

EVALUATING SATELLITE-OBSERVED CHANGES IN IMPERVIOUS SURFACE COVER IN  
RELATION TO ECONOMIC CHANGES AND SPATIALLY VARIABLE SOCIOECONOMIC  
CONDITIONS IN CENSUS DATA IN SOUTHEASTERN MICHIGAN

by  
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A thesis submitted  
in partial fulfillment of the requirements  
for the degree of  
Master of Science  
(Natural Resources and Environment)  
In the University of Michigan  
August 2013

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*Abstract*

From space, the Earth can be observed over time. Satellite imagery has documented human influences on the landscape. I examined the effect of economic fluctuations on the landscape across the urban to rural gradient in Southeastern Michigan. Using Landsat satellite imagery, I described and compared land-cover changes observed from Landsat during 2001 – 2005, a five-year period before the Great Recession, to those observed during the period 2007 – 2011, a five-year period during and after the recession. I used dense time-series satellite observations to observe changes in impervious surfaces, compared these over time, and related them to socioeconomic variables collected by the US Census Bureau over census tracts. The results suggest that a suite of socioeconomic factors and landscape characteristics influence the amount of impervious surface change occurring within each census tract. On average impervious surface areas did not increase at a faster rate during the period before the recession, decrease at a slower rate, or change from increasing to decreasing, when compared to the post-recession period. In addition, the socioeconomic composition of individual communities was strongly associated with how the landscapes changed through time and space. Overall, I demonstrate that the socioeconomic characteristics of communities have land use, ecological, and carbon sequestration implications.

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## ***Introduction***

From space, the human mark on the planet is unmistakable; satellite observations have been used to track cropland expansion (Fry et al., 2011; Ramankutty, Evan, Monfreda, & Foley, 2008), conversion of tropical forests (Morton et al., 2006; Phalan et al., 2013), and urban growth (Schneider, Friedl, & Potere, 2009; Seto, Fragkias, Güneralp, & Reilly, 2011; Xian & Crane, 2005). Human-dominated landscapes now cover more of Earth's terrestrial surface than natural landscapes and have contributed to a new global epoch of human impact: the anthropocene (Crutzen & Stoermer, 2000; Ellis & Ramankutty, 2008; Foley et al., 2005). As part of human transformation of the Earth's surface, urban development has added 58,000 km<sup>2</sup> of the "most irreversible and human-dominated form of land use" to the planet over a period of thirty years from 1970 to 2000 (Seto et al., 2011, p. 1). These urban areas include a broad range of heterogeneous impervious surfaces (e.g. buildings and infrastructure) at various densities and a variety of types and densities of vegetation that together create a complex and intricate urban landscape of coupled human-natural systems (Cadenasso, Pickett, & Schwarz, 2007; Pickett et al., 2011; Pickett, Cadenasso, & Grove, 2005). Density of urban development (ranging from urban to suburban and exurban) has a large effect on the types and patterns of land covers that are present (Robinson, 2012; Moffatt, McLachlan, & Kenkel, 2004; Luck & Wu, 2002; Wear, Turner, & Naiman, 1998). Additionally, while urban development changes land covers at the time of conversion (e.g., from forest or agricultural uses), vegetation can continue to change within the urban matrix (Luck & Wu, 2002; Tait, Daniels, & Hill, 2005). This suggests that urbanization does not create a one-directional or fixed change to urban landscape patterns.

How does the rate of change in these land-cover patterns vary over time and across space, and can these variations be linked directly to boom and bust cycles of the economy? The drivers of land cover change can be linked to patterns of economic and population growth through market forces that determine the demand for land (Angel, Parent, Civco, & Blei, 2011; Seto & Kaufmann, 2003; Geist & Lambin, 2001). In addition, it has been demonstrated that energy use and housing construction fluctuate with economic cycles (Borozan, 2013; Belke, Dobnik, & Dreger, 2011), and that the amount of night time light can be used to measure economic GDP and total income growth (Henderson, Storeygard, & Weil, 2009; Henderson, Storeygard, & Weil, 2011). However, the relationships between general patterns of economic growth and the effects of urban, suburban, and exurban growth on landscape change are not well documented. Over time, these variations are influenced by variations in economic demand for land uses and land availability. Over space, both natural and socioeconomic characteristics of communities influence landscape change differently during periods of economic growth and decline.

The “Great Recession” of December 2007 to June 2009 spelled a large disruption to the US housing market (US Bureau of Labor Statistics, 2012; Patton, 2012). The national rate of new household formation during and after this downturn has remained exceptionally low (Paciorek, 2013). Between 2006 and 2011, approximately 550,000 new households formed per year in contrast to the 1.35 million new households forming annually between 2001 and 2005 (Paciorek, 2013). Michigan, and in particular the Detroit Metropolitan area, was especially hard hit by the Great Recession: an estimated 78,000 buildings and nearly 100,000 homes were left vacant in the City of Detroit (Brennan, 2013). However, Detroit’s fall from one of America’s largest cities to one in consistent population decline can be traced back to the post-World War II era. As early as the 1950s, residents began to move from the urban core to the suburban ring precipitating large-scale urban and economic decay. Similar processes have occurred throughout Midwestern industrial cities as manufacturing declined over the past half-century (Henley, 2013; Mallach et al., 2008). While a slowing economy has negative consequences for homeowners, personal income, employment, and livelihoods, it could have positive effects on natural land covers by both reducing the rate of conversion to new developments and by allowing vegetation to recover and mature in existing developed and undeveloped areas, thus increasing air and water quality, biodiversity, farmland availability, and carbon storage.

My study highlights the effect of economic fluctuations on the landscape across the urban to rural gradient using the natural experiment of the Great Recession in Southeastern Michigan (Figure 1). I investigated changes in impervious surface,<sup>1</sup> such as roads, houses, and parking lots, during the periods immediately before versus during and after the Great Recession. I described and compared landscape changes observed from Landsat during 2001 – 2005, which was the five-year period since 1980 with the highest rate of new home construction in the Midwest, to those observed during the period 2007 – 2011, during which new-home construction collapsed to its lowest rate since 1980 (Figure 2; US Census Bureau, 2013). I hypothesize that, because differences in the rates of new construction and the possibility of vegetation regrowth during periods of low activity in housing construction, impervious surface area increased at a faster rate during the period before the recession, decreased at a slower rate, or changed from increasing to decreasing, when compared with the period during and after the recession.<sup>2</sup>

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<sup>1</sup> Impervious surfaces are anthropogenic features through which water cannot infiltrate into the soil (Weng, 2012). They include pavement, cement, or asphalt (e.g. roads, sidewalks, parking lots, and buildings).

<sup>2</sup> The period during and after the recession is hereafter referred to as simply “post-recession.”

In addition to comparing the rates of landscape change between these two periods, I examined how changes in impervious surfaces varied geographically in association with the socioeconomic structure of communities (Figure 3). I used dense time-series satellite observations from Landsat to observe changes in impervious surfaces, compare these over time, and relate them to socioeconomic variables collected by the US Census Bureau over census tracts. I hypothesize a greater growth in impervious surfaces in communities with higher socioeconomic status and less deprivation due to greater economic potential for demand for new businesses and new housing developments. Furthermore, I hypothesize that these variables will have had a greater importance during the Great Recession as compared to the economic period prior, because I expect areas with higher rates of socioeconomic deprivation to experience sharper declines in economic activity than their counterparts.

### ***Study Area***

The study region includes four counties in Southeastern Michigan (Lenawee, Monroe, Washtenaw, and Wayne) spanning a full range of conditions along an urban-rural gradient from the City of Detroit and medium-sized cities, such as Ann Arbor, to fragmented forests and a patchwork of agricultural fields. In between the ends of this spectrum lies a heterogeneous mosaic landscape of sprawling subdivisions and small rural towns intermixed within a rural matrix (Figure 4).

Overall, the region has experienced a decline in agricultural area since its peak in the mid-20<sup>th</sup> century, largely replaced by secondary growth forests and residential land uses (Robinson, Brown, & Currie, 2009). It is now composed of 46% agricultural, 31% developed, and 12% forested land covers (Figure 4; Fry et al., 2011). The region is currently home to over two million people (US Census Bureau, 2010) and has experienced suburbanization and exurbanization since the 1950s, while the city of Detroit has consistently declined in population (Brown, Johnson, Loveland, & Theobald, 2005; Zhao, Brown, & Bergen, 2007). In 2010, Detroit's population hit its lowest point since the 1910 Census (Linebaugh, 2011). However, other cities and counties within the region have either grown or maintained their population as whites and middle-class blacks moved out of the city and into the suburban ring around the declining urban core (Linebaugh, 2011; Mallach et al., 2008).

### ***Methods***

Image selection and preprocessing. Satellite images of Southeastern Michigan from Landsat 5 and 7, processed to Standard Terrain Correction (Level 1T),<sup>3</sup> were acquired from the US Geological Survey's (USGS) Global Visualization Viewer (GloVis; <http://glovis.usgs.gov>; accessed 2012) between years 2001 and 2011. Each scene (Path/Row: 20/31; Figure 1) was selected to minimize cloud cover, reduce snow cover as much as possible, and achieve high overall image quality (Maxwell & Sylvester, 2012). In total, 102 images with 60% or less cloud cover were collected for the calendar dates March 1 to October 31 for all years (Appendix). The number of images per year ranged from 5 to 18 with a median of 9 (Table 1). Each Landsat scene was radiometrically and atmospherically corrected to produce measures of surface reflectance and cloud masks using NASA's Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS; Masek et al., 2012).

Subpixel Analysis. Estimates of the fraction of each Landsat pixel in all 102 images for impervious surface were derived from the pre-processed Landsat images using a non-parametric supervised subpixel spectral classification within Erdas Imagine 2010 (Intergraph Corp., Huntsville, AL). This classifier identified the percentage of each pixel with specific materials of interest (MOI; i.e. light, medium, medium-brown, and dark impervious surfaces) in increments of 10%, beginning with a minimum of 0-19%. To detect MOIs, spectral libraries were created to train the spectral classification algorithm. Spectral libraries were digitized for each annual image of impervious surface (using unique libraries for light, medium, medium-brown, and dark impervious color shades) using the USDA's Farm Service Agency's National Agriculture Imagery Program (NAIP) aerial imagery and Google Earth historical imagery as reference imagery. Each spectral library was designed to capture the range of spectral reflectances for each category of impervious surface (Flanagan & Civco, 2001). Two parameters governed the classification process: classification confidence levels, which adjusts the number of extraneous pixels included in the spectral signature, varied from 0.4 to 0.8, and tolerance intervals, which controls the quantity of residuals considered in the spectral signature, from 1.0 to 1.2, depending on the characteristics of each MOI (ERDAS, 2009).

Postprocessing. Detection layers, representing estimated sub-pixel fractions for each MOI, were recoded from intervals to individual integers (Table 2), stacked for each year (in unique files), and a maximum value for each stacked cell was calculated. This technique harnesses the power of dense time-series imagery to create a more complete representation of impervious surface by accounting for cloud cover

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<sup>3</sup> Level 1T processing "provides systematic radiometric and geometric accuracy by incorporating ground control points while employing a Digital Elevation Model (DEM) for topographic accuracy" (US Department of the Interior & US Geological Survey, 2013).

and seasonal phenological changes that may alter the quantity of impervious surface visible by satellite at any one point in time. The stacked images for each MOI were summed to produce a surface representing the percentage of impervious surface and subsequently rescaled to the range 0 -100 based on the observed minimum and maximum values (Equation 1).

$$\text{Stretched pixel value} = \left( \frac{\text{cell value} - \text{minimum value}}{\text{maximum value} - \text{minimum value}} \right) * 100 + 0 \quad (1)$$

Next, for each five-year period, the slope ( $\beta$ ) of a best-fit line was calculated for each pixel to represent the rate of change in percent impervious surface across the five years in each period (Equation 2).

$$\beta = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^N (x_i - \bar{x})} \quad (2)$$

Finally, pixels in each annual composite image and the beta values describing the rate of change for each five-year period were apportioned into and averaged across 2010 census tracts using ArcMap10 (ESRI, Redlands, CA).

Validation. The annual estimates of impervious surface for 2001 and 2006 were plotted against corresponding values from the National Land Cover Database (NLCD; <http://www.mrlc.gov/>; accessed 2013) for the same years (Fry et al., 2011; Hossain et al., 2007). The correlations were calculated between the supervised subpixel classification surfaces and NLCD data as a means of validating the subpixel estimates and benchmarking them to a widely-used product (Figures 5 and 6). The  $R^2$  values for the relationship between our estimated 2001 and 2006 impervious values and NLCD values were 0.86 and 0.82, respectively. Despite relatively strong  $R^2$  values, both 2001 (Equation 3) and 2006 (Equation 4) subpixel values were systematically underestimated at all levels of impervious surface compared to the NLCD data, as shown by the slopes of both equations being substantially less than one.

$$y = 0.58x - 9.35 \quad (3)$$

$$y = 0.51x - 9.82 \quad (4)$$

These discrepancies between the supervised subpixel classification surfaces and the NLCD data might be indications of error or bias in the supervised subpixel classification estimates, but they could also be due to differences in the methodologies. An important difference is that the NLCD data on percent impervious

surface relies upon a suite of input data not included in our analysis, including land cover classification, nighttime stable-light satellite imagery from the National Oceanic and Atmospheric Administration (NOAA) Defense Meteorological Satellite Program (DMSP), and non-urban masks (Xian et al., 2011). For this reason, while the supervised subpixel classification for impervious surface represents only visible impervious surfaces that are exposed to sky view and does not account for impervious surfaces that may be covered by vegetation, the NLCD data can be interpreted more broadly to include most impervious or developed surfaces.

**Census and Land Cover Variables.** US Census Bureau data were acquired for the 2000 Decennial Census and 2007-2011 American Community Survey (ACS) by census tract from Social Explorer (US Census Bureau, 2000; US Census Bureau, 2012; [www.SocialExplorer.com](http://www.SocialExplorer.com); accessed 2013). The census tract boundaries from the 2000 Decennial Census were interpolated to match 2010 census tract boundaries using area and population weights (Logan, Xu, Stults, & Chunyu, 2012) within Stata 11 (Stata Corp, LP., College Station, TX). Variables for both Census surveys were derived from data available from the US Census (Table 3). Variables selected for characterizing community composition as a means of understanding geographic variations in the land-cover-change rates included race, education, income, employment, and home ownership status (Table 3). In addition, the proportions of land covers in different land-cover classes within each census tract were derived from the NLCD data from 2001 and 2006 using ArcGIS 10 (Table 3; Hossain et al., 2007; Fry et al., 2011).

**Statistical Analysis.** The beta values describing the rates of change in impervious surfaces (Equation 2) for the pre- and post-recession periods were compared by calculating their means, medians, and standard deviations across all pixels in the study area. In addition, for each pixel I calculated the difference between the calculated betas for each period and summarize these differences to understand, regionally, the direction and magnitudes of change.

The independent variables for analysis of variations by community composition were derived from socioeconomic and land-cover input variables using factor analyses in R 2.15.1 (R Core Team, Vienna, Austria, 2012). The factor analyses for both the 2001-2005 (based on inputs from the 2000 Census data) and 2007-2011 (based on inputs from the 2007-2011 ACS data) time periods were used to estimate six factors using the varimax rotation. The resulting factors were compared between the time periods and used to describe spatial variation in percent impervious surface using regression models.

A conditional autoregressive (CAR) regression model was used to identify associations between census-tract-level variations in the rates of change of impervious surface and the factors representing the socioeconomic and land-cover characteristics hypothesized to explain geographic variations in those changes over the pre- and post-recession periods, and the differences in rates between these two time periods. This model, estimated in R 2.15.1 (R Core Team, Vienna, Austria, 2012), accounts for both spatial autocorrelation among census tracts and the large differences in the geographic area of census tracts (0.22 to 284.83 km<sup>2</sup>) by adjusting the variance-covariance matrix to include spatial weights based on queen's rule of adjacency and weights on the observations based on census tract areas (Waller & Gotway, 2004; Bivand, Pebesma, & Gómez-Rubio, 2008).

### ***Results and Discussion***

The results comparing impervious change between the pre- and post-recession periods present a mixed picture relative to the hypothesized differences. Average differences in the rates of change in impervious surface between pre- and post-recession periods were counter to those hypothesized. The first period had a mean slope of -0.18 and median of 0 with a standard deviation of 1.81, while the second period had a mean slope of -0.13 and median of 0 with a standard deviation of 1.71 (Figures 7 and 8). The mean difference between these two periods of time was 0.06 with a standard deviation of 2.34. These mean values translate to an average decline in percent impervious detected of 0.18% per year during the pre-recession period, a decline of only 0.13% per year during and after the recession, and an increase in the slope of 0.06 between the two periods. The zero medians are dominated by large numbers of cells with zero change. Focusing on the area that experienced an increase in the rate of impervious surface was greater pre-recession (6.34%) versus post-recession (6.14%; Figure 9). This is consistent with the hypothesis that there would be more increase pre- versus post-recession. This is mitigated, however, by the fact that more cells decreased their impervious surface percentages in the pre- (9.05%) vs. post-recession (8.57%) periods as well, suggesting more overall change in both directions in the pre-recession period. That the majority of beta values in both time periods are zero likely stems from the categorical nature of the impervious surface estimates, and means that many cells never changed category.

These results could indicate that change in the area of exposed impervious surface is not always associated with economic activity. Specifically, the interpretation of changes in impervious surface may be more nuanced and vary across space. While the typical expectation would be for impervious surface to increase over time as the economy grows, tree and vegetation maturation, even in economically vibrant communities, can result in a decrease in the amount of exposed impervious surface. For example: in areas with relatively high socioeconomic status, an increase in impervious could initially suggest positive

economic growth and might be subsequently followed by a decrease in visible vegetation, as landscaping matures, and conversely in areas with relatively low socioeconomic status, a decrease in impervious surface could occur from abandoned houses and underutilized pavement becoming vegetated by weeds, small shrubs, and opportunistic trees. Therefore, interpreting impervious surface change in isolation from other variables may not be directly associated with the economy.

Alternatively, the mixed results of the comparison between pre- and post-recession periods could indicate that, despite a regional construction boom and crash in the Midwest from the pre- to post-recession periods, the differences in economic activity and construction in Southeastern Michigan were not as great as in other places. Michigan was the only state in the US to have lost population during the 2000-2010 period (Mackun, Wilson, Fischetti, & Goworowska, 2011). This weakened pre-recession economy could have produced low levels of building construction, new housing subdivisions, and new roads; each leading to low rates of increase, or high rates of decrease, in impervious surface area. Furthermore, perhaps a portion of the Michigan's \$8.8 billion of the federal stimulus funding in the post-recession period, of which \$1.4 billion was allocated to transportation and over \$839 million to infrastructure, compensated for some of the impervious surface that might have been lost otherwise (Recovery.gov, 2013).

The factor analyses produced six factors that were similar across the two time periods. They were not identical because the input variables differed based on the way some of the variables were measured in the 2000 decadal census versus the ACS 2007-2011. Based on the pattern of factor loadings (Tables 4 and 5), we interpret and label the factors as follows. Though the associations were consistent across periods, the orders in which they were identified by the two analyses were different. The Deprivation factor was positively associated with the proportion of the population that was black, unemployed, below the national poverty line, and had a high school education or less and low income (<\$25,000). It was also positively associated with the proportion of homes that were vacant and negatively associated with the proportion of the population that was white, married, and had a high income (>\$75,000). The Rurality factor was negatively correlated with the proportion of each census tract that was developed and positively correlated with the proportion that was agriculture, forest, wetlands, shrub, and grass. It was also positively correlated with the size of the census tract, suggesting a positive correlation with rural (large and sparsely populated) census tracts. The Wealth/Education factor was positively associated with the proportion of the population that completed a bachelor's degree or higher, had a high income (>\$75,000), lived in houses valued at greater than \$300,000, and was Asian. In addition, it was negatively correlated with the proportion of the population with a high school degree or less. The Ethnicity factor

was positively associated with the proportion of the households that were linguistically isolated<sup>4</sup> and the proportion of the population that was Hispanic. It was negatively correlated with the proportion black and of English-only speaking households. The Families factor was positively correlated with the proportion of the population that was married, living in single-family dwellings, and under age 18, and negatively correlated with the proportion of homes that were rental units.<sup>5</sup> The White (Not Black) factor is positively correlated with the proportion of the population that was white and negatively correlated with the proportion of the population black. Overall, these six factors explained 59% and 57% of the cumulative variance for the selected Census and NLCD variables in 2001-2005 and 2007-2011, respectively (Tables 6 and 7).

The rate of change in impervious surface was closely associated with community structure as hypothesized (Table 8). While the statistical methods do not produce an  $R^2$  value, to measure the overall explanatory power, we interpret the significant variables for their relationship with changes in impervious surface. During both the pre- and post-recession periods, communities with greater Deprivation experienced lower rates of increase, or higher rates of decrease, in impervious surface area. This could be because these neighborhoods are in comparatively greater states of disrepair, with less construction and more vegetation growth over previously exposed impervious surfaces. This association held for both the pre- and post-recession periods.

Greater Ethnicity in the population was associated with lower rates of impervious surface increase (or higher rates of decrease) during the pre-recession period ( $p < 0.001$ ). Perhaps this is due to ethnic populations improving, greening, and taking care of their communities. Latinos and new immigrants in Detroit are reducing urban blight, bringing in new investment, and transforming their communities (Williams, 2008). Miller and Martinez (2010) document Hispanic population growth in Michigan and suggest that as a workforce Hispanics are becoming an increasingly important part of the Michigan economy. However, the Ethnicity factor was not statistically significant during the post-recession period potentially due to the communities maintaining status quo and not investing money into their community during challenging economic times.

During the post-recession period, the Family factor was negatively associated with the rate of impervious surface change ( $p < 0.001$ ), perhaps due to the affinity of families with children to live in suburbs and

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<sup>4</sup> A “linguistically-isolated household” is defined as a household where all adults (person > 14 years old) speak a language other than English and no one speaks English at a self-reported level of “very well” (Siegel, Martin, & Bruno, 2007).

<sup>5</sup> The factor analysis for the ACS 2007-2011 also identified the proportion of new movers to the community as being positively correlated.

exurbs with larger lots and more open space. Furthermore, as these family-friendly suburban developments mature, the vegetation could grow and expand to cover previously exposed impervious surfaces, such as tree canopies covering roads and driveways, creating a decrease in the rate of impervious surface. It is interesting to note that the Family factor was not statistically significant during the pre-recession period, perhaps because these regrowth processes were balanced with new single-family home construction in these areas.

Similarly, the Wealth/Education factor was statistically significant only during the post-recession period. This outcome could be due to wealthy and highly-educated individuals also favoring landscaped developments in the exurbs (similar to the Family factor). However, this factor's lack of statistical significance during the pre-recession period suggests that low socio-economic status (i.e. Deprivation) was a more important threshold than differences between middle- and upper-class statuses in determining changes in impervious surface.

In addition to socioeconomic variables proving to have significant relationships with impervious surface change, overall land cover composition was also important in understanding impervious surface changes in both time periods ( $p < 0.001$ ). The Rurality of an area was positively associated with the rate of impervious surface change during both periods ( $p < 0.001$ ). Large rural census tracts with more forest, agriculture, scrub, grass, and wetlands experienced greater increases in impervious, or lower decreases, most likely due to the availability of large areas of open land available for development. Additionally, these areas often started with a much lower fraction of their areas in impervious surfaces, so a smaller addition of total area in impervious was needed to increase the percentage of impervious area compared to census tracts with higher initial amounts of impervious. The increases in impervious surface area in predominately rural census tracts could reflect eastern US trends of exurbanization as well (Brown et al., 2005).

In contrast to the findings from the individual periods of times, the rate of change in impervious surface was most different between the two time periods in communities with greater socioeconomic Deprivation and Ethnicity and also in less Rural areas with less Wealth/Education. Greater deprivation was characteristic of areas where impervious surface increased at a higher rate, or decreased at a lower rate, during the post-recession period. This could potentially be due to targeted public spending either through the federal stimulus package or traditional welfare avenues. Further supporting this finding is that the less Rural areas (more urban) experienced increased impervious surface areas alongside areas with higher proportions of less educated individuals and ethnic populations. Each variable suggests that historically

economically-challenged communities saw impervious increase at a higher rate. These results could once again be a result of stimulus funding as well as other public support directed towards struggling communities. The results indicate a suite of sociofactors and landscape characteristics influence the amount of impervious surface change occurring within each census tract.

Overall, these results do not suggest a clean, direct effect of the economy on the landscape and indicate the need to expand the current research beyond the focus of impervious surface change. It would be useful to explore the impacts of the economy on tree canopy and vegetation. While it has been documented that eastern forests have increased and decreased over the past century as a result of human activity (Drummond & Loveland, 2010), it would be interesting to examine forest change with an economic lens to understand how tree cover responds to “boom and bust” economic cycles. In addition, expanding forests to include all forms of vegetation could provide an opportunity to study a broader range of change, including weed-covered land and overgrown lots. These types of vegetation would be especially useful to capture and assess in the City of Detroit, a metropolitan area that has witnessed a decline in maintenance of its housing over time (Ryznar & Wagner, 2001).

In addition to evaluating change in both impervious surface and vegetation covers, it could be useful to explore alternative subpixel classification techniques, such as artificial neural networks or Linear Spectral Mixture Analysis (Weng, 2012). These techniques could provide a more robust methodology for assessing the quantity of impervious surface and ultimately resolve some of the systematic under-estimation issues experienced in this study. Another methodological improvement could stem from better representing change in MOIs over time, perhaps by exploring the use of a panel data analysis to model the changes over time more explicitly. This would allow us to exploit the rich time-series data we collected and prepared.

It could also be helpful to develop stronger image selection criteria. For example: all images were included in the study if they were processed to level 1T, had 60% or less cloud cover, were collected for the calendar dates March 1 to October 31, and did not have any scan line correction issues. This broad suite of criteria produced over 18 viable images in 2001 and only 5 in 2009 with a median of 9 images per year. In addition, for the validation years only nine images were available for 2006 leading an  $R^2$  of 0.82 as compared to 2001, which used twice as many images (18) and improved the  $R^2$  to 0.86. This suggests that more images may create a more robust impervious surface layer by compensating for clouds cover and phenological variation. Future research could explore implementing both a floor and ceiling for a

allowable minimum and maximum number of annual images, which could prevent some of the artificial inflation and deflation that may have occurred due to a wide range of annual images.

Ultimately, the validation procedure for the impervious surface estimates was limited by the mismatch between the definitions used in this study versus those in the NLCD study. Additional work to estimate uncertainties could improve the study. We know that the estimates are not 100 percent accurate, but are unable, at this point, to estimate how errors in the impervious surface estimates affect the slopes (betas) on the change estimates. Our hope is that by calculating slopes over five years, some of the uncertainties are reduced. Alternatively, using shorter time periods may help to focus directly on the period of economic recession and therefore remove time from the study during which the economy was improving. However, this may introduce uncertainty into the results.

Regardless of methodology, linking socio-economic data to landscape change is inherently challenging: census data are not constant across time and there are a wide variety of landscape-change causes beyond housing construction and destruction. Furthermore, it is not a closed system; there are impacts on landscape change in Michigan that reflect, not just the midwest economy, but the global economy, as well as policies made at local, state, and federal levels. Additionally, while we assumed linear relationships between socioeconomic factors, future work should explore non-linear relationships as well. It could be that the Rurality factor has a quadratic relationship with impervious change, with the greatest rates of change occurring at the urban-rural fringe, rather than at either end of the continuum.

Given these obstacles, are the results of the study an artifact of methodology or reflective of true economic processes? To answer this question at least one other methodology would need to be explored to assess whether the results from this study were an anomaly. It might also be valuable to perform a parallel analysis in a region in the country that experienced both a documented population and economic boom between 2001 and 2005 and compare the rates of change in impervious surface and vegetation to the post-recession values, but also back to Southeastern Michigan. This would help understand if Southeastern Michigan is representative of other regions in the US in terms of losing impervious surface during the pre- and post-recession periods, but also help to validate and confirm initial results.

### ***Conclusion***

Over the past forty years satellites have been used to observe Earth from space. Combining images with on-the-ground socioeconomic data presents opportunities for understanding how the economy affects the planet over short economic cycles. Our results relative to our hypotheses are somewhat mixed, but on

average impervious surface areas did not increase at a faster rate during the period before the recession, decrease at a slower rate, or change from increasing to decreasing, when compared to the post-recession period. However, this preliminary finding necessitates further research to identify if it is methodological artifact, a product of Michigan's depressed economy, or observable across other geographic areas.

Just as the landscape is a heterogeneous mosaic of various land covers, our research suggests that the forces acting upon it are also heterogeneous in nature. The socioeconomic composition of individual communities plays an important role in shaping how a landscape changes through time and space. Overall, we demonstrate that the socioeconomic characteristics of communities have land use, ecological, and carbon sequestration implications.

*Tables and Figures***Table 1. Landsat image count by year: 2001 – 2011.**

<b>Year</b>	<b>Number of Images</b>
2001	18
2002	13
2003	9
2004	6
2005	9
2006	9
2007	7
2008	9
2009	5
2010	8
2011	9

**Table 2. Intervals from the subpixel classification were recoded to the median integer for each interval.**

<b>Interval</b>	<b>Integer</b>
0- 19%	10
20-29%	25
30-39%	35
40-49%	45
50-59%	55
60-69%	65
70-79%	75
80-89%	85
90-100%	95

**Table 3. US Census Bureau and NLCD derived-variables**

<b>Census Variables</b>	<b>NLCD Variables</b>
White	Low, medium and high levels of development
Black	Forest
Married	Agriculture
Less than high school	Wetlands
Unemployment	Open water
Income less than \$25,000	Barren
Vacancy	Area
House value less than \$50,000	Scrub & shrub
House values \$150,000 – 300,000	Grass
Below poverty line	
High school or less	
More than college	
Income greater than \$75,000	
Income greater than \$100,000	
House value greater than \$300,000	
Median house value	
Rental units	
Single family house	
Community stability	
Hispanic	
English-only speakers	
Language isolated (no English speakers)	
Total population	
Age less than 18	
Age greater than 65	
Group quarters	
Labor Force	
Mobile home dwellers	
Households without mortgage	
Troubled Areas – “houses under water”	
New to community	
Median year structure built	

Table 4. Factor Analysis for 2001- 2005 (Census 2000 and NLCD 2001).

	<b>Factor 1: Deprivation</b>	<b>Factor 2: Rurality</b>	<b>Factor 3: Wealth/ Education</b>	<b>Factor 4: Ethnicity</b>	<b>Factor 5: Families</b>	<b>Factor 6: White (not black)</b>
<b>Proportion white</b>	-0.69	0.35				0.6
<b>Proportion black</b>	0.66	-0.32		-0.37		-0.55
<b>Proportion married</b>	-0.74	0.36			0.36	
<b>Proportion unemployed</b>	0.81					
<b>Proportion with income below \$25,000</b>	0.92					
<b>Proportion with income above \$75,000</b>	-0.63		0.55			
<b>Proportion of rental houses</b>	0.71				-0.52	
<b>Proportion of vacant properties</b>	0.73					
<b>Proportion housing value below \$50,000</b>	0.76					
<b>Proportion below poverty line</b>	0.88					
<b>Census tract area</b>		0.68				
<b>Proportion shrub</b>		0.67				
<b>Proportion grass</b>		0.65				
<b>Proportion forest</b>		0.75				
<b>Proportion developed</b>		-0.89				
<b>Proportion wetlands</b>		0.72				
<b>Proportion agriculture</b>		0.78				
<b>Proportion Asian</b>			0.53	0.37		
<b>Proportion with high school education or less</b>	0.52		-0.75			
<b>Proportion with a bachelor's degree or more</b>	-0.35		0.91			
<b>Proportion housing value above \$300,000</b>			0.65			
<b>Proportion Hispanic</b>				0.77		
<b>Proportion English-only speakers</b>				-0.78		
<b>Proportion language isolated</b>				0.85		
<b>Proportion under 18 years of age</b>	0.31				0.63	
<b>Proportion one unit houses</b>	-0.43				0.75	
<b>Total population</b>						
<b>Proportion over 65 years of age</b>						0.35
<b>Proportion living in group quarters</b>					-0.4	
<b>Proportion in labor force</b>	-0.47		0.32			
<b>Proportion mobile homes</b>		0.4				
<b>Proportion without mortgage</b>	0.45				0.36	
<b>Proportion in troubled areas (one or more mortgages)</b>						
<b>Proportion water</b>						
<b>Proportion barren</b>						

Table 5. Factor analysis of 2007-2011 (American Community Survey 2007 – 2011 and NLCD 2006).

	<b>Factor 1: Deprivation</b>	<b>Factor 2: Rurality</b>	<b>Factor 3: Families</b>	<b>Factor 4: Ethnicity</b>	<b>Factor 5: Wealth/ Education</b>	<b>Factor 6: White (Not black)</b>
Proportion white	-0.79	0.3				0.52
Proportion black	0.78			-0.31		-0.43
Proportion married	-0.71	0.36	0.43			
Proportion unemployed	0.76					
Proportion with income below \$25,000	0.89					
Proportion with income above \$25,000	-0.71				0.45	
Proportion of rental houses	0.64		-0.52			
Proportion of vacant properties	0.78					
Proportion housing value below \$50,000	0.73					
Proportion properties without a mortgage	0.53					
Proportion below the poverty line	0.87					
Proportion forest		0.75				
Census tract area		0.69				
Proportion scrub		0.65				
Proportion grass		0.65				
Proportion developed	0.33	-0.89				
Proportion agriculture		0.79				
Proportion wetlands		0.71				
Proportion under 18 years of age	0.32		0.58			
Proportion one unit houses			0.74			
Proportion new movers to communities			0.77			
Proportion Hispanic				0.65		
Proportion English-only speakers				-0.87		
Proportion language isolated				0.87		
Proportion Asian				0.33	0.5	
Proportion with high school education or less	-0.59				-0.66	
Proportion with bachelors degree or more	-0.5				0.85	
Proportion house value more than \$300,000					0.68	
Proportion water						
Proportion barren		0.31				
Total population	-0.32					
Proportion more than 65				-0.32		
Proportion Arab				-0.46		
Proportion living in group quarters			-0.44			
Proportion in labor force	-0.41					
Proportion mobile homes		0.37				
Proportion troubled areas (more than one mortgage)						
Proportion new to communities			-0.48		0.38	

**Table 6. Proportion variance and cumulative variance explained by 2001-2005 factors.**

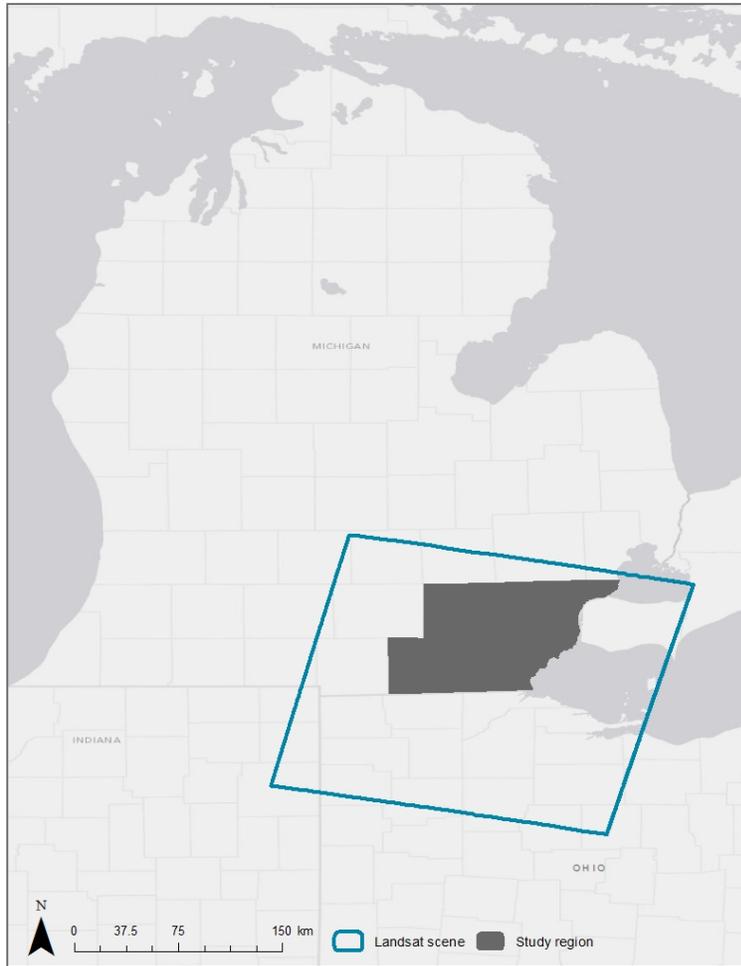
	<b>Factor 1: Deprivation</b>	<b>Factor 2: Rurality</b>	<b>Factor 3: Wealth/ Education</b>	<b>Factor 4: Ethnicity</b>	<b>Factor 5: Families</b>	<b>Factor 6: White (not black)</b>
<b>Proportion variance</b>	0.20	0.14	0.08	0.07	0.06	0.03
<b>Cumulative variance</b>	0.20	0.34	0.43	0.50	0.56	0.59

**Table 7. Proportion variance and cumulative variance explained by 2007 – 2011 factors.**

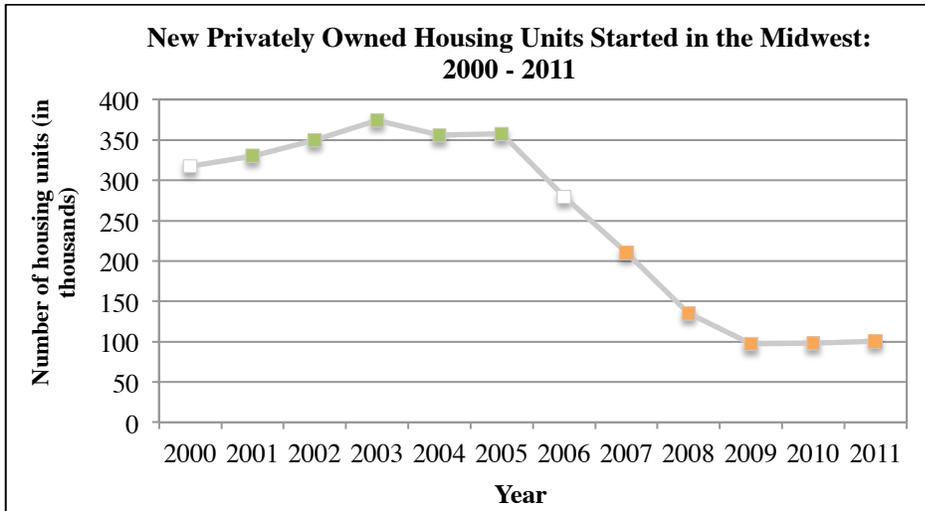
	<b>Factor 1: Deprivation</b>	<b>Factor 2: Rurality</b>	<b>Factor 3: Families</b>	<b>Factor 4: Ethnicity</b>	<b>Factor 5: Wealth/ Education</b>	<b>Factor 6: White (Not black)</b>
<b>Proportion variance</b>	0.20	0.13	0.07	0.07	0.07	0.02
<b>Cumulative variance</b>	0.20	0.33	0.40	0.48	0.55	0.57

Table 8. Regression models. Asterisk (\*) indicates statistically significant variable at  $\alpha = 0.01$ 

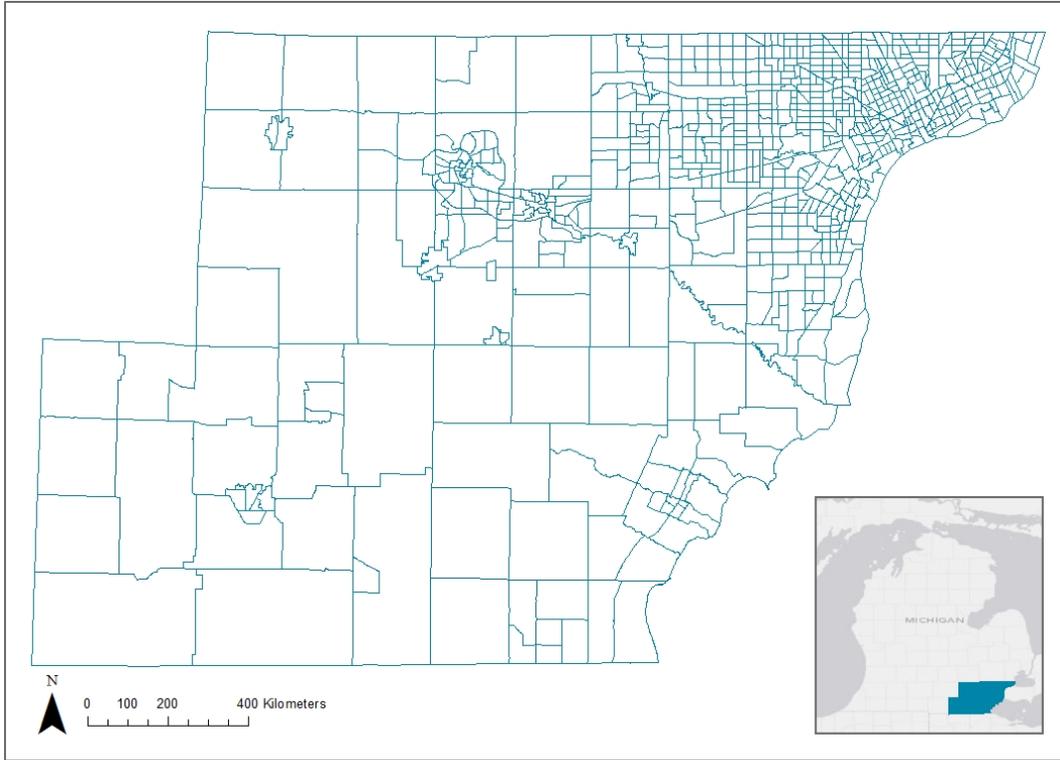
<b>a. CAR Model: Housing growth period (2001-2005)</b>				
	<b>Estimate</b>	<b>Standard Error</b>	<b>Z value</b>	<b>Pr (&gt; z )</b>
<b>Intercept</b>	-1.226	0.049	-24.710	< 0.001
<b>Deprivation</b>	-0.423	0.041	-10.240	< 0.001*
<b>Rurality</b>	0.331	0.020	16.511	< 0.001*
<b>Wealth/Education</b>	-0.034	0.026	-1.307	0.190
<b>Ethnicity</b>	-0.247	0.048	-5.121	< 0.001*
<b>Families</b>	0.044	0.031	1.424	0.154
<b>White(not black)</b>	0.214	0.035	6.101	< 0.001*
<b>b. CAR Model: Housing decline period (2007-2011)</b>				
	<b>Estimate</b>	<b>Standard Error</b>	<b>Z value</b>	<b>Pr (&gt; z )</b>
<b>Intercept</b>	-1.424	0.053	-26.502	< 0.001
<b>Deprivation</b>	-0.371	0.043	-8.618	< 0.001*
<b>Rurality</b>	0.380	0.018	21.114	< 0.001*
<b>Families</b>	-0.076	0.028	-2.657	0.007*
<b>Ethnicity</b>	0.054	0.041	1.322	0.186
<b>Wealth/Education</b>	-0.109	0.026	-4.1712	< 0.001*
<b>White(not black)</b>	0.150	0.030	5.0149	< 0.001*
<b>c. SAR Model: Difference between housing decline and housing growth periods</b>				
	<b>Estimate</b>	<b>Standard Error</b>	<b>Z value</b>	<b>Pr (&gt; z )</b>
<b>Intercept</b>	0.267	0.115	2.305	0.021
<b>Deprivation</b>	0.240	0.061	3.921	< 0.001*
<b>Rurality</b>	-0.040	0.036	-1.110	0.266
<b>Wealth/Education</b>	-0.092	0.036	-2.513	0.011*
<b>Ethnicity</b>	0.210	0.063	3.322	< 0.001*
<b>Families</b>	-0.023	0.034	-0.671	0.501
<b>White(not black)</b>	0.063	0.048	1.298	0.194



**Figure 1. Southeastern Michigan study region, with the outline of the Landsat WRS-2 path/row used for selection and analysis of images.**



**Figure 2. New Privately Owned Housing Units Started in the Midwest: 2000 – 2011.** Green points indicate economic growth and orange points indicate economic downturn. Source: US Census Bureau Housing, New Residential Construction for Housing Starts ([http://www.census.gov/construction/nrc/historical\\_data](http://www.census.gov/construction/nrc/historical_data)).



**Figure 3. Census tract boundaries in the four county study region.**

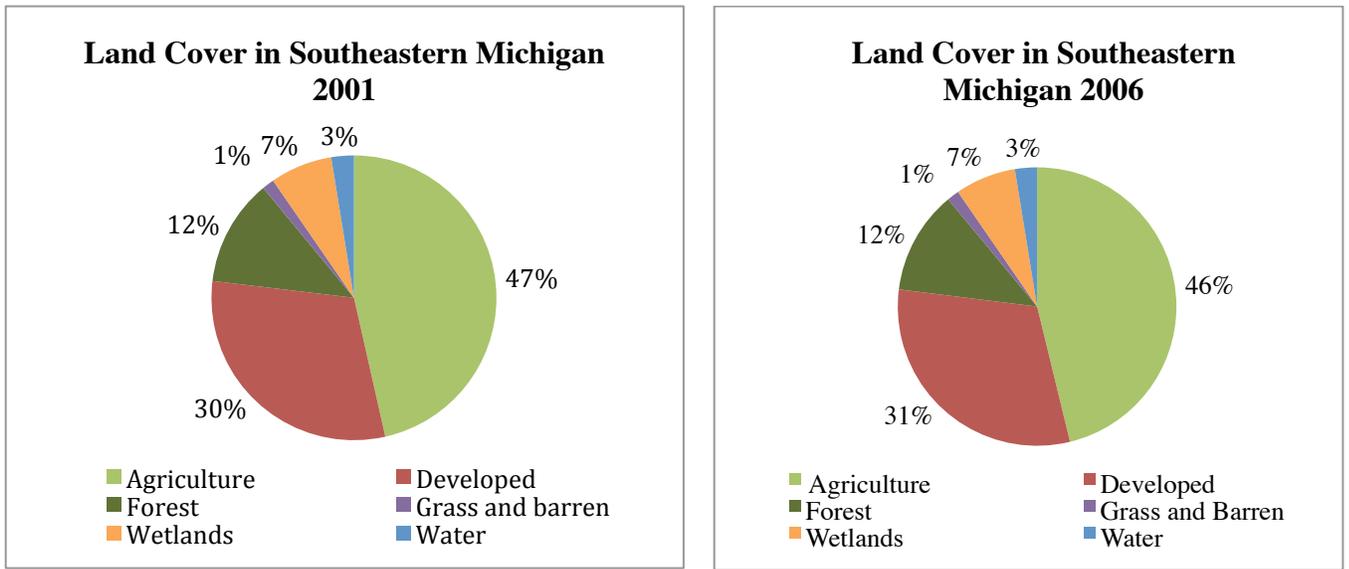
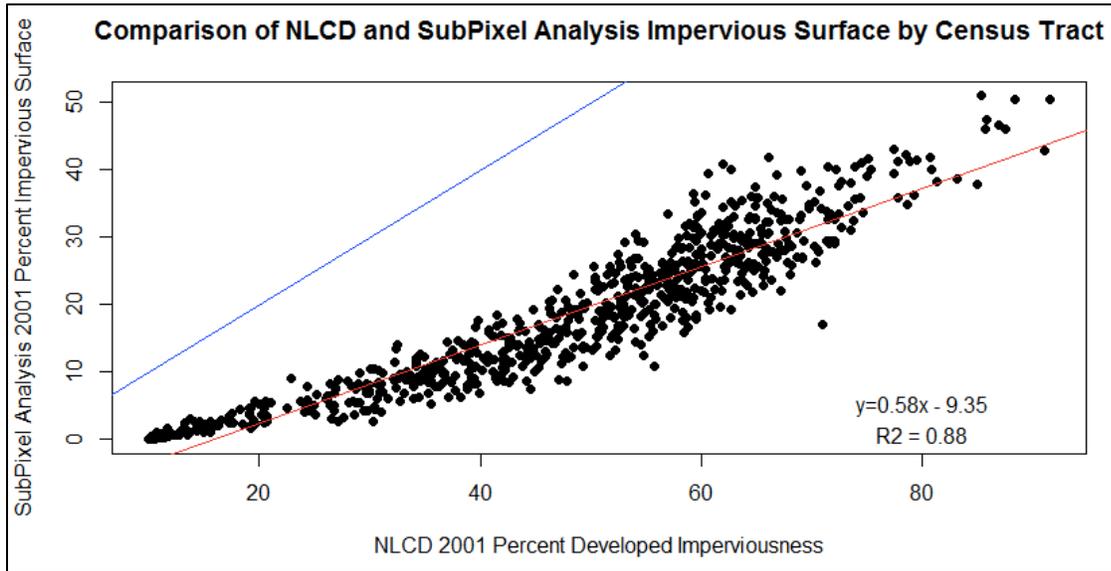


Figure 4. Land Cover in Southeastern Michigan. Source: NLCD 2001 and 2006.



**Figure 5. Comparison of 2001 NLCD and subpixel analysis surface by census tract. The blue line indicates the 1:1 line; the red line indicates the best-fit line for the regression.**

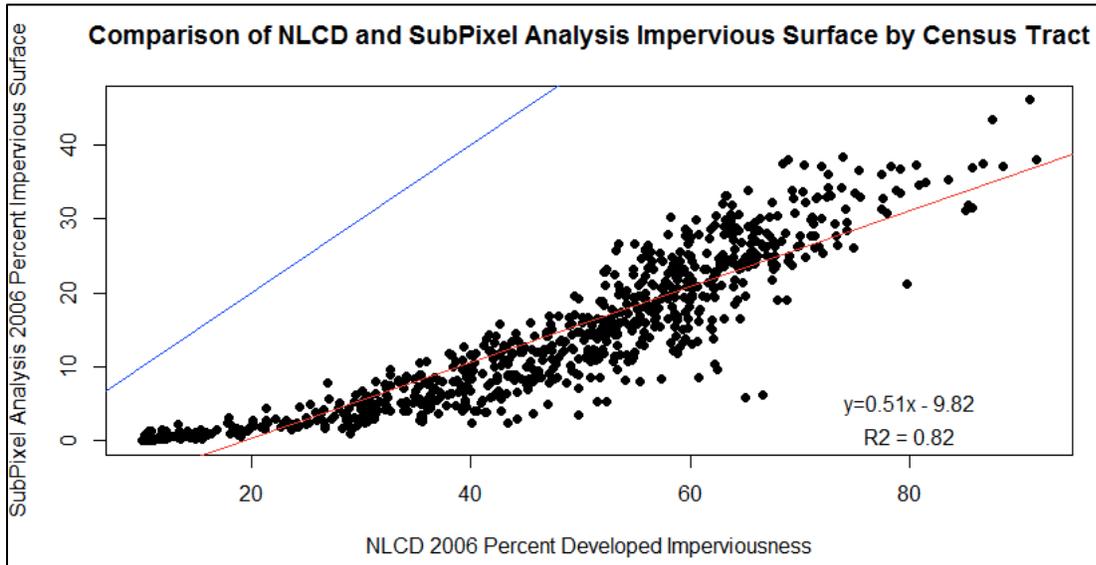


Figure 6. Comparison of 2006 NLCD and subpixel analysis surface by census tract. The blue line indicates the 1:1 line; the red line indicates the best-fit line for the regression.

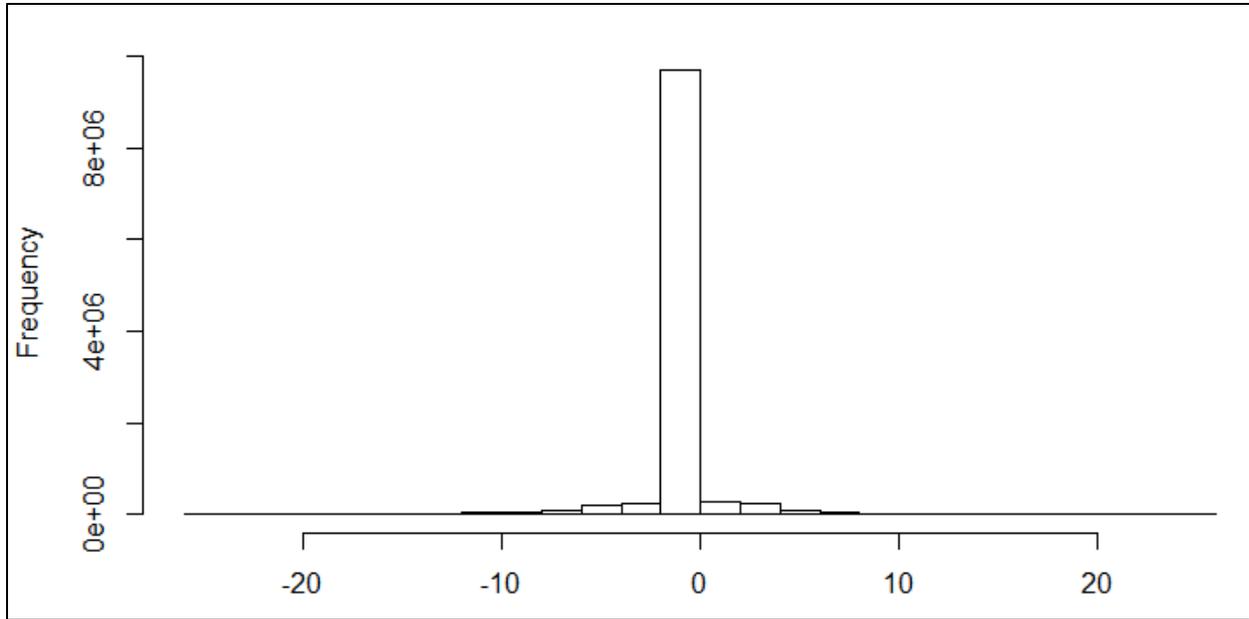


Figure 7. Histogram of beta values for 2001-2005.

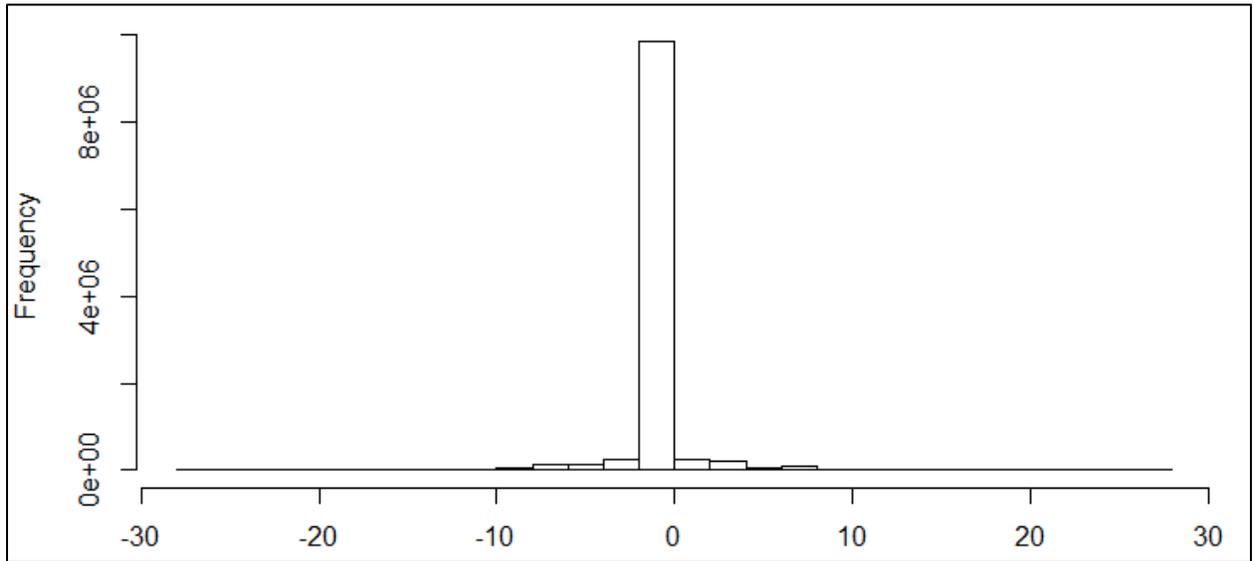
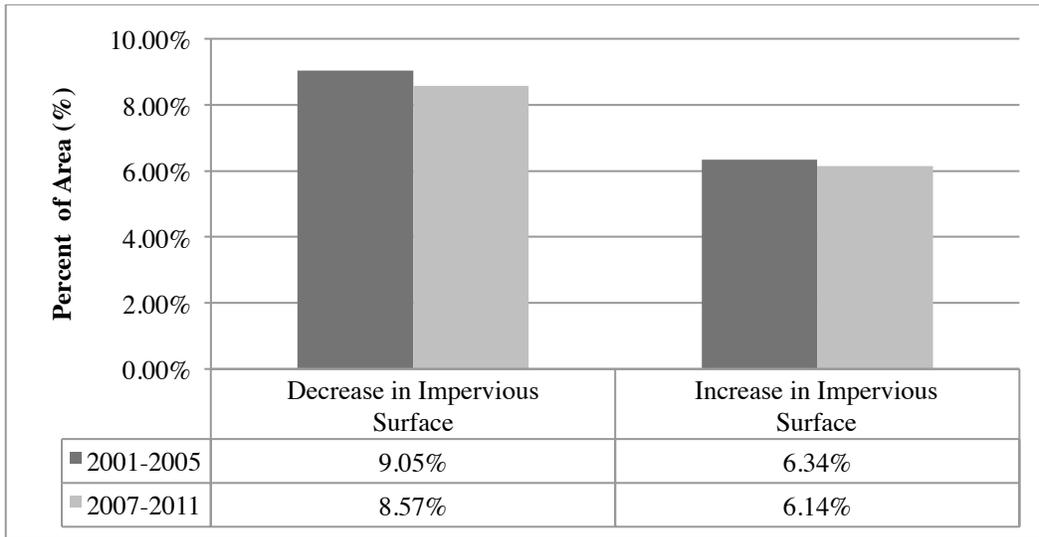


Figure 8. Histogram of beta values for 2007-2011.



**Figure 9. Percent area of decrease and increase in impervious surface during pre- and post-recession periods.**



### *Citations*

- Angel, S., Parent, J., Civco, D. I., & Blei, A. M. (2011). Making Room for a Planet of Cities *Policy Focus Report*. Cambridge, MA: Lincoln Institute of Land Policy.
- Belke, A., Dobnik, F., & Dreger, C. (2011). Energy consumption and economic growth: New insights into the cointegration relationship. *Energy Economics*, 33, 782-789.
- Bivand, R. S., Pebesma, E. J., & Gómez-Rubio, V. (2008). *Applied Spatial Data Analysis with R*. New York, NY: Springer Science +Business Media.
- Borozan, D. (2013). Exploring the relationship between energy consumption and GDP: Evidence from Croatia. *Energy Policy*, 59, 373–381.
- Brennan, M. (2013). How Bankruptcy Will Impact Detroit's Housing Market. *Forbes*.
- Brown, D. G., Johnson, K. M., Loveland, T. R., & Theobald, D. M. (2005). Rural Land-Use Trends in the Conterminous United States, 1950-2000. *Ecological Applications*, 15(6), 1851-1863.
- Cadenasso, M. L., Pickett, S. T. A., & Schwarz, K. (2007). Spatial Heterogeneity in Urban Ecosystems: Reconceptualizing Land Cover and a Framework for Classification. *Frontiers in Ecology and the Environment*, 5(2), 80-88.
- Crutzen, P. J., & Stoermer, E. F. (2000). The ‘Anthropocene’. *Global Change Newsletter*, 41, 17-18.
- Drummond, M. A., & Loveland, T. R. (2010). Land-use pressure and a transition to forest-cover loss in the Eastern United States. *Bioscience*, 60(4), 286-298.
- Ellis, E. C., & Ramankutty, N. (2008). Putting people in the map: anthropogenic biomes of the world. *Frontiers in Ecology and the Environment*, 6(8), 439–447.
- ERDAS. (2009). *IMAGINE Subpixel Classifier™ User’s Guide*. Norcross, GA.
- Flanagan, M., & Civco, D. L. (2001). *Subpixel Impervious Surface Mapping*. Paper presented at the American Society of Photogrammetry and Remote Sensing, St. Louis, MO.
- Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., . . . Snyder, P. K. (2005). Global Consequences of Land Use. *Science*, 309, 570-574.
- Fry, J. A., Xian, G., Jin, S., Dewitz, J. A., Homer, C. G., Yang, L., . . . Wickham, J. D. (2011). Completion of the 2006 National Land Cover Database for the Conterminous United States. *Photogrammetric Engineering & Remote Sensing*, 77(9), 858-864.

- Geist, H. J., & Lambin, E. F. (2001). What Drives Tropical Deforestation? A meta-analysis of proximate and underlying causes of deforestation based on subnational case study evidence *LUCC Report Series* (Vol. 4). Louvain-la-Neuve, Belgium.
- Henderson, J. V., Storeygard, A., & Weil, D. N. (2009). Measuring Economic Growth from Outer Space *NBER Working Paper Series*. Cambridge, MA: National Bureau of Economic Research.
- Henderson, J. V., Storeygard, A., & Weil, D. N. (2011). A Bright Idea for Measuring Economic Growth. *American Economic Review: Papers & Proceedings*, 101(3), 194–199.
- Henley, W. (2013, August 28, 2013). Detroit: how can regeneration solve city bankruptcy and abandonment? *The Guardian*. Retrieved from <http://www.theguardian.com/sustainable-business/detroit-regeneration-bankruptcy-abandonment>
- Hossain, N., Larson, C., Herold, N., McKerrow, A., VanDriel, J. N., & Wickham, J. (2007). Completion of the 2001 National Land Cover Database for the Conterminous United States. *Photogrammetric Engineering & Remote Sensing*, 73(4), 337-341.
- Linebaugh, K. (2011). Detroit's Population Crashes: Census Finds 25% Plunge as Blacks Flee to Suburbs; Shocked Mayor Seeks Recount *Wall Street Journal*. Retrieved from <http://online.wsj.com/article/SB10001424052748704461304576216850733151470.html>
- Logan, J., Xu, Z., Stults, B., & Chunyu, M. (2012). US2010: Discover America in a New Century.
- Luck, M., & Wu, J. (2002). A gradient analysis of urban landscape pattern: a case study from the Phoenix metropolitan region, Arizona, USA. *Landscape Ecology*, 17(4), 327-339.
- Mackun, P., Wilson, S., Fischetti, T., & Goworowska, J. (2011). Population Distribution and Change: 2000 to 2010 *2010 Census Briefs*: US Census Bureau.
- Mallach, A., Basu, S., Gazillo, S. A., King, J., Lynch, T., Marty, E., . . . Simmons, E. (2008). *Leaner, Greener Detroit*: The American Institute of Architects.
- Masek, J. G., Vermote, E. F., Saleous, N. Z., Wolfe, R., Hall, F. G., Huemmrich, F., . . . Lim, T.-K. (2012). *LEDAPS Calibration, Reflectance, Atmospheric Correction Preprocessing Code*. Retrieved from: <http://daac.ornl.gov>
- Miller, S. R., & Martinez, R. O. (2010). Measuring the Economic and Fiscal Contributions of Michigan's Latino Population. Lansing, MI: Michigan State University.
- Moffatt, S. F., McLachlan, S. M., & Kenkel, N. C. (2004). Impacts of land use on riparian forest along an urban–rural gradient in southern Manitoba. *Plant Ecology*, 174(1), 119-135.

- Morton, D. C., DeFries, R. S., Shimabukuro, Y. E., Anderson, L. O., Arai, E., Espirito-Santo, F. d. B., . . . Morisette, J. (2006). Cropland expansion changes deforestation dynamics in the southern Brazilian Amazon. *Proceedings of the National Academy of Sciences*, *103*(39), 14637–14641.
- Paciorek, A. D. (2013). The Long and the Short of Household Formation (D. o. R. S. a. M. Affairs, Trans.) *Finance and Economics Discussion Series*. Washington, D.C. : Federal Reserve Board.
- Patton, M. (2012). Home Sweet Home: The Housing Market in Perspective. *Forbes*.
- Phalan, B., Bertzky, M., Butchart, S. H. M., Donald, P. F., Scharlemann, J. P. W., Stattersfield, A. J., & Balmford, A. (2013). Crop Expansion and Conservation Priorities in Tropical Countries. *PLOS ONE*, *8*(1), 1.
- Pickett, S. T. A., Cadenasso, M. L., & Grove, J. M. (2005). Biocomplexity in Coupled Natural-Human Systems: A Multidimensional Framework. *Ecosystems*, *8*, 225-232.
- Pickett, S. T. A., Cadenasso, M. L., Grove, J. M., Boone, C. G., Groffman, P. M., Irwin, E. G., . . . Warren, P. (2011). Urban ecological systems: Scientific foundations and a decade of progress. *Journal of Environmental Management*, *92*, 331-362.
- R Core Team. (2012). R: A language and environment for statistical computing (Version 2.15.1). Vienna, Austria: R Foundation for Statistical Computing. Retrieved from <http://www.R-project.org>
- Ramankutty, N., Evan, A. T., Monfreda, C., & Foley, J. A. (2008). Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles*, *22*(GB1003), 19.
- Recovery.gov. (2013). Michigan Funding Overview. from <http://www.recovery.gov/espsearch/Pages/advanced.aspx?data=recipientAwardsList&State=MI&AwardType=CGL>
- Robinson, D. T. (2012). Land-cover fragmentation and configuration of ownership parcels in an exurban landscape. *Urban Ecosystems*, *15*, 53-69.
- Robinson, D. T., Brown, D. G., & Currie, W. S. (2009). Modelling carbon storage in highly fragmented and human-dominated landscapes: Linking land-cover patterns and ecosystem models. *Ecological Modelling*, *220*, 1325–1338.
- Ryznar, R. M., & Wagner, T. W. (2001). Using Remotely Sensed Imagery to Detect Urban Change: Viewing Detroit from Space. *Journal of the American Planning Association*, *67*(3), 327-336.

- Schneider, A., Friedl, M. A., & Potere, D. (2009). A new map of global urban extent from MODIS satellite data. *Environmental Research Letters*, 1-11.
- Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K. (2011). A Meta-Analysis of Global Urban Land Expansion. *PLOS ONE*, 6(8), 1-9.
- Seto, K. C., & Kaufmann, R. K. (2003). Modeling the Drivers of Urban Land Use Change in the Pearl River Delta, China: Integrating Remote Sensing with Socioeconomic Data. *Land Economics*, 79(1), 106-121.
- Siegel, P., Martin, E. A., & Bruno, R. (2007). Language Use and Linguistic Isolation: Historical Data and Methodological Issues *Statistical Policy Working Paper 32: 2000 Seminar on Integrating Federal Statistical Information and Processes*. (pp. 1-23). Washington, D.C. : US Bureau of Census.
- Tait, C. J., Daniels, C. B., & Hill, R. S. (2005). Changes in Species Assemblages within the Adelaide Metropolitan Area, Australia, 1836-2002. *Ecological Applications*, 15(1), 346-359.
- US Bureau of Labor Statistics. (2012). The Recession of 2007-2009 *BLS Spotlight on Statistics the recession of 2007-2009*.
- US Census Bureau. (2000). *2000 Decennial Census*.
- US Census Bureau. (2010). *2010 Decennial Census*.
- US Census Bureau. (2012). *American Community Survey: 2007-2011*.
- US Census Bureau. (2013). *New Residential Construction*. Retrieved from: <http://www.census.gov/construction/nrc/>
- US Department of the Interior, & US Geological Survey. (2013). Landsat Processing Details. from [http://landsat.usgs.gov/Landsat\\_Processing\\_Details.php](http://landsat.usgs.gov/Landsat_Processing_Details.php)
- Waller, L. A., & Gotway, C. A. (2004). *Applied Spatial Statistics for Public Health Data*. Hoboken, NJ: John Wiley & Sons, Inc. .
- Wear, D. N., Turner, M. G., & Naiman, R. J. (1998). Land cover along an urban-rural gradient: implications for water quality. *Ecological Applications*, 8(3), 619-630.
- Weng, Q. (2012). Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. *Remote Sensing of Environment*, 117, 34-49.
- Williams, C. (2008, February 28, 2008). New Latino wave helps revitalize Detroit. Retrieved from [http://usatoday30.usatoday.com/news/nation/2008-02-28-2962316916\\_x.htm](http://usatoday30.usatoday.com/news/nation/2008-02-28-2962316916_x.htm)

- Xian, G., & Crane, M. (2005). Assessments of urban growth in the Tampa Bay watershed using remote sensing data. *Remote Sensing of Environment*, 203-215.
- Xian, G., Homer, C., Dewitz, J., Fry, J., Hossain, N., & Wickham, J. (2011). Change of Impervious Surface Area Between 2001 and 2006 in the Conterminous United States. *Photogrammetric Engineering & Remote Sensing*, 77(8), 758-762.
- Zhao, T., Brown, D. G., & Bergen, K. M. (2007). Increasing Gross Primary Production (GPP) in the Urbanizing Landscapes of Southeastern Michigan. *Photogrammetric Engineering & Remote Sensing*, 73(10), 1-9.