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Statistical Analysis of Land Cover Conversion Trends in Northwest Ohio

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Summary of Results and Recommendation

There were three results from this project:

1. Conversion between cropland and development was concentrated at the urban fringe of cities in Northwest Ohio and the rate of development slowed from 2011-2016 compared to 2001-2011.
2. Cropland loss was mitigated by the conversion from hay/pasture to cropland during the study period.
3. Little is known about factors that influence land cover conversion of non-marginal lands. While bio-geophysical factors such as soil, slope, demographics, weather, and distance from cities or bodies of water play an influential role in varied landscapes, they are less influential in homogenous regions like Northwest Ohio where farmer attitudes and production subsidies may make the difference between preserved agricultural land and new development.

The results of this study show that the Black Swamp Conservancy's Food to Farm Initiative has promise to mitigate the conversion of cropland to development. Since the Food and Farm Initiative requires farmers to sell to local markets, their farms are likely to be near urban areas, protecting land that would otherwise be under pressure from development.

The focus of the Food and Farm Initiative on beginning farmers may also help mitigate conversion of agricultural land to development as land transfers often occur when older generations retire (van Vliet et al 2015). The Food to Farm Initiative may also impact production decisions as farmer attitudes towards production and the environment influence intensification or deintensification of land management (van Vliet et al 2015).

Introduction

The Black Swamp Conservancy is a local non-profit land trust with a service area that includes 16 counties in Northwest Ohio. This organization is interested in land cover conversion trends within their service area to help them plan and prioritize farmland acquisition and protection. The Conservancy is devoted to future generations who will depend on our land management choices for food, energy, shelter, water quality, and access to the natural environment. The way we structure rural and urban society will have long lasting impacts on quality of life and the natural environment in Northwest Ohio for decades to come.

Background

Existing studies of land cover conversion in the Midwest focus on the conversion of marginal grasslands into cropland in the westernmost portion of the region and corresponding conversion of higher-quality cropland into developed land in the eastern and central portions of the region. (Rashford et al 2011, Emili and Greene 2014, Homer et al 2020, Wright and Wimberly 2013, Durant and Otto 2019). Although many studies attribute the conversion of marginal grasslands to biofuel subsidies, there is compelling evidence that changes in the acreage limits of the Conservation Reserve Program (Hendricks and Er 2018, USDA 2009, USDA 2018) and technological advances in productivity (Auch and Laingen 2015) play a more significant role.

Although academics hotly debate whether cropland to urban conversion is adequately mitigated by advances in production (Shrestha et al 2019) or if it represents a permanent threat to the long-term stability of our food system (Theobald et al 2016), the debates is misplaced because crop yields are only one measure of the value of agricultural land. Development and productivity impact both economic and social facets of rural communities including on farm incomes (DeMartini 2017) and preservation of the natural environment (Andreas and Knoop 1992, Durant and Otto 2019, Mitsch 2017). The diminishing economic returns for agricultural work due to decreased commodity prices could transform both the landscape and the rural communities that depend on it in the coming years.

Agriculture has traditionally played an important role in Northwest Ohio. Over 75% of the region is covered by crops to this day (MRLC 2019). Little has changed since it was transformed in the late 19th century from a swamp covered landscape into prime agricultural land (Kaatz 1955). The Black Swamp Conservancy is working to preserve the agricultural heritage, landscape, and support local industry through their conservation easements and the Farm and Food Initiative.

Project Questions

What are the land cover conversion trends in the region? Has this relatively modest corner of the world been subject to the same urbanization pressure as other portions of the Midwest? If so, where? What factors determine whether an area of land is converted from agricultural to nonagricultural use? This report seeks to investigate these questions by analyzing the National Land Cover Database 2016.

Data

Numerous land cover datasets with a variety of temporal extents and resolutions, spatial resolution, statistical collection processes and land cover classes are available. A survey of available datasets is provided Table 1.

Report	**Publisher**	**Dates**	**Spatial Resolution**	**Details**
National Land Cover Reports				
The National Resources Inventory	USDA	1982, 1987, 1992, 1997, 2000 – 2015 5 year releases	NA	State-Level
The Major Land Uses Report	USDA ERS	1945 – 2012 Yearly	NA	State-Level Acres of Land Use
The National Land Cover Database	MRLC/USGS	2001 – 2016 2-3 year intervals	30m x 30m	Sub-County Level
National Agricultural Reports				
Census of Agriculture	Census Bureau USDA NASS	1840 - 1996 1997 - 2017 Every 5 years	NA	County-Level
Cropland Data Layer	USDA NASS	2006 – 2019 Yearly	56m x 56m 30m x 30m	Sub-County Level
Crop Acreage Reports	USDA FSA	2009 – 2019 Yearly	NA	County-level

				Reported by farms participating in FSA programs
National Agriculture Imagery Program	USDA FSA	2004 – 2019 Yearly	1m x 1m 2m x 2m	Sub-County Level Aerial Photographs 1m x 1m spatial resolution
County Estimates	USDA NASS Ohio Field Office	2018, 2019 Yearly	NA	County-level Acres Planted, Harvested, Yield, Production
USDA: United States Department of Agriculture NASS: National Agriculture Statistics Service FSA: Farm Service Agency ERS: Economic Resource Service (a branch of the USDA) MRLC: Multi Resolution Land Characteristics Consortium USGS: United States Geological Survey.				

Table 1 Survey of publicly available of Land Cover datasets.

The National Land Cover Database (2016 NLCD) was chosen for this project because it describes the spatial distribution of land cover conversion at a sub-county level. This characteristic gives the 2016 NLCD an advantage over land cover reports that are survey-based and valid at the county-level such as the USDA NASS National Resources Inventory (NRI) and USDA NASS Census of Agriculture (CoA). The USDA NASS Cropland Data Layer (CDL) would also provide sub-county data, but the classification methodology for the CDL is not propagated to previous years, making it less appropriate for studying land cover change over time. Also, the CDL depends on the 2016 NLCD for its accuracy of non-crop land cover classes (Lark et al 2017). Since the project focuses equally on non-cropland classes, it is better to use the 2016 NLCD because it is balanced across land cover classes.

The 2016 NLCD was published by the Multi-Resolution Land Characteristics Consortium (MRLC), a group of federal agencies including the United States Geological Survey (USGS). The data includes seven land cover maps for 2-3-year intervals between 2001 to 2016 and one change index map. The development class is based on impervious surface and only changes for epochs 2001, 2006, 2011, and 2016. The other classes change for every epoch. The maps have a spatial resolution of 30m x 30m, with each grid cell representing one of sixteen land cover categories. The classification was created using Landsat 5, 7, and 8 images and ancillary data from a variety of sources and has 83% accuracy according to validation data from 2011 (Homer et al. 2020).

Methodology

I downloaded a portion of the 2016 NLCD from the MRLC Viewer, cropped it to cover Northwest Ohio and masked all grid cells outside of the sixteen counties of interest. The maps were then reclassified from sixteen land cover categories to nine. Consolidating the development, forest, wetland, and other categories should improve the accuracy of the classification. Since the National Land Cover Database 2016 may overestimate the area of rural roads, I kept the “open space development” class separate from the other development classes. After reclassification, the grid cells were aggregated from 30m x 30m resolution to 90m x 90m. It is important to note that the area estimations using the cell-counting method are not precise because grid cells often contain multiple land cover classes on the ground (Lark et al 2017). Please see the appendix for a full discussion of methods used to mitigate errors associated with this data source.

Part 1: Northwest Ohio

The purpose of this section is to describe the study area and provide context on the distribution of land cover classes and location of cities. The first map shows the major interstates, highways, and cities within the Black Swamp Service area and the results of reclassifying and aggregating the 2016 NLCD maps follow.

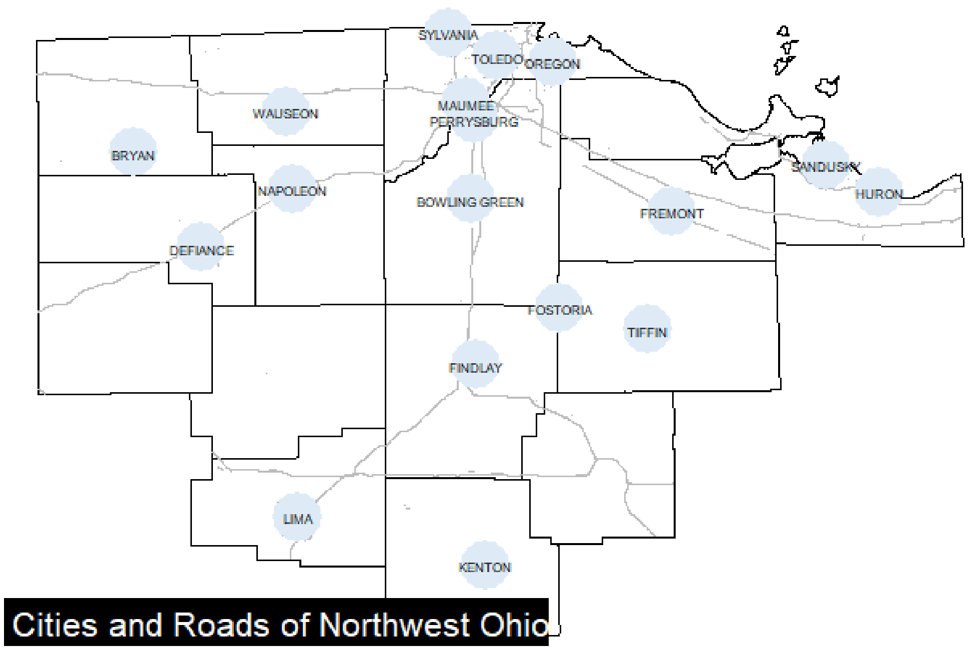

Figure 1 Cities and Roads of the Black Swamp Conservancy Service Area in Northwest Ohio.

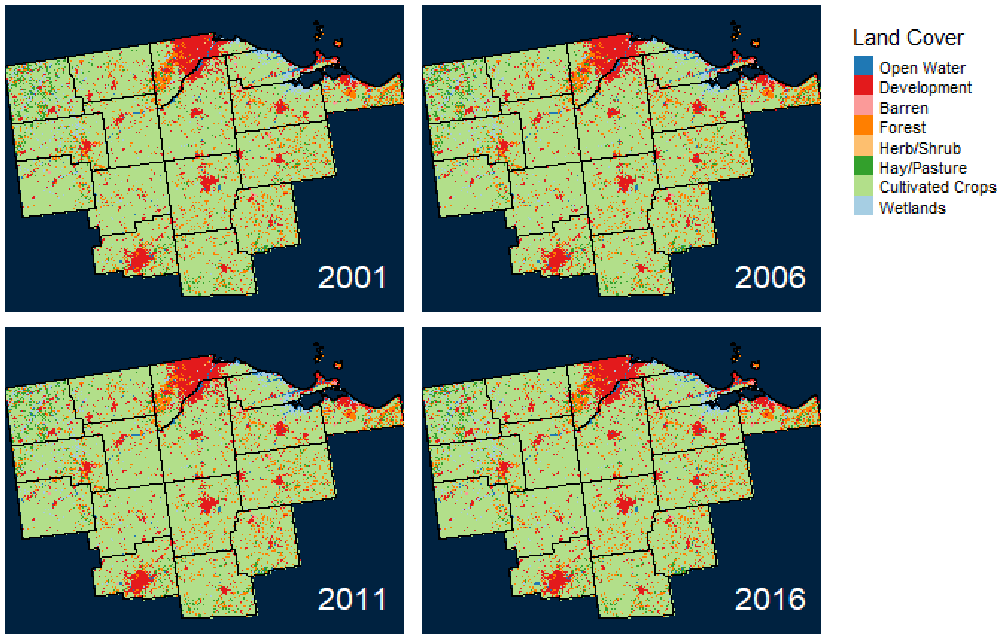

Figure 2 2016 NLCD Maps of Land Cover in Northwest Ohio reclassified into eight land cover categories and aggregated to a 90m x 90m grid cell size

Northwest Ohio is covered mostly by cropland, followed by urban area, then forested land. Hay/Pasture and wetlands make up a small portion of the region. The exceptionally fertile soil in Northwest Ohio comes from the oak forest and wetlands known as the "Great Black Swamp" that formerly covered the region and delayed its development until the late 1800s (Kaatz 1955). The urban centers remain around the swamp's former borders to this day (Kaatz 1955).

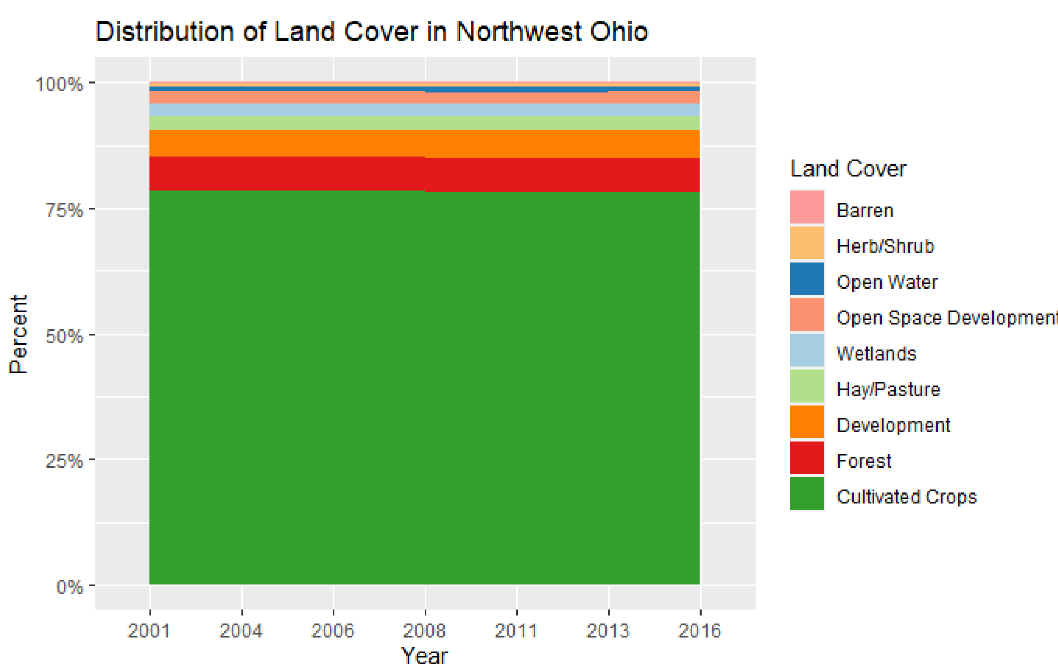

Figure 4

Part 2. Trends in Development

The purpose of this section is to summarize the trends in land cover conversion to developed land in Northwest Ohio between 2001-2016. The first finding was that the rate of change of development per six-year interval decreased from over 4% between 2001 and 2011 to less than 2% between 2011 and 2016.

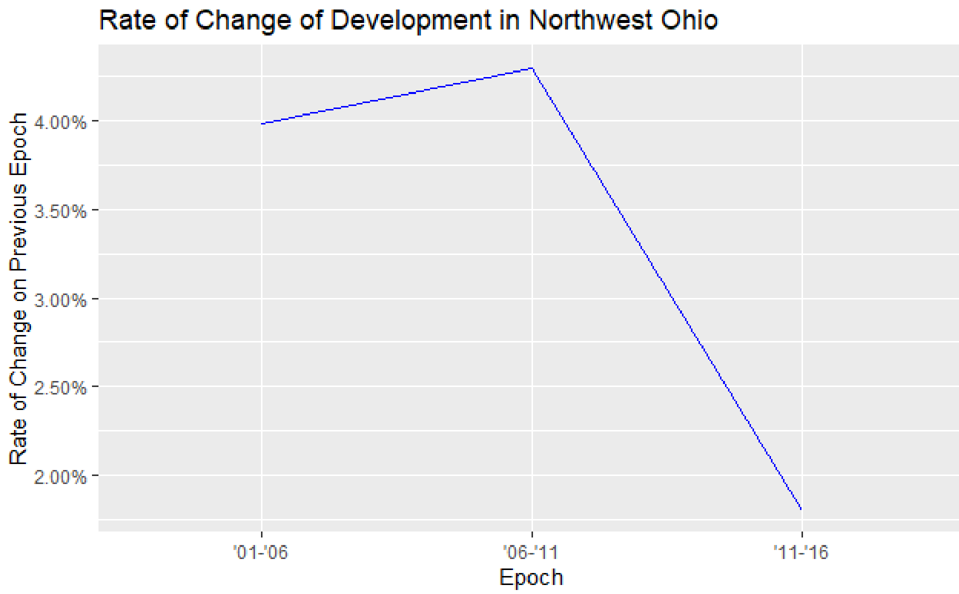

Figure 5

Second, land cover conversion to development was concentrated in the urban fringe of Toledo, Findlay, and Lima. There was also some development around Sandusky, Huron, Tiffin, and Bowling Green.

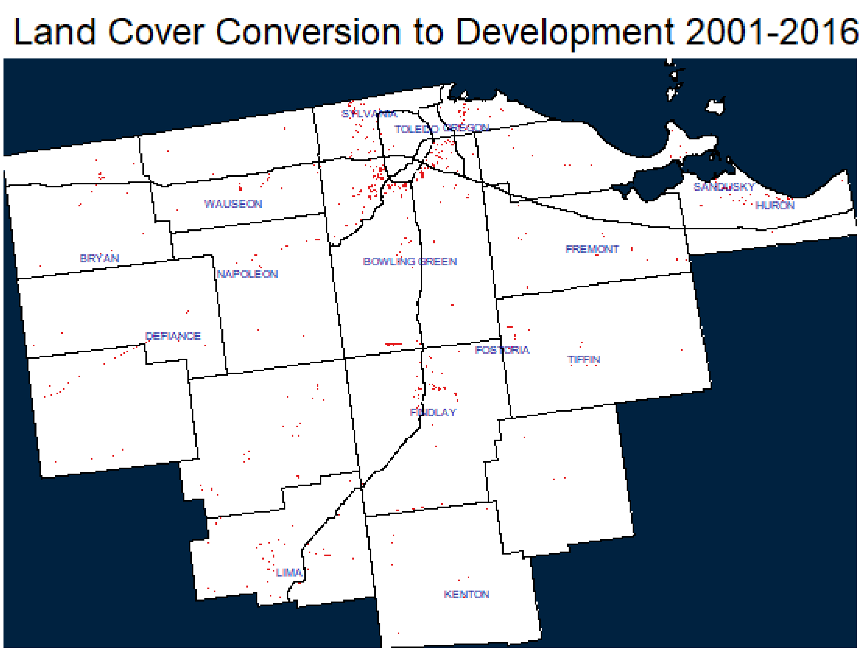

Figure 6

Third, most gains in development came at the expense of cropland. This trend is unsurprising because cropland is the most common land cover type in Northwest Ohio: random selection of land for development would select mostly cropland for conversion.

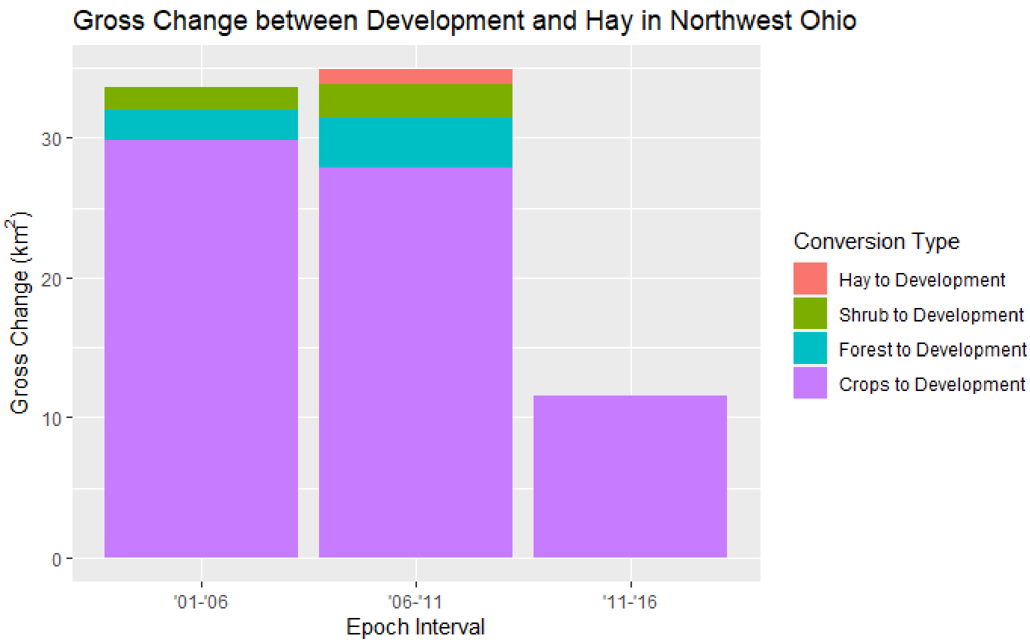

Figure 7

Development was concentrated in a few counties. The rate of change of development was highest in Hancock and Wood counties between 2001-2006 and Putnam county between 2006-2011. From 2011-2016, it was higher in Paulding, Williams, and Wood counties.

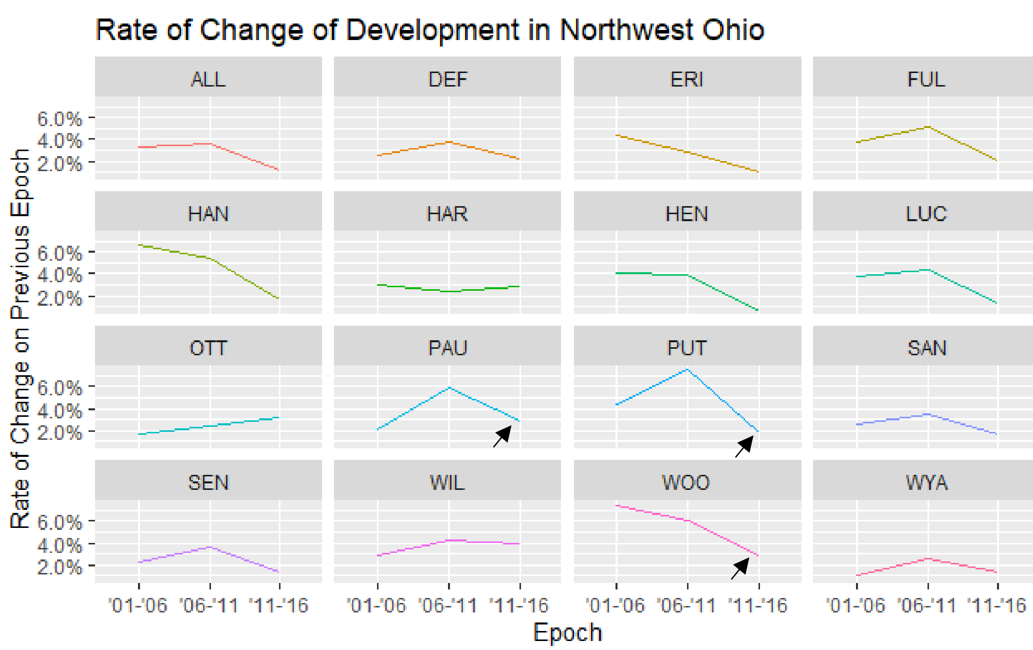

Figure 9

Part 3. Cropland, Forest, and Hay/Pasture.

The purpose of this section is to describe trends in cropland conversion in Northwest Ohio between 2001-2016. The first finding was that the rate of cropland loss slowed between 2013 and 2016.

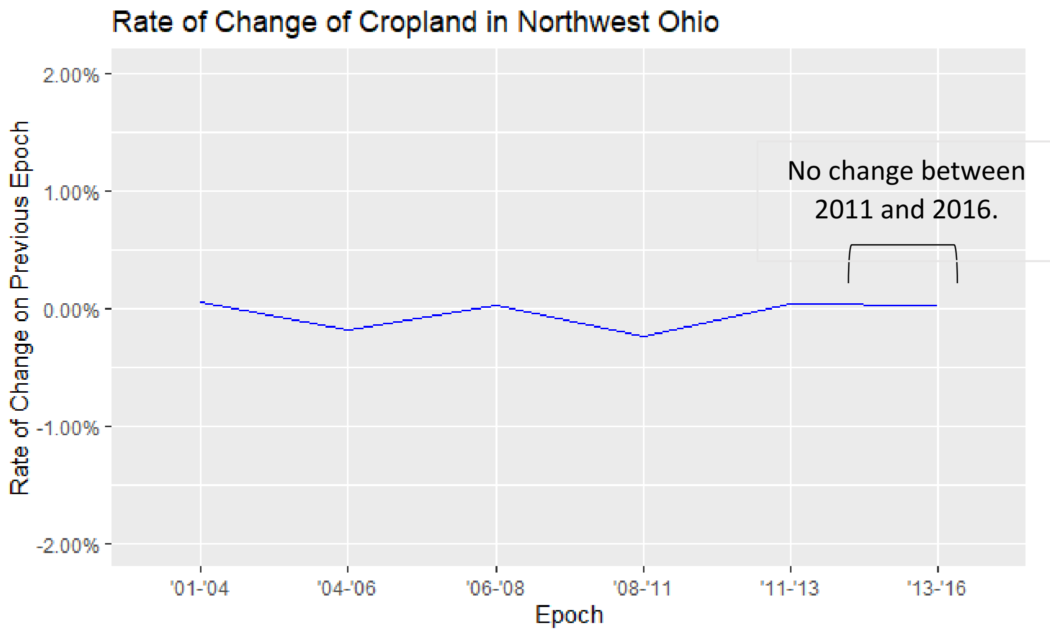

Figure 10

Cropland loss was concentrated in a few counties. Erie, Lucas, and Wood counties had variable rates of cropland conversion across 2001 – 2016, but rates slowed between 2011-2016. Most counties saw rates of cropland conversion near zero, but except for Williams county.

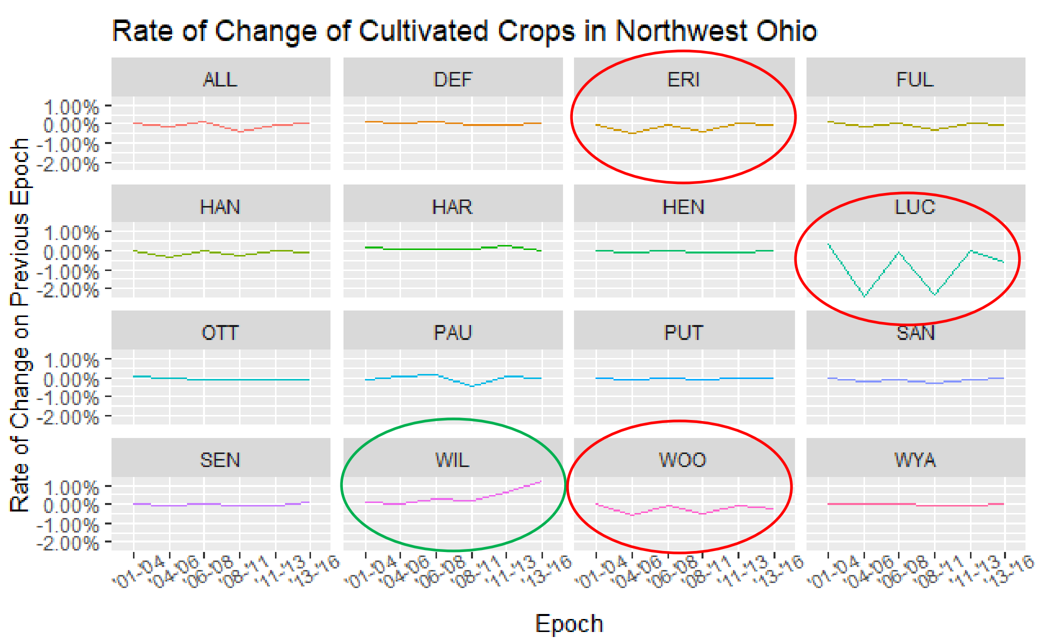

Figure 11

The rate of conversion of cropland, hay/pasture, and forested land in Northwest Ohio was either negative or close to zero between 2001 and 2013.

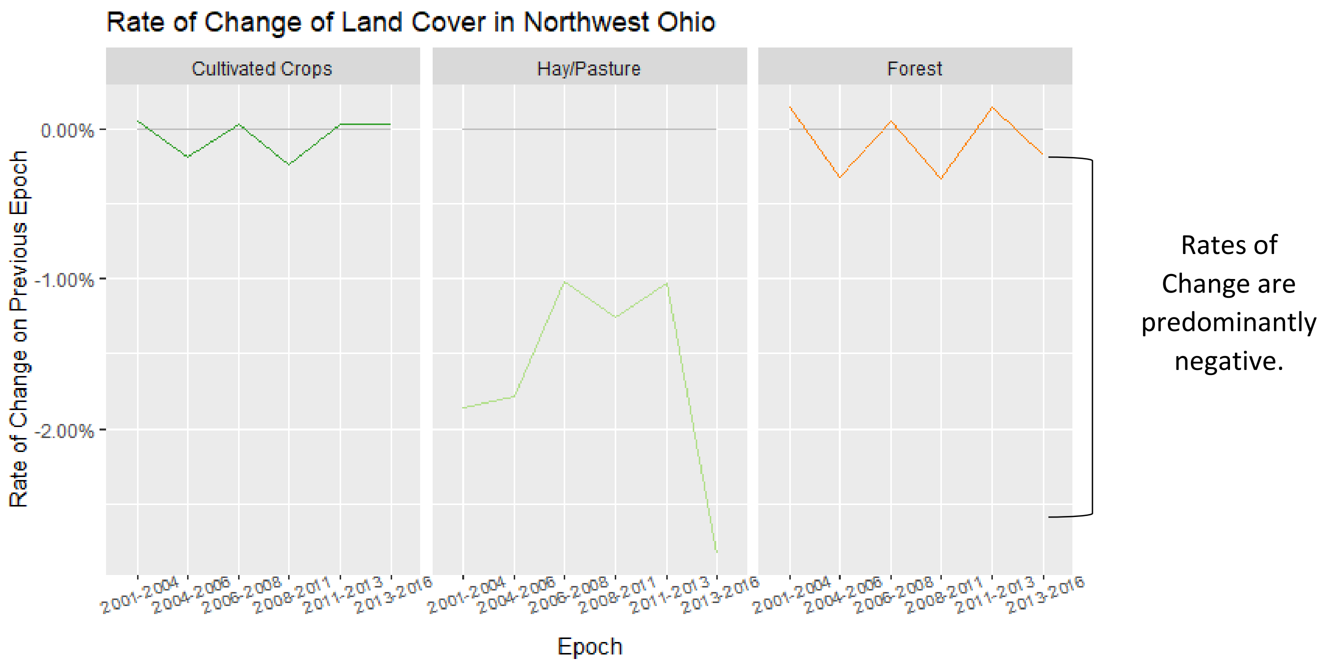

Figure 12

Cropland loss is mitigated by conversion of hay/pasture into crops. Since 2004 more land converted from Hay to Crops each year than converted from Crops to Hay.

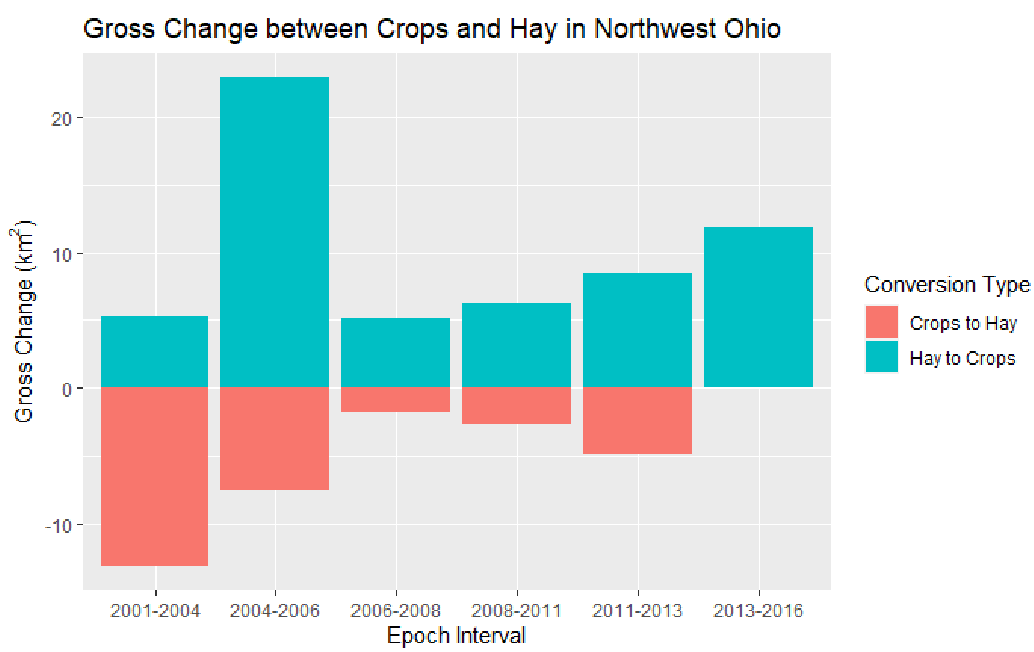

Figure 13

While most cropland loss occurred in Lucas, Wood, and Hancock counties, most conversion of hay or pasture into cropland occurred in Williams and Hardin counties. This trend is not surprising the former contain the more populous cities in the region, while the latter contains the most land suitable for hay/pasture.

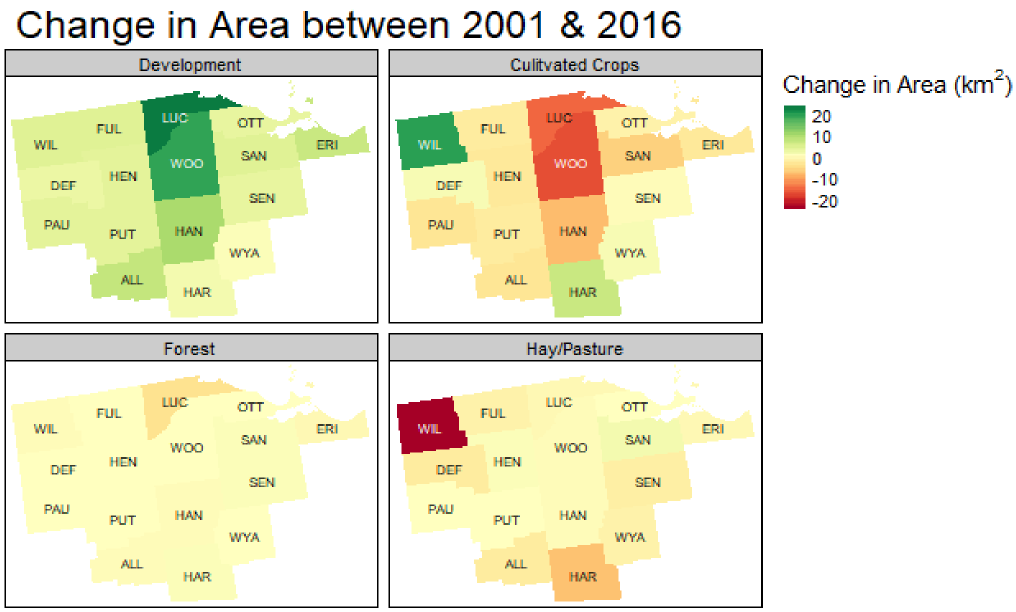

Figure 14 Map of net changes in area for four different land cover classes in Northwest Ohio.

Factors Associated with Land Cover Change

Land cover change is driven by many factors. Models of land cover change may include factors relating to demographic, economic, technological, institutional, and location factors and farmer characteristics (Vliet et al 2014). Demographic and locational factors including soil properties, precipitation, population density, and slope or elevation are commonly used because they are often readily available when other factors are not (Fuchs et al 2013, Verburg et al 2002, Moulds et al 2018, Theobald et al 2016). One of the goals of this project was to find a list of factors associated with land cover change in Wood county.

I did a preliminary examination of associations between land cover type and locational or bio-geophysical factors in Wood county. I used soil type using data from USGS, population and housing data at the census tract level from the American Community Survey for 2011, 2013, and 2016, and distance to the nearest interstate and city in Wood County calculated using data from the Ohio Department of Transportation. I also examined the relationship between market value of the parcels, annual tax, size, and land cover for the years 2001/2002 and 2008/2009.

Unsurprisingly, parcel size (number of acres) was correlated with land cover type. The most strongly associated factors in land cover type were distance from the nearest city and distance from the nearest interstate. Housing density and total adult population were also correlated with land cover type.

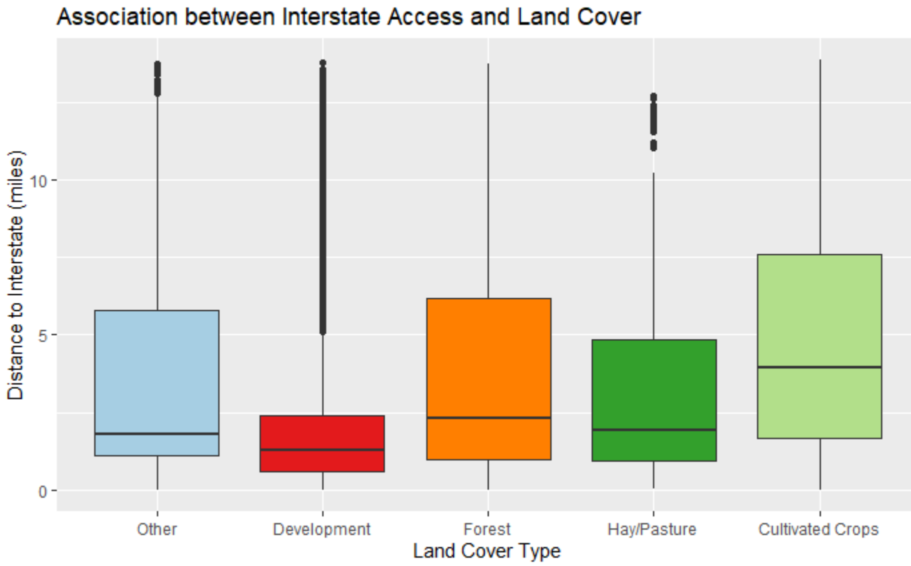

Figure 15

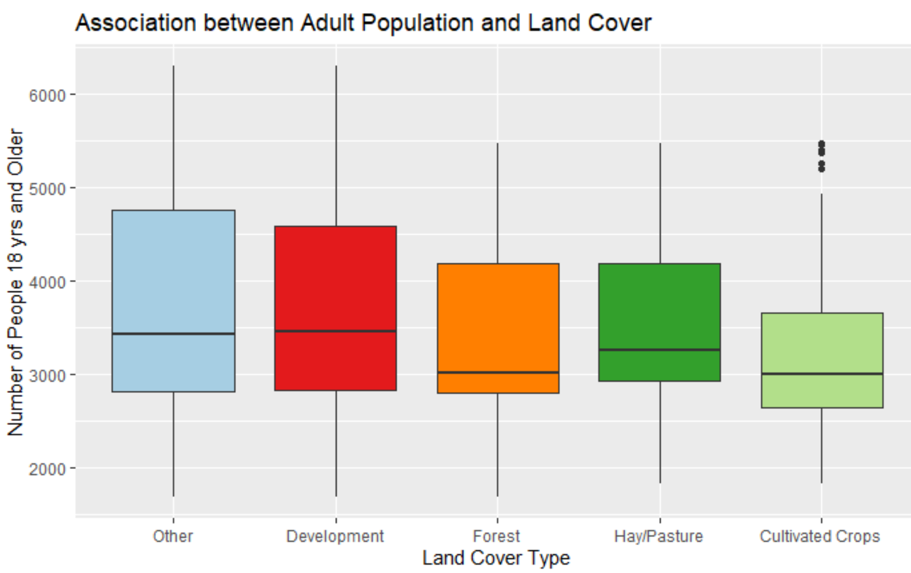

Figure 16

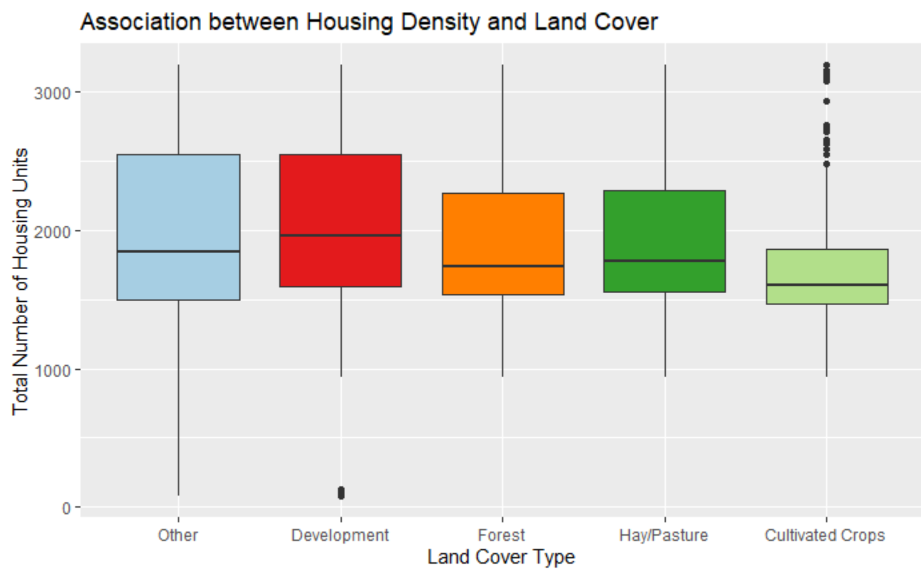

Figure 17

The relationships between land cover type and the examined factors is not strong. The distribution of these factors and land cover type overlap substantially, making modeling challenging. Also, since these factors only explain location, modeling conversion between land in similar locations is not possible. Since most conversion occurs at the urban fringe, future work should focus on factors that vary within the urban fringe. Compared to regions where locational or bio-geophysical factors are strongly correlated with land cover, Wood county is homogenous. The result of this exploratory analysis was that bio-geophysical factors are not sufficient to understand or model land cover conversion in Northwest Ohio.

Future work on modeling land cover change in Northwest Ohio should examine driving factors of change rather than locational factors since Northwest Ohio is a relatively homogenous region. The CLUE-S (Conversion of Land Use and its Effects at Small regional extent) model is one possible model as it was designed to include both driving factors of change and locational factors of change (Verburg 2002). Other approaches may also be promising.

Economic factors may play a larger role in land cover conversion in areas with land use fragmentation like the urban fringe (Pijanowski and Robinson 2011, Levia and Page 2000). One way that economic factors may influence land cover conversion is explained by the agricultural adaptation hypothesis which describes the shift of conventional agricultural production to goods such as fruits and vegetables and nurseries that are better suited to urban markets (Pijanowski and Robinson 2011). A more detailed study of the fringe around Toledo, OH that included economic factors would be of greater use to explain the drivers of cropland conversion in the region than locational factors.

Cropland conversion at the urban fringe could also be impacted by farmer attitudes. Many studies have found that farms with the same location have different conversion trends due to farmer attitudes including reason for farming, attitude towards production, and whether the farmer is nearing retirement (Vliet et al 2014). The "impermanence syndrome" is another farmer attitude that describes the phenomenon of reducing agricultural activities because urban encroachment seems inevitable, unintentionally improving the relative gains of development (Pijanowski and Robinson 2011). Future work to model cropland conversion in Northwest Ohio should carefully consider how farmer decisions impact land use and land cover change in the region.

Finally, it would be valuable to compare land cover conversion trends in NW Ohio to another predominantly agricultural area with similar demographic and environmental characteristics. The national statistics are averages of a very diverse landscape and therefore unlikely to be representative of any given place.

Conclusion

The 2016 NLCD provided detailed information about the distribution of land cover conversion at a sub-county level in Northwest Ohio. Although the estimates of area changed are not precise, the trends described in this paper are accurate and suggest that the Black Swamp Conservancy's Food and Farm Initiative is a promising program to mitigate loss of agricultural land in the region. Furthermore, this project identified that land cover prediction efforts in the region should focus on the urban fringe and non-locational factors.

Future work should also take advantage of the new data product LCMAP scheduled for release by USGS in 2020. LCMAP uses the Continuous Change Detection and Classification data to provide change detection land cover product from 1985 – 2017 at 30m resolution with plans for annual releases. Although LCMAP was not available in time for this project it will be an invaluable resource to land management organizations such as the Conservancy going forward.

Appendix

I used R statistical software for all data processing, analysis, and visualization.

Processing

First, I downloaded a small portion of the 2016 NLCD Database using the MRLC Viewer tool. Then, I reclassified the land cover categories from sixteen to nine classes using the reclassify() function in the raster package. Using the same package, I cropped and masked the region using the crop() and mask() functions so that the raster included only the Black Swamp Conservancy service area. Finally, I aggregated the area from 30m x 30m spatial resolution to a 90m x 90m spatial resolution using the aggregate() function with the fact parameter set to 2. I assigned the most frequently occurring land cover class. If there was not one class that occurred the most frequently, then the cell in the upper left corner of the aggregation would become the aggregated class by default.

Statistics

The raster package includes a function called freq(), which returns a matrix of the frequency of each land cover type within a region. Since each grid cell represented a 90m x 90m area (the coordinate reference system of the raster was an equal area projection), I was able to calculate area of each land cover type in kilometers squared for each epoch. The extract() function from the raster package was used to return land cover statistics for each county.

It is important to note that the area estimations using the cell-counting method are not precise because grid cells often contain multiple land cover classes on the ground (Lark et al 2017). I used several strategies to mitigate errors associated with statistically classified remote sensing data as follows:

1. Misclassification is more common when land cover classes are very similar. I consolidated the land cover classes from the 2016 NLCD from 16 classes to 9 classes to mitigate errors.
2. I also aggregated the land cover maps from 30m x 30m spatial resolution to 90m x 90m spatial resolution. This measure should have further reduced misclassified cells since similar land cover classes tend to be near one another.
3. I minimized the use of net change statistics in this report, which are likely to over or underestimate change in any two epochs. Instead, I focused on changes from one epoch to the next consecutive epoch.
4. To reduce the error in estimating gross land cover conversion, I applied a one-quarter kilometer threshold to change conversion patterns to consider them "legitimate" and include them in my calculations.
5. Finally, I compared the acreage estimates from the 2016 epoch of the 2016 National Land Cover Database with the acreage estimate for Land in Farms from the Census of Agriculture data for year 2017. The results are displayed in the chart below:

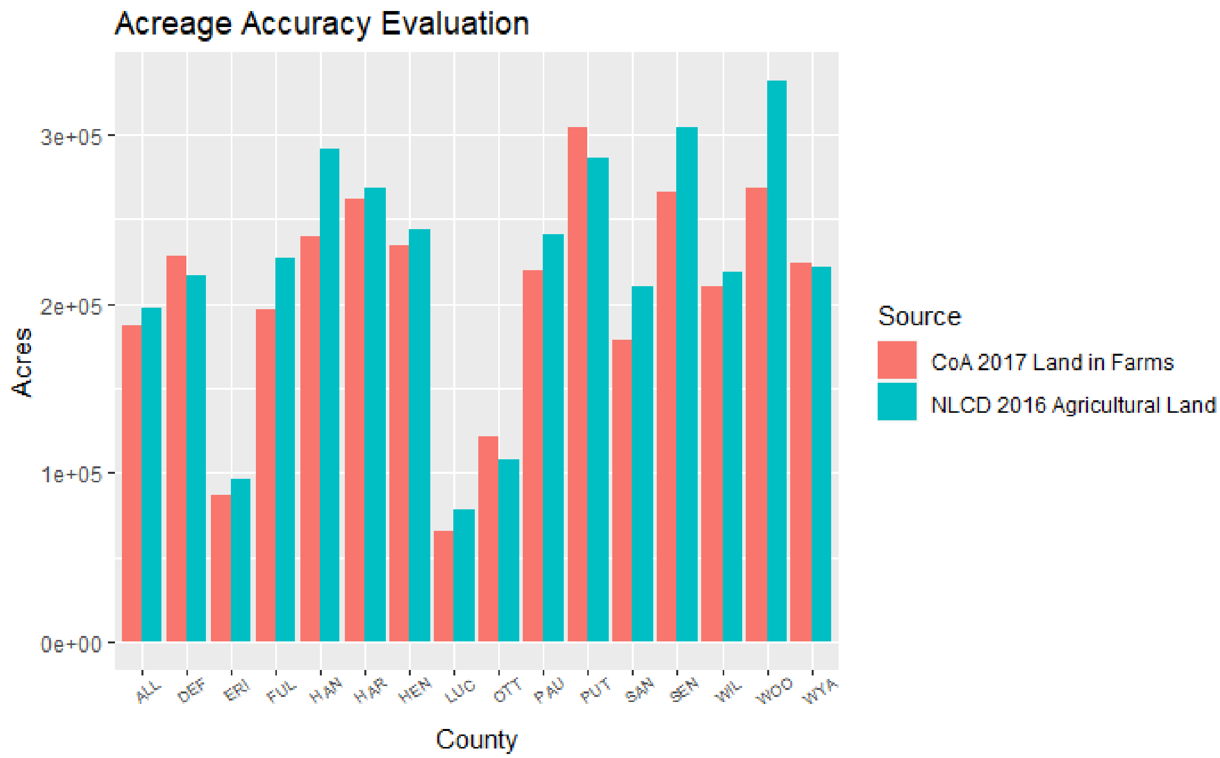

Figure 19

The acreage is not perfectly aligned for several reasons. First, CoA includes land in farms that are not devoted to crops, while “Agricultural Land” in the 2016 NLCD includes only cropland and hay/pasture. Second, acreage in each county may vary from one year to the next. The key takeaway from this chart is that the 2016 NLCD acreage are not exact measurements of acreage change but represent relatively close approximations.

Calculating Change Conversion

In addition to net cover change for each year, we were interested in which land cover types were changing into other land cover types or the gross changes. I used a pairing function to produce a unique key for each land cover conversion pattern that occurred. Then, I used raster algebra to apply the pairing function to each land cover map. Each land cover conversion pattern was used to identify number of changes per cell, land cover change categories such as crops conversion to development, and in which year changes occurred. Recording when and in which direction changes occurred makes these maps more valuable than the change index provided as part of the 2016 NLCD. Once the change conversion raster was created, I applied a one-quarter of a kilometer filter on each change conversion pattern to eliminate most misclassified cells. I used the same process to extract statistics from the change conversion raster as I used for the original 2016 NLCD raster. The following map shows every location that changed between 2001 and 2016 after applying the one-quarter kilometer raster.

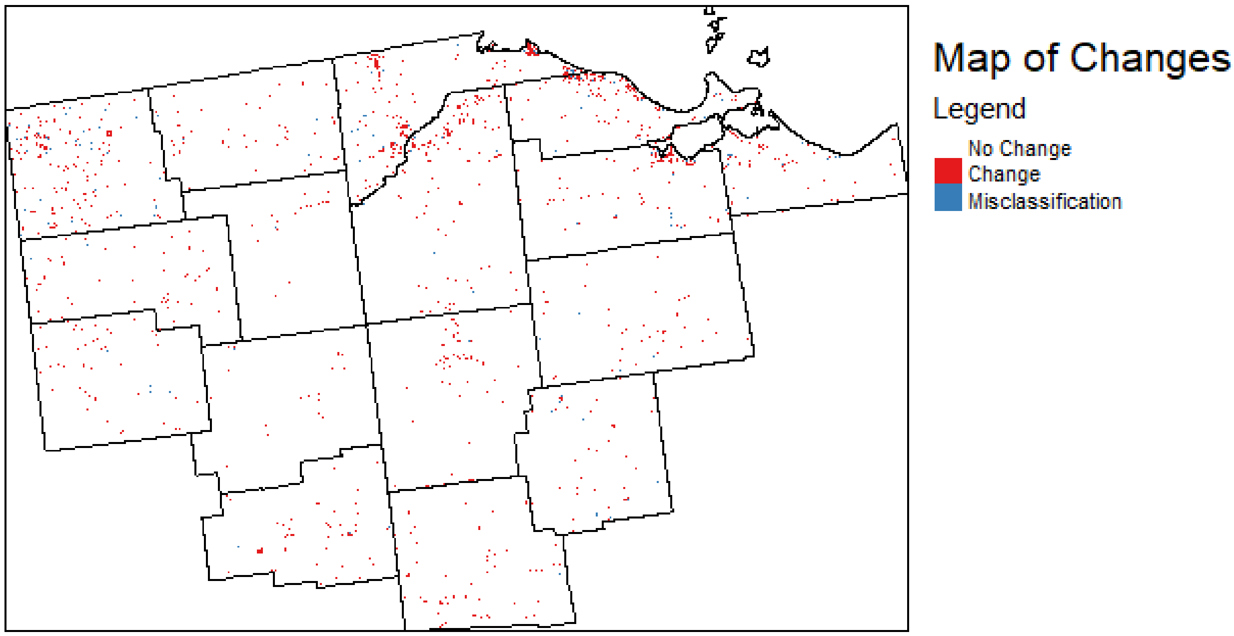

Figure 18

Once I had area information for each land cover class, each change type, and each county, then I calculated the following statistics for the service area and for each county:

- Area (km^2)
- Proportion of BSC service area for each land cover type and year
- Proportion of county for each county, land cover type and year
- Rate of Change: Rate of change was calculated by dividing the land cover value for one epoch by the land cover value for the previous epoch.
- Net Change: Net change was the difference between land cover area in 2016 and 2001. It is not a perfect representation of area changes as it obscures the dynamic nature of land cover conversion and has a large margin of error due to classification errors in any one year; therefore, I minimized its use in the final report.

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