Urban Growth and Development Using SLEUTH: Philadelphia Metropolitan Region

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1.0 Introduction

The metropolitan and suburban regions of Philadelphia and its surrounding counties have experienced a tremendous amount of growth in the past fifty years and continue to grow at unprecedented rates. The city of Philadelphia alone expects 100,000 additional residents and 40,000 more jobs in Philadelphia by 2035 (Philadelphia City Planning Commission date?). Land use changes as a result of increased development impact ecological and hydrologic aspects of environments. Future land cover can be modeled based on past patterns and current trends to identify areas of growth and make estimations of environmental implications (Dietzel and Clarke 2007).

SLEUTH is the evolutionary product of the Clarke Urban Growth Model that uses cellular automata, terrain mapping and land cover deltatron modeling to address urban growth (Chaudhuri and Clarke 2013). The SLEUTH model projects land-cover change based on historical trends in development patterns (Claggett et al. 2004). It has been successfully implemented in San Francisco, Chicago, Washington-Baltimore, Sioux Falls and now on the South Coast of California.

2.0 Purpose

The objective of this study is to examine and analyze past land use change and utilize the SLEUTH model to predict future growth and development for the Philadelphia Metropolitan Area and surrounding counties (Montgomery, Chester, Bucks, Delaware, Burlington, Camden, Mercer and Gloucester Counties). Models provide an opportunity to explore and evaluate land use policies, and help to visualize alternative futures.

By analyzing the past urban growth trends, we hope to accurately depict areas of potential development for future land uses. Because Philadelphia County has limited

developmental areas, we expanded our study area to adjacent counties in hope of providing additional results as well as a firm understanding of future land uses in the region.

Figure 1: Factors that determine attraction or repel urban development.

3.0 Data and Methods

3.1 Modeling Approach

SLEUTH is a cellular automata projection model, used to forecast urban growth and land cover change (Silva and Clarke 2002). The acronym 'SLEUTH' is derived from the input layers that allow the model to operate: slope, land use, excluded areas, urban, transportation, and hillshade.

For the purpose of this study only the urban model was used, allowing each cell (30m x 30m) to have two possible states, urbanized or non-urbanized. A cell may or may not become

urbanized based on four growth rules: spontaneous growth, new spreading center growth, edge growth, and road-influenced growth (Table 1).

Table 1. Simulated Growth Types of the SLEUTH Model.

Growth Cycle Order	***Growth Type***	***Controlling Coefficients***	***Summary Description***
1	Spontaneous	Dispersion	Randomly selects potential new growth cells.
2	New Spreading Center	Breed	Growing urban centers from spontaneous growth.
3	Edge	Spread	Old or new urban centers spawn additional growth.
4	Road Influenced	Road-Gravity Dispersion, Breed	Newly urbanized cell spawns growth along transportation network.
Throughout	Slope Resistance	Slope	Effect of slope on reducing probability of urbanization.
Throughout	Excluded Layer	User Defined	User specifies areas resistant or excluded to development.

Clarke et al. (1997), Clarke and Gaydos (1998) and US Geological Survey (USGS, 2003)

Spontaneous growth simulates the random urbanization of a single pixel. This has the potential to capture low-density development and is independent of nearby existing urban areas or transportation. The probability that a single non-urbanized cell will become urbanized is determined by the dispersion coefficient (Clarke et al 1997; Clarke and Gaydos, 1998; US Geological Survey, USGS, 2003).

New spreading center growth models the emergence of newly urbanized centers by creating up to two nearby urban cells around areas that have been urbanized through spontaneous growth. The probability that a pixel is produced through spontaneous growth will also have new spreading center growth is determined by the breed coefficient explained further in section 3.3 (Clarke et al 1997; Clarke and Gaydos, 1998; US Geological Survey, USGS, 2003).

Edge growth can be experienced by newly urbanized cluster can also experience edge growth, which simulates outward growth from the edge of new and existing urban development.

Edge growth is controlled by the spread coefficient explained further in section 3.3, which influences the probability that a non-urban cell with at least three urban neighbors will also become urbanized.

Road-influenced growth simulates the influence of transportation networks on growth patterns by creating spreading centers along roads. Road-influenced growth occurs when newly urbanized cells are randomly selected by the breed coefficient. For each selected cell, the presence of a road within a search radius defined by the road-gravity coefficient explained further in section 3.3 (Claggett et al 2004). If a road is found near the selected cell then a temporary urban cell is placed at the closest location along the road. At this point the temporary urban cell looks along the road for a permanent location. The direction of the search along the road is random and the search distance is determined by the dispersion coefficient explained further in section 3.3. The permanent location will then become a new spreading center, with up to three urbanized cells along the road (Clarke et al 1997; Clarke and Gaydos, 1998; US Geological Survey, USGS, 2003).

3.2 Data Layers

3.2.1 Slope

The slope layer was calculated from a series of digital elevation models (DEM) provided by the USGS, combined together (mosaic) to show percent slope compared to slope degrees.

3.2.2 Land Use

The land use layer was not included in the calibration. Instead, our focus was strictly on the urban layer, which was derived from the Coastal Change Analysis Program (C-CAP).

3.2.3 Exclusion Layer and Roads

The excluded data was gathered through the Protected Areas Database of the United States (PAD-US), and managed by USGS. This layer illustrates and describes public land ownership, management and other conservation lands, including voluntarily provided privately protected areas. This dataset is one of the most important inputs into the model. Areas of protected lands carried strong coefficients and projections will indicate the inability for growth to occur in these areas. Primary and secondary roads in our study region were subset from the U.S. Census Bureau TIGER/Line Northeast Roads shapefile.

3.2.4 Urban Dataset

The Coastal Change Analysis Program (C-CAP) produces a nationally standardized database of land cover and land change information for the coastal regions of the U.S. These products provide inventories of coastal intertidal areas, wetlands, and adjacent uplands with the goal of monitoring these habitats by updating the land cover maps every five years. C-CAP products are developed using multiple dates of remotely sensed imagery and consist of raster-based land cover maps for each date of analysis, as well as a file that highlights what changes have occurred between these dates and where the changes were located.

3.2.5 Hillshade

In order to give spatial context to the urban extent data, a background image is incorporated into image output. This must be a grayscale image, and a hillshaded DEM is commonly used. In our project hillshade was used solely as a background image; values were reclassified to values of 255.

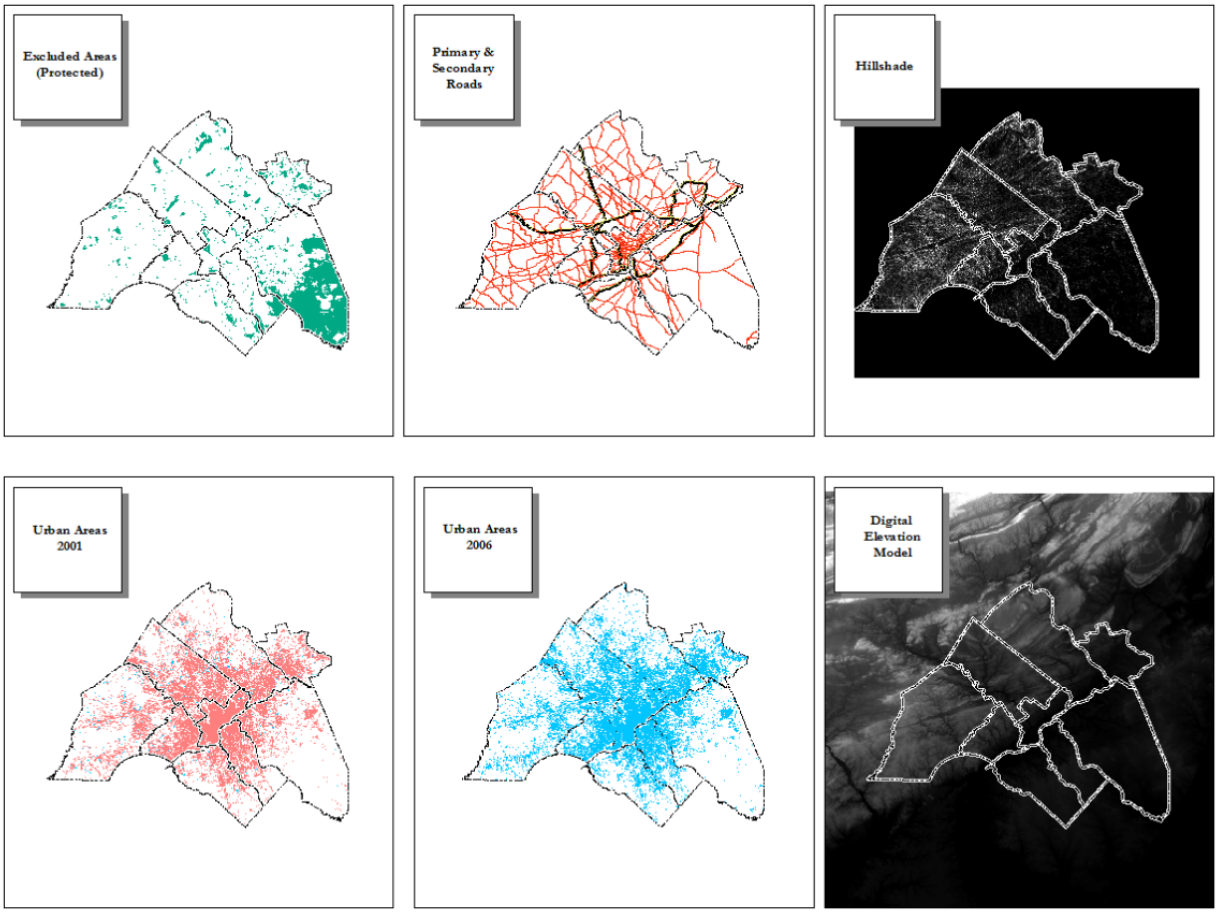

Figure 2: Factors that determine attraction or repel urban development. This figure needs to be references in the text.

3.2.6 Input Image Formatting

SLEUTH requires grayscale graphic image files (GIFs) as necessary inputs. For all images, 0 is a null value, while any other value is considered an existing value (Chaudhuri and Clarke 2013). Format standards for all data types must be the same:

- Grayscale GIF images
- Images are derived from grids in the same projection
- Images are derived from grids of the same map extent
- Images have identical dimensions (row x column count is consistent)
- Images follow the required naming format

3.3 Model Calibration

The goal of calibration is to create a set of values for the growth parameters that can effectively model growth during the historic time period, in this case 2001 - 2006. Calibration of the SLEUTH model uses the brute-force Monte Carlo method meaning every possible combination of its control parameters is tested (Dietzel and Clarke 2007). The outcomes are then compared to prior data to determine their success at replicating it. Calibration produces a set of five coefficients, each of which can range from 1 – 100, that are determined by a set of spatial metrics and are the controlling factors of growth processes (Silva and Clarke 2002). The five coefficients that control growth are:

1. *Diffusion*- Determines the overall scatter of the growth and controls the number of times that a pixel will be randomly selected for possible urbanization.
2. *Breed coefficient*- The likelihood that a newly generated detached settlement will start on its own growth cycle.
3. *Spread Coefficient*- controls how much contagion diffusion radiates from existing settlements.
4. *Slope resistance factor*- Influences the likelihood of development on steep slopes.
5. *Road gravity Factor*- An attraction factor that draws new settlements towards and along roads

Calibration was done in two phases. The first calibration assigned values of 1, 25, 50, 75, and 100 to each of the five growth parameters and tested all possible combinations, a total of 3,125, as initial conditions (Dietzel and Clarke 2007; Yang et al 2003). Each growth coefficient is indicative of the relative influence of each parameter on development patterns. Higher values have more influence on potential development and results of SLEUTH display the probability of any given location becoming urbanized (Jantz and Morlock 2011). Monte Carlo trials were performed in which urban patterns were simulated for each year based on each set of parameters (Jantz et al 2003). The calculated changes were then averaged for all Monte Carlos and

compared to the historical data. The parameter sets were examined for the results from the first calibration and five runs that exhibited the best fit were determined (Table 2).

For this study the metrics used to determine goodness of fit were area, edges, and clusters. The fractional difference of each metric was examined to determine runs with outcomes closest to zero. The closer to zero the less under or overestimation that occurred. Runs were chosen that exhibited low percentages of under or overestimation for each metric and for all three metrics.

Table 2. The five runs that were chosen from the first calibration as best fit.

Run	***Diffusion***	***Breed***	***Spread***	***Slope Resistance***	***Road Gravity***	***Fractional Difference (converted to percentage)***		
						Area	Edges	Cluster
20	1	1	1	100	1	-1.67%	1.48%	4.26%
100	1	1	100	1	1	24.09%	2.25%	-3.87%
170	1	25	25	100	1	4.13%	4.65%	7.91%
624	1	100	100	100	100	20.68%	3.26%	-0.69%
1750	50	100	1	1	1	0.03%	6.83%	38.52%

After the parameters that best fit the historical data were determined, the five runs chosen were used for the next calibration. The same process was repeated after the second calibration by performing one hundred Monte Carlos. Two runs (#0170 & #1750) were then chosen whose parameters appeared to best fit the historical data and were used for the final forecast of urban growth to 2030.

3.4 Forecasting

Unlike other SLEUTH reports, our forecasting rates of future urbanization were derived by comparing simulated urban change to observed urban cover for 2006. Other reports utilize additional layers and datasets, but for this analysis, a total of two forecasts were chosen to simulate urban growth for the Greater Philadelphia Region.

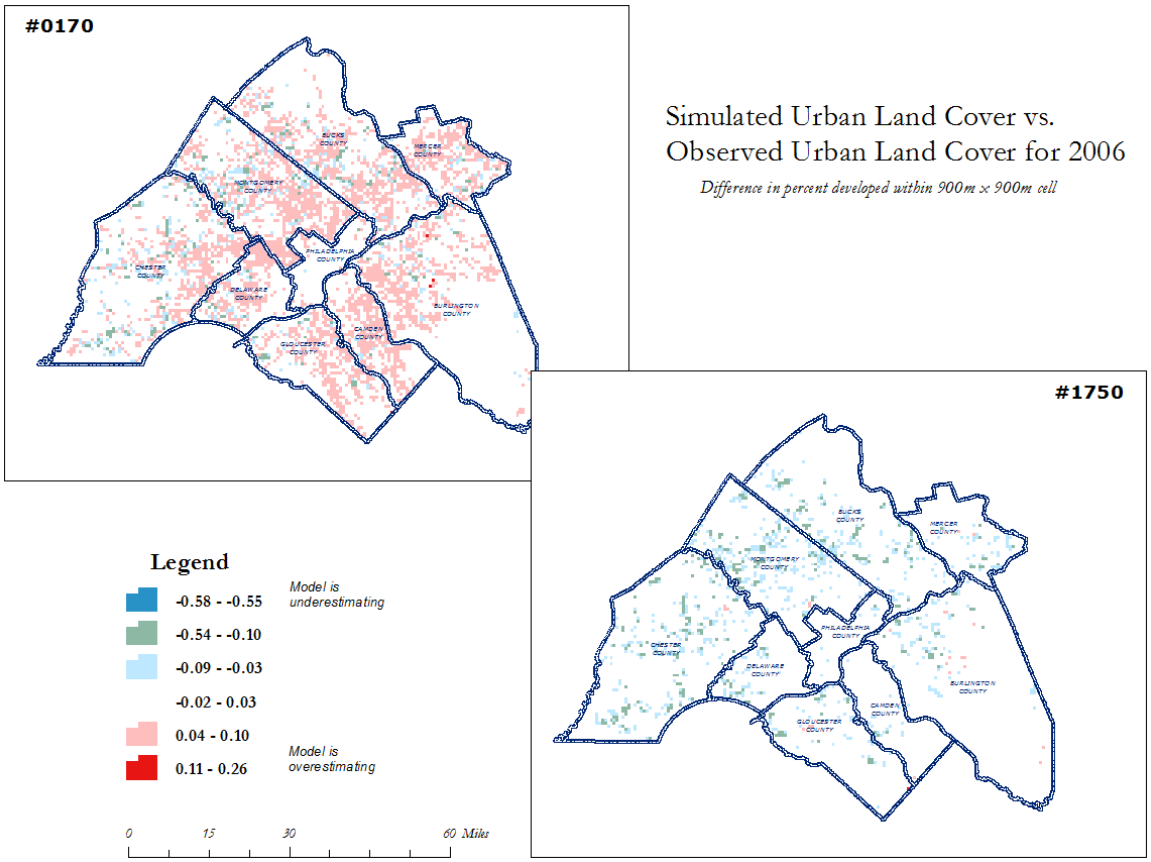

Figure 2: Simulated urban cover differenced by observed urban cover. This belongs in results and also needs a reference in the text.

4.0 Results and Discussion

Chosen from the initial calibration, twenty-five Monte Carlos for two forecasts were run (#1750, #0170), with each representing two different urban growth rates and spatial patterns. Figure 4 shows projected urban growth from 2007 to 2030 in the Philadelphia metropolitan area for run model #1750. This figure identifies a steady increase of urban growth forecasted for the region to the year 2030. Although Figure 4 depicts a continued growth it is important to highlight that the rate of growth is projected to decrease nearly every year as seen in Figure 5. Forecasting results for run model #0170 also show a projected steady increase of urban growth to the year 2030 (Figure 5). As seen in Figure 7, for model #0170 there is again a steady decrease

in projected urban growth percentage over time, meaning that the rate of urbanization for the Philadelphia region is projected to slow down from 2008-2030.

There are a handful of observations that can be drawn from looking at Figures 4-7. Both of the two forecasting runs project the region to steadily increase its urban area to the year 2030. With forecasting model #1750 projecting an addition of 271,208,700 square meters, and forecasting model #0170 projecting a growth of 842,043,276 m^2 from 2007 to 2030.

Figure 8 illustrates projected regions of growth for the Philadelphia metropolitan area. It also shows that for both models, growth and development is focused around current urban development, projecting Philadelphia to experience edge spread, compared to new spreading centers or spontaneous growth.

Figure 8 also displays the influence of roads on urban growth. In both models, main highways are projected to experience urban development more so than new spreading centers or spontaneous growth. Finally, both models predict the rate of urban growth to slowly decrease from 2008-2030, although run model #1750 only initially projected a growth rate of .37 percent in 2008, it only projected an overall growth of .03 percent to the year 2030. While run model #0170 initially projected a growth rate of 1.16 percent, it saw a larger decrease in growth rate over time of .31 percent to the year 2030.

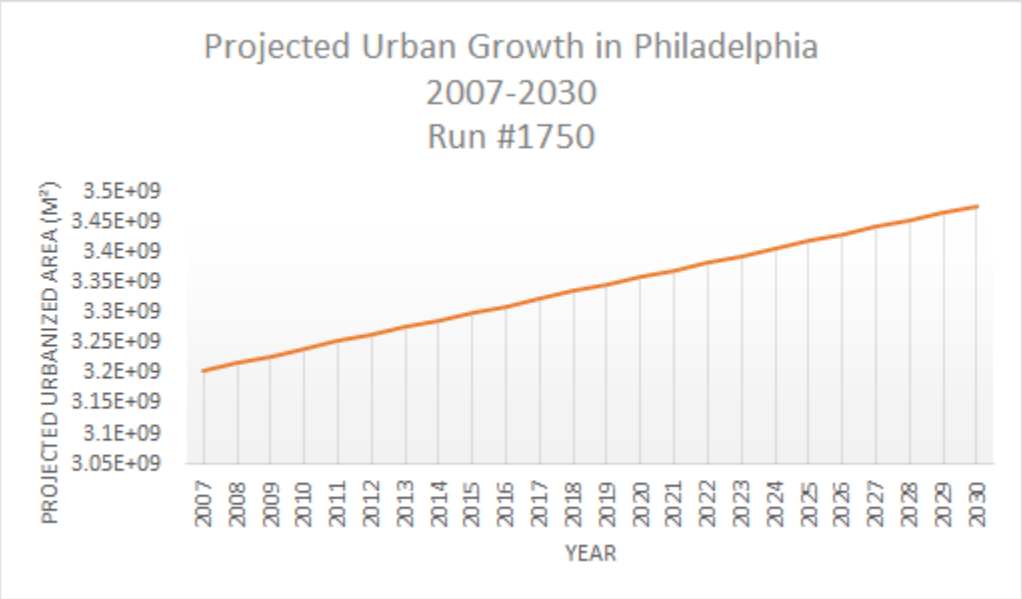

Figure 4: Projected Urban Growth: Projection #1750

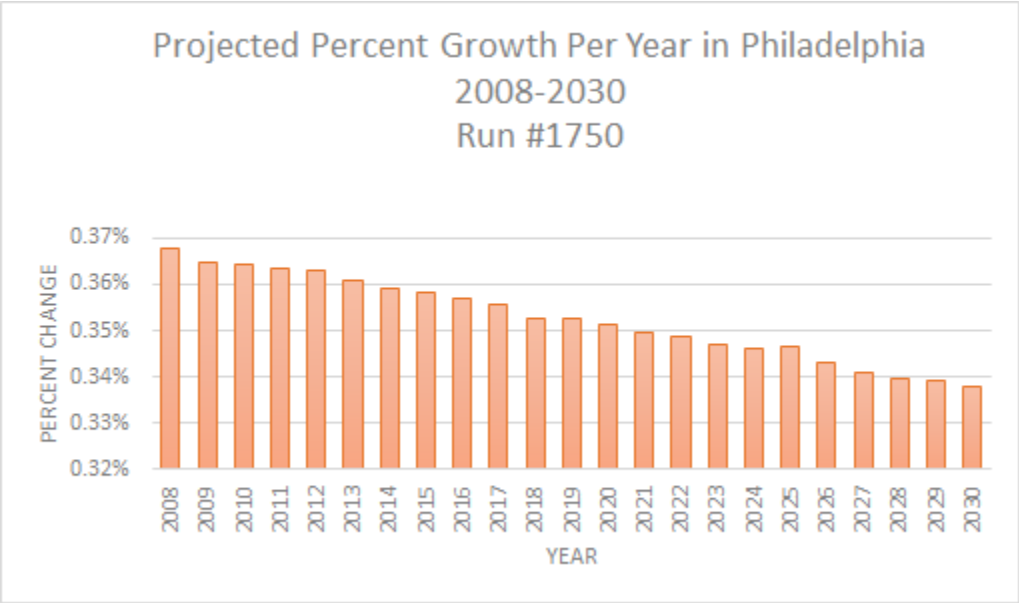

Figure 5: Projected Percent Growth per year: Projection #1750

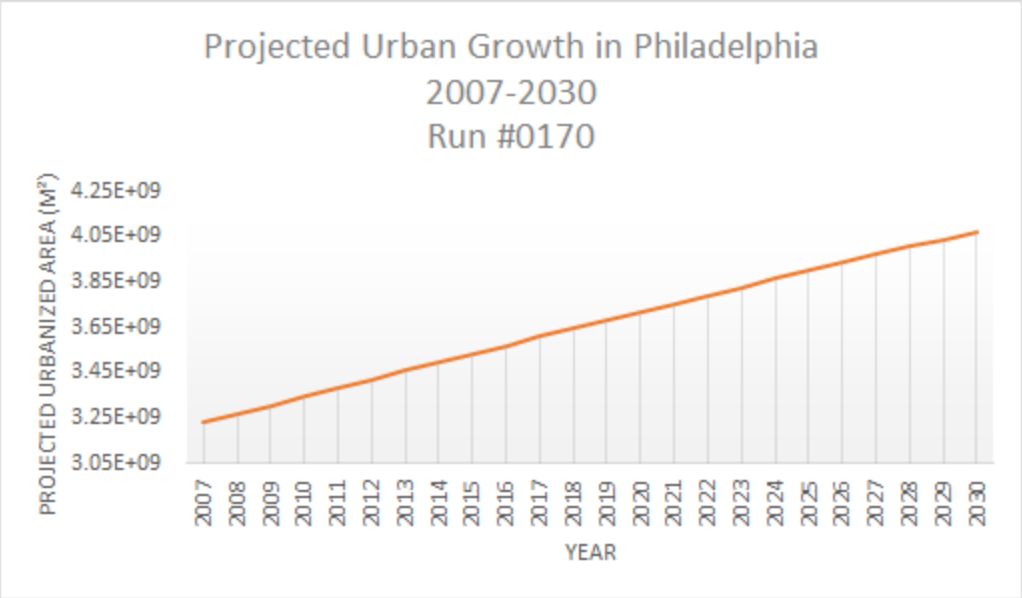

Figure 6: Projected Urban Growth: Projection #0170

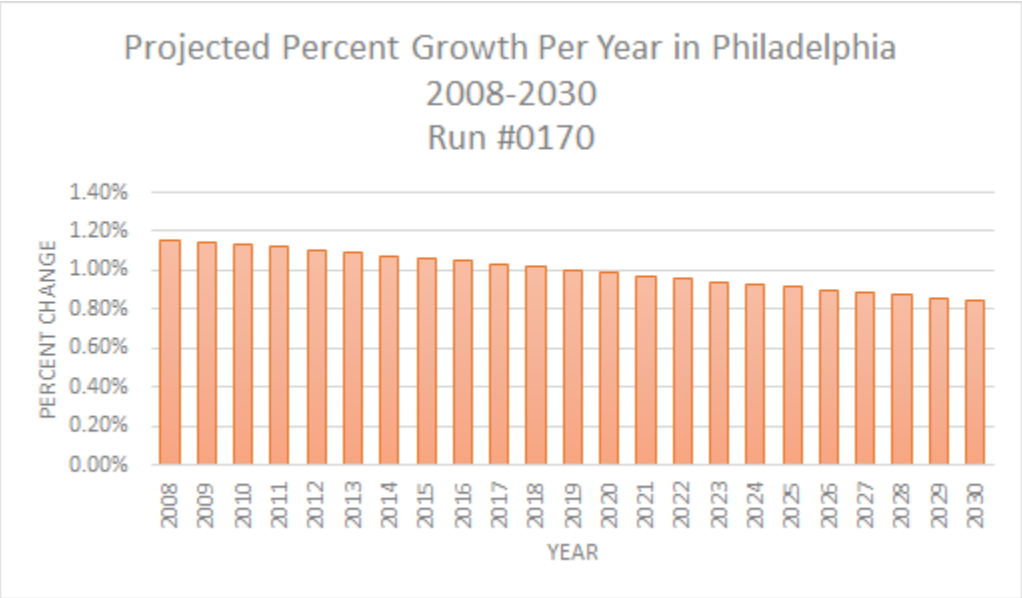

Figure 7: Projected Percent Growth per year: Projection #0170

As shown in Figure 5 & 7, projected percent growth within the region is expected to decline in the future. Because of the dense urbanization currently, the percent of land required to develop is slowing declining due to space limitations. These results were expected over time. Figure 8 shows the percent developed in 2006 and the difference of percent developed from 2006-2030.

Expected results show minimal development around Philadelphia County, with most of the predicted development in surrounding counties.

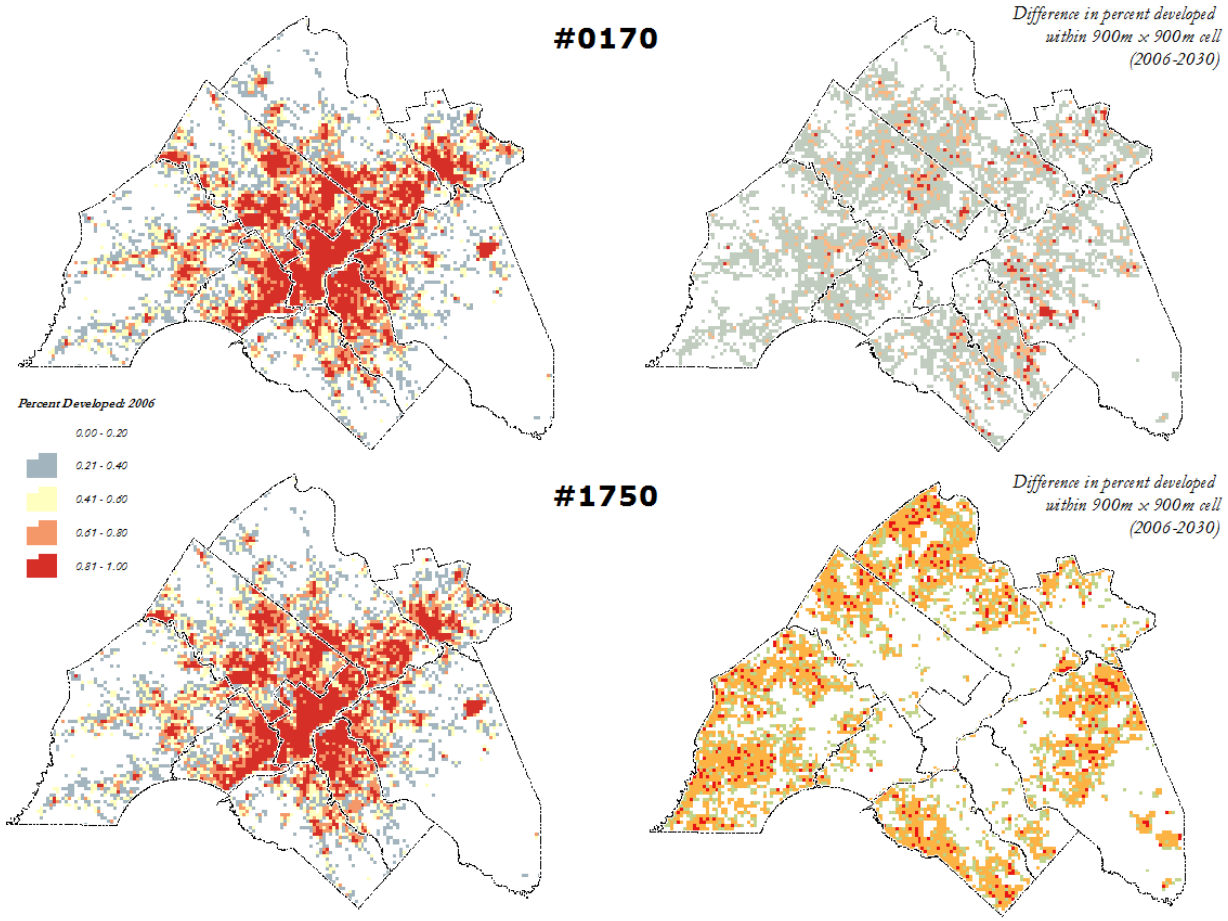

Figure 8: Percent of urbanized cover: 2006 and difference between percent developed: 2006-2030. For percent difference (right), darker values indicate predicted growth areas.

5.0 Conclusions

This study has shown the importance of GIS and the efficiency of the SLEUTH model to forecast urban and regional modeling. This model is an appropriate model for many regions, given the appropriate datasets needed to calculate results (Lopez et al 2001). Minor changes to

the model are required to improve performance for the Philadelphia region. SLEUTH is an urban growth model and has shown its importance in gauging potential developmental areas. Future research for this region would include additional datasets such as land uses, instead of strictly urban/non-urban coverage.

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