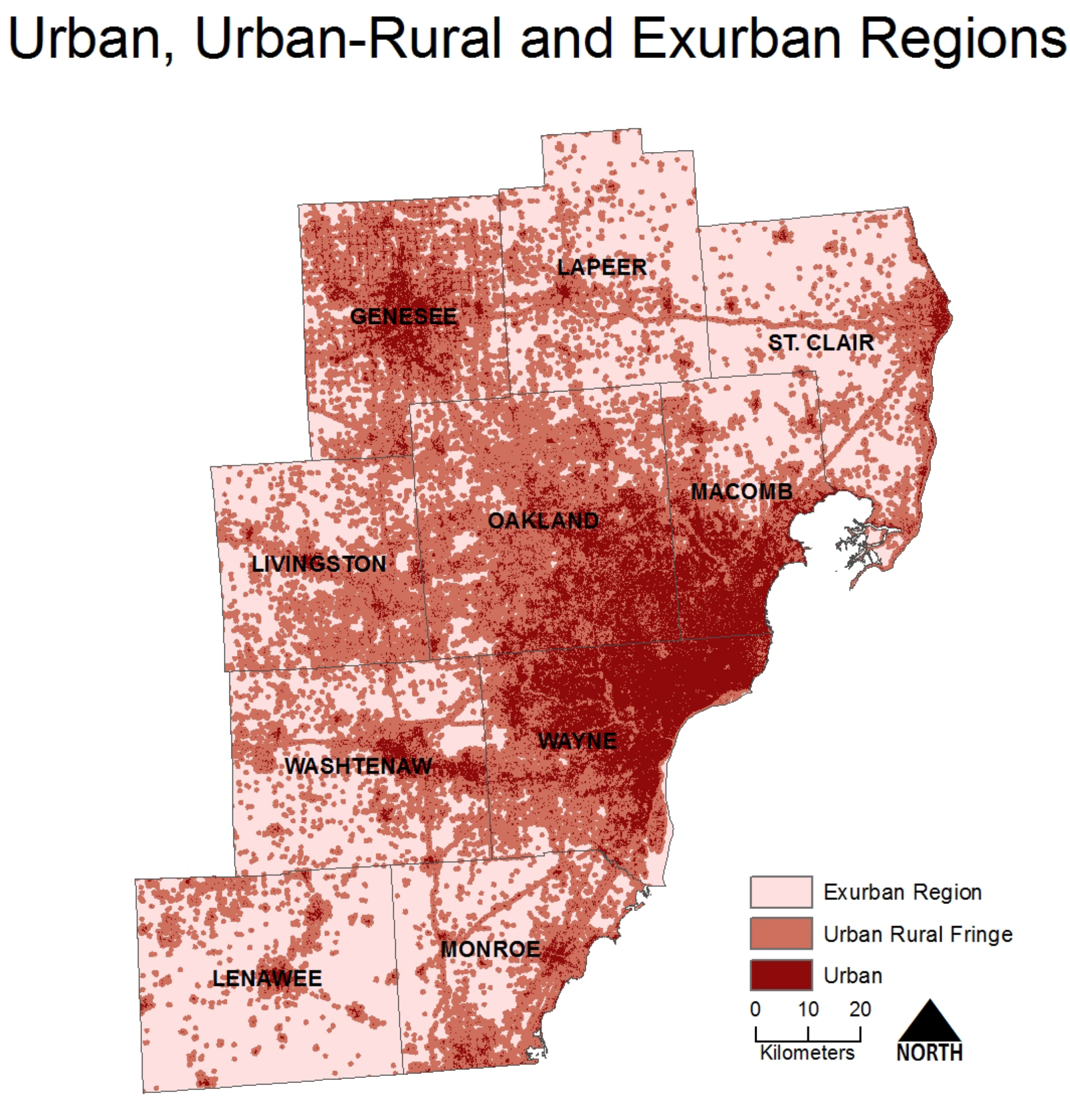

Table 1 Study region landcover in 2001 (from NLCD).

Landcover	Percent Cover 2001
Agriculture	40
Urban	31
Forest	16
Wetland	10
Grassland	2
Barren	.3

Table 2- Landcover agriculture converted into from 1992-2001 (Fry et. al, 2008)

Landcover	Square kilometers	Percent of converted agriculture
Urban	3733	60
Forest	1037	17
Wetland	904	15
Water	207	3
Grass	194	3
Barren	119	2

Table 3 CDL crop types designation (USGS, 2001)

Crop Type	Crops Included
Commodity	corn, sorghum, soybeans, barley, spring wheat, winter wheat, other small grains, winter wheat/ soybeans double cropped, rye, oats, millet, spelt, canola, flaxseed, safflower, rape seed, mustard, alfalfa, other hays, clover, wildflower and other crops
Specialized	sunflowers, sugar beets, dry beans, potatoes, sugarcane, sweet potatoes, miscellaneous fruits and vegetables, watermelon, pickles, chick peas, lentils and peas, peaches, apples, grapes, other tree nuts and fruits, and other non-tree fruits

Table 4 Predictor variables tested for inclusion in GLM.

Predictor Variable	Data Used	Creation	Units	Year
Developed in Vicinity	CDL/ NLCD	Focal Statistic defined as the sum of cells within 5 cell circular radius that are developed	# cells	1992, 2001
Agriculture in Vicinity	CDL/ NLCD	Focal Statistic defined as the sum of cells within 5 cell circular radius that are agriculture	# cells	1992, 2001
Population Density	2000 Census from MI GDL	Population divided by area for each census block group	People per square kilometer	1990, 2000
Slope	Digital Elevation Model from the MIGDL	Slope calculation from DEM	Degrees	1995
Soil	SSURGO soils	Drainage values extracted from SSURGO data files	Value	2000
Distance to Water	MIGDL	Distance of any one cell to the nearest water	Kilometers	2008
Distance to Roads	MIGDL	Distance of any one cell to the nearest Road	Meters	2003
Distance to Railways	MIGDL	Distance of any one cell to the nearest Railway	Meters	2003

Table 5 GLM results for predictor variables

Independent Variable	**β Value**	**p-value**
Intercept	-0.480	0.811
Developed in Vicinity	-0.031	0.055
Agriculture in Vicinity	0.016	0.009
Population Density	0.003	0.054
Slope	-0.200	0.268
Soil	1, 0.218; 2, 0.356; 3, 0.803	0.148
Distance to Water Divided by 1000	-0.241	0.001
Distance to Roads	-0.001	0.363
Distance to Railways	0.000	0.730

Table 6 Area of cropland by county according to the 1992 Agricultural Census (USDA, 1992)

County	Specialized Crops (km^2)	Total Cropland According to Ag Census (km^2)	Proportion of crops that are specialized	Agricultural Area According to NLCD (km^2)
Genesee	6123	486,303	1.26%	948,281
Lapeer	17057	644,381	2.65%	1,138,893
Lenawee	19716	1,235,271	1.60%	1,620,076
Livingston	10194	376,839	2.71%	874,890
Macomb	20202	254,952	7.92%	566,561
Monroe	16823	821,714	2.05%	1,149,296
Oakland	4994	142,753	3.50%	746,033
St. Clair	4508	651,180	0.69%	1,141,792
Washtenaw	10166	634,033	1.61%	1,178,936
Wayne	5544	77,934	7.11%	349,006

Table 7- Summary of area of agriculture, both specialized and non-specialized in the total region, urban-rural fringe and exurban regions. Ag is agriculture, and U-R fringe is urban-rural fringe

All areas are in kilometers squared	**Specialized Ag in U-R Fringe, 1992**	**Specialized Ag in Exurban, 1992**	**Total Ag, 1992**	**Total Specialized Ag, 1992**	**Total Non-Specialized Ag, 1992**	**Non-Specialized Ag in U-R Fringe, 1992**	**Non Specialized Ag in Exurban, 1992**
Region	7006.05	962.55	323732.16	7968.6	315763.56	144317.43	171446.13
Genesee	406.62	4.17	31607.49	410.79	31196.7	23796.24	7400.46
Lapeer	710.79	311.31	37965.24	1022.1	36943.14	12136.29	24806.85
Lenawee	524.04	338.97	53953.59	863.01	53090.58	10264.05	42826.53
Livingston	722.85	63.24	29167.41	786.09	28381.32	15782.04	12599.28
Macomb	1409.37	83.76	18904.83	1493.13	17411.7	8138.49	9273.21
Monroe	702.03	102.39	38314.44	804.42	37510.02	17026.2	20483.82
Oakland	868.44	2.1	24873.87	870.54	24003.33	19816.08	4187.25
St. Clair	227.85	38.13	38057.85	265.98	37791.87	10537.5	27254.37
Washtenaw	615.81	12.48	39270.03	628.29	38641.74	17328.75	21312.99
Wayne	818.25	6	11617.41	824.25	10793.16	9491.79	1301.37

Table 8- Summary of agricultural loss in the total region, urban-rural fringe and exurban regions. Ag is agriculture, and U-R fringe is urban-rural fringe

All areas are in kilometers squares	**Total Specialized Ag lost to Urban 1992-2001**	**Total Non-Specialized Ag Lost to Urban, 1992-2001**	**Total Ag Lost to Urban, 1992-2001**	**Total Specialized Ag Lost in U-R Fringe, 1992-2001**	**Total Non-Specialized Ag Lost in U-R Fringe, 1992-2001**	**Total Specialized Ag Lost in Exurban, 1992-2001**	**Total Non-Specialized Ag Lost in Exurban, 1992-2001**
Region	373.8	3409.8	3783.6	366.9	2936.76	6.9	473.04
Genesee	12.87	226.44	239.31	12.66	216.93	0.21	9.51
Lapeer	14.49	26.31	40.8	14.46	23.67	0.03	2.64
Lenawee	12.9	59.61	72.51	12.9	52.86	0	6.75
Livingston	61.83	336.12	397.95	59.55	315.69	2.28	20.43
Macomb	83.79	376.86	460.65	81.63	301.38	2.16	75.48
Monroe	14.25	140.13	154.38	14.25	111.51	0	28.62
Oakland	48.54	845.49	894.03	48.54	773.07	0	72.42
St. Clair	4.71	58.05	62.76	4.71	53.07	0	4.98
Washtenaw	47.22	444.54	491.76	46.5	318.96	0.72	125.58
Wayne	73.2	896.25	969.45	71.7	769.62	1.5	126.63

Table 9- Summary of the rates of agricultural loss in total region, urban-rural fringe, and exurban regions. Ag is agriculture, and U-R fringe is urban-rural fringe

	Rate of Specialized Ag Lost to Urban (Specialized Ag Lost 1992-2001/ Total Specialized Ag, 1992 * 100)	Rate of Non-Specialized Ag Lost to Urban (Non-Specialized Ag Lost, 1992-2001/ Total Non Specialized Ag, 1992)	Rate of Total Ag Lost to Urban (Ag Lost, 1992-2001/ Total Ag, 1992)	Rate of Specialized Ag Lost in U-R Fringe (Specialized Ag Lost in U-R Fringe 1992-2001/Total Specialized Ag in U-R Fringe, 1992)	Rate of Non-Specialized Ag Lost to Urban in U-R Fringe (Non-Specialized Ag Lost in U-R Fringe, 1992-2001/Total Non-Specialized Ag in U-R Fringe, 1992)	Rate of Specialized Ag Lost to Urban in Exurban (Specialized Ag Lost in Exurban, 1992-2001/Total Specialized Ag in Exurban, 1992)	Rate of Non-Specialized Lost in Exurban (Non-Specialized Ag Lost in Exurban, 1992-2001/Total Non-Specialized Ag in Exurban, 1992)
Region	4.69	1.08	1.17	5.24	2.03	0.72	0.28
Genesee	3.13	0.73	0.76	3.11	0.91	5.04	0.13
Lapeer	1.42	0.07	0.11	2.03	0.2	0.01	0.01
Lenawee	1.49	0.11	0.13	2.46	0.52	0	0.02
Livingston	7.87	1.18	1.36	8.24	2	3.61	0.16
Macomb	5.61	2.16	2.44	5.79	3.7	2.58	0.81
Monroe	1.77	0.37	0.4	2.03	0.65	0	0.14
Oakland	5.58	3.52	3.59	5.59	3.9	0	1.73
St. Clair	1.77	0.15	0.16	2.07	0.5	0	0.02
Washtenaw	7.52	1.15	1.25	7.55	1.84	5.77	0.59
Wayne	8.88	8.3	8.34	8.76	8.11	25	9.73

Table 10 Contingency matrix indicating the model's predictive capabilities

	Predicted Specialized in 2001	Predicted Non-Specialized in 2001
Specialized in 2001	141	103
Non-Specialized in 2001	103	137

Works Cited

Brown, D. G., K. Johnson, T. Loveland and D. Theobald. 2005. Rural land-use trends in the conterminous United States, 1950-2000. *Ecological Applications*, 15(6):1851-63.

Craig, Michael. A history of cropland data layer at NASS. 2010. 13 Oct. 2010. http://www.nass.usda.gov/research/Cropland/CDL_History_MEC.pdf.

Fields, S. 2004. The fat of the land. *Environmental Health Perspectives*, 112(14): A821-3.

Freemark, Kathryn, Céline Boutin and Cathy Keddy. 2002. Importance of farmland habitats for conservation of Plant Species. *Conservation Biology*, 16(2): 399-412.

Fry, J.A., Coan, M.J., Homer, C.G., Meyer, D.K., and Wickham, J.D. 2009. Completion of the National Land Cover Database (NLCD) 1992-2001 Land Cover Change Retrofit product: U.S. Geological Survey Open-File Report 2008. 1379-97.

Gross, L.S., L. Li, E. S. Ford, S. Liu. 2004. Increased consumption of refined carbohydrates and the epidemic of type 2 diabetes in the United States: an ecological assessment. *American Journal of Clinical Nutrition*, 79:774-9.

Hansen, A.J., and Brown, D.G. 2005. Guest Editorial: Land-Use Change in Rural America: Rates, Drivers, and Consequences. *Ecological Applications,* 15(6): 1849-1850

Hendrickson, J., G.F. Sassenrath, D. Archer, J. Hanson and J. Halloran. 2008. Interactions in integrated US agricultural systems: the past, present and future. Renewable Agriculture and Food Systems 23(4): 314-324.

Holloway, Steven R. James Schumacher and Roland L Redmond. 1999. People & place: dasymetric mapping using Arc/Info. *GIS Solutions in Natural Resource Management*, 283-91

Homer, C. C. Huang, L. Yang, B. Wylie and M. Coan. 2004. Development of a 2001 National Landcover Database for the United States. *Photogrammetric Engineering and Remote Sensing*, 70(7): 829-40.

Kimmons, Joel, Cathleen Gillespie, Jennifer Seymour, Mary Serdula and Heidi Michels. 2009. Fruit and vegetable intake among adolescents and adults in the United States: percentage meeting individualized recommendations. *The Medscape Journal of Medicine,* 11(1):26

Lepczyk, Christopher, Roger Hammer, Susan Stewart and Volker Radeloff. 2007. Spatiotemporal dynamics of housing growth hotspots in the North Central U.S. from 1940 to 2000. *Landscape Ecology*, 22: 939-52.

Michigan department of agriculture. Michigan specialty crops. 13 Oct. 2010. http://www.michigan.gov/documents/mda/MDA_Crops_Brochure_low-resolution_324586_7.pdf.

Michigan department of technology, management and budget. Center for geographic information. Michigan Geographic Data Library. 13 Oct 2010 http://www.mcgi.state.mi.us/mgdl/.

SEMCOG. 2001. 2030 regional development forecast for southeast Michigan: population, households, and jobs, for cities, villages, and townships 1990-2030.

SEMCOG. 2002. Historical population and employment by minor civil division, Southeast Michigan.

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Soil Survey Geographic (SSURGO) Database for Michigan. 2010. 13 Oct. 2010. http://soildatamart.nrcs.usda.gov.

Petit, S. 2009. The dimensions of land use change in rural landscapes: lessons learnt from the GB countryside surveys. *Journal of Environmental Management*, 90: 2851-56.

Perfecto, I and J. Vandermeer. 2010. The agroecological matrix as alternative to the land-sparing/agriculture intensification model. Proceedings of the National Academy of Sciences of the United States of America 107(13): 5786-91

Rayburn, Andrew and Lisa Schulte. 2009. Landscape change in an agricultural watershed in the U.S. Midwest. *Landscape and Urban Planning,* 93: 132-41.

Sinclair, R. 1967. Von Thünen and urban sprawl. *Annals of the Association of American Geographers*, 57: 72–87.

Theobald, D.M. 2001. Land-use dynamics beyond the American urban fringe. *Geographical Review*, 91(3): 544-64.

Theobald, D.M. 2005. Landscape patterns of exurban growth in the USA from 1980 to 2020. *Ecology and Society*, 10(1):32.

United States Department of Agriculture. National Agricultural Statistics Service. 1997 Census of Agriculture.13 Oct. 2010. http://www.agcensus.usda.gov/Publications/1997/index.asp.

United States Department of Agriculture. National Agricultural Statistics Service. Cropland Data Layer. 2001. 13 Oct. 2010. http://www.nass.usda.gov/research/Cropland/SARS1a.htm.

United States Department of Agriculture. National Agricultural Statistics Service. 2002 Census of Agriculture. 13 Oct. 2010. http://www.agcensus.usda.gov/Publications/2002/index.asp.

United States Department of Agriculture. National Agricultural Statistics Service. 2007 Census of Agriculture. 13 Oct. 2010. http://www.agcensus.usda.gov/Publications/2007/Full_Report/index.asp.

U.S. Department of Agriculture and U.S. Department of Health and Human Services. 2010. Report of the Dietary Guidelines Advisory Committee on the Dietary Guidelines for Americans, 2010. 13 Oct. 2010. Available from http://www.cnpp.usda.gov/DGAs2010-DGACReport.htm

Verberg, P.H., J. van de Steeg, A.S. Veldkamp, L. Willemen. 2009. *Journal of Environmental Management*, 90: 1327-35.

Vogelmann, J.E., S.M. Howard, L. Yang, C. R. Larson, B. K. Wylie, and J. N. Van Driel. 2001. Completion of the 1990's National Land Cover Data Set for the conterminous United States. *Photogrammetric Engineering and Remote Sensing*, 67: 650-662.

Waisanen, Pamela and Norman Bliss. 2002. Changes in population agricultural land in conterminous Unites States counties, 1790 to 1997. *Global Biogeochemical Cycles*, 16(4): 1137.

Wallinga, David. 2010. Agricultural policy and childhood obesity: a food systems and public health commentary. *Health Affairs*, 29(3): 405-10.