SHIPPENBURG UNIVERSITY

Evaluating SLEUTH Model Accuracy at Different Geographic Scales Around Two National Parks

Graduate Research Project

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Abstract: Protected areas such as national parks are attractive areas to live around, and may attract urban development near their borders. In the United States, National Park officials often need some knowledge of the future characteristics of changes near their borders as well as broader, regional changes. The SLEUTH urban land use model is one widely used tool to estimate future land use changes at regional scale. Because of this use, National Park officials may be interested in parcel level changes for more focused land management around their parks than the regional scale. At this time, the SLEUTH model has not yet been rigorously evaluated for its effectiveness at modeling parcel-scale changes that would be relevant to National Park officials. This study evaluates the SLEUTH urban land use model for its effectiveness at predicting land use changes at local scales. The study is focused on the Chesapeake and Ohio Canal National Historic Park and the Antietam National Battlefield and evaluates the model's performance at multiple scales: 150m, 300m, and 600m grid sizes. These results suggest that the SLEUTH model is more effective at broader scales and has difficulty accurately simulating parcel-level changes. Thus, the SLEUTH model is more effective at predicting regional land use changes than local land use changes. While SLEUTH may not be optimal for local-scale predictions, land use managers can nevertheless benefit from knowledge gained regarding spatial patterns of regional growth pressure.

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Introduction:

Land use planning for lands managed by the United States National Park Service (NPS) and other protected lands often require unique land management techniques to minimize the impacts of increasing population, pollution, loss of sensitive land areas, or other urban impacts. Some knowledge of future conditions is potentially invaluable for these land managers to plan for changing conditions around the parks that they manage. Land use policy is a source that land use managers can utilize to evaluate the possible future conditions in an area (Carter, M, Hitchcock, J, Personal Communication, Jan.13, 2012) such as changes in zoning density. Another predictive tool that can be used is the SLEUTH urban land cover model which predicts possible future urban conditions in an area based on user inputs (Clarke, Gaydos, Hoppen, 1997, Jantz, Goetz, and Shelly, 2003). Land use managers at the Chesapeake and Ohio Canal and the Antietam National Battlefield have expressed interest in using the SLEUTH model as a supplementary resource when planning for future conditions around their respective national parks, in particular to act as a tool to guide land protection strategies such as land acquisitions. However, it is unclear how effective the SLEUTH model is at predicting such small scale land use changes. As such, this study evaluates the SLEUTH model's effectiveness at predicting observed urban conditions around these two national parks in Maryland at different geographic scales, and thus, whether or not this tool would be an effective resource for the NPS officials to aid them in their land management methods.

Literature Review:

The United States and other countries around the world place great value on places which have high aesthetic value, historical significance, contain desirable or endangered species of flora and fauna, or other similar beneficial and desirable aspects. These areas are often designated as protected areas which severely limit or prohibit all forms development within the protected area boundaries. The source of the protection may be varied, with protection in the United States coming in the form of federal agencies like the National Park Service (NPS), state park designation, or local government protection in the form of municipal protected lands. No matter the source of protection, the intention is the same: to protect these land areas for the public today and for future generations. Protected areas provide a myriad of services, including watershed protection, biodiversity protection, and other, less tangible aspects such as recreation, cultural preservation and spiritual benefits (DeFries *et al.*, 2007). While it is impossible to develop within these areas, these land areas are often desirable areas to visit and experience. Simply put, these areas often present the opportunity for desirable activities, and living in close proximity to these protected areas is very desirable for many people. For these aforementioned reasons, among others, protected areas often potentially attract further development (Gimmi *et al.*, 2011, Georgi, 2010) which makes land management more difficult when preserving the protected lands for future enjoyment.

Protected areas attract urban growth in more ways than the initial draw of aesthetics and other desirable characteristics, though. Inside protected lands is often the opportunity for sports related activity (Joppa *et al.*, 2009) or other activities which the protected lands promote. This, along with the other benefits of protected lands, increases the opportunity for economic growth around an area in the form of tourism or other business which capitalize on the recreational activities in the protected areas This, in turn, increases the amount of job opportunities around the protected areas as well (Gimmi *et al.*, 2011). There are other potential causes for urban growth and/or environmental displacement around protected areas as well. However, the aforementioned reasons are among the primary drivers that may attract urban growth around the two National Parks of concern in this study. While these drivers may exist, other researchers (Joppa *et al.*, 2009) suggest that population growth near protected areas is not greater than other rural areas, and that the growth may simply be attributed to the general expansion of urban centers. However, this region has two extremely large and influential urban centers which are expanding: Washington D.C. and the Baltimore area, which makes this study unique in that it has the potential to have a large amount of urban growth.

These areas are protected from urban development for a very simple reason: urban development is very detrimental to natural and sensitive areas in many ways. One of the most obvious detrimental effects of urbanization is the fact that replacing forests or other natural lands with buildings permanently ruins the natural characteristics of an area. However, some of the most notable impacts of urban areas manifest themselves outside of the developed areas, particularly if they are of a sensitive nature. Urban lands can cause significant degradation to the quality of areas downstream and in the vicinity of the developed areas. Examples of degradation caused by urban areas include increased storm water runoff, which increases the flashiness and erosion of the downstream areas, increased toxin levels from automobiles and sewage treatment byproducts, and other similar human impacts

(Horton, 2003). These problems are compounded in areas which have naturally high urban pressures from large urban centers. One such case where urban lands are encroaching on culturally valuable protected lands is in southern Maryland, where urban expansion of Washington, DC and the spillover effects that this city has in other counties (Frederick County Department of Planning, 2011) has created the risk of encroachment on at least two NPS landholdings; the Chesapeake and Ohio Canal (C&O) and the Antietam National Battlefield (Carter, M, Hitchcock, J, Personal Communication, January 13, 2012). These two National Parks display a microcosm of at least two major eras of American History; the onset of the Industrial Revolution and the American Civil War. They are within driving distance of one of the most populous urban centers in the United States: the Washington, DC-Baltimore metropolitan area. Because of this proximity, special consideration needs to be given to the land uses and the risks to the NPS land areas and how land managers will plan for those risks (Carter, M, Hitchcock, J, Personal Communication, Jan.13, 2012).

The attractiveness of protected lands and the impacts of urban lands on natural areas present a unique problem for the people who manage the protected lands around the world, including the Canal and the Battlefield. One of the strategies for managing these lands includes selecting where to set up protective measures using different land management methods whether it is acquiring new parcels of land, working with local conservation groups to create land easements, or other protective measures (Carter, M, Hitchcock, J, Personal Communication, Jan.13, 2012). Conceptually, these are guided with some knowledge of the future in selecting areas which have greater pressures from development. This is particularly important, considering that the patterns of land use change are shifting in Maryland. Based on initial conversations with NPS officials at the C&O, certain zoning designations may change in the local area around the National Park. Specifically, certain residential zones in the Maryland, which contains the NPS lands in this study, may be changed from low density to a higher density zoning designation to stimulate economic growth in the region (Carter, M, Hitchcock, J, Personal Communication, January 13, 2012). This may change how land use densities change within Maryland, and thus increase how much impact urban areas have on the park lands. Changing land use dynamics as well as urban expansion may increase the difficulty of protecting these lands in the future can compound the difficulty park managers have when considering which risks to minimize.

One of the tools that researchers have attempted to use to approximate the future urban state of several areas has been the SLEUTH urban land use model. The SLEUTH urban land use model is a cellular automata (CA) model which is used to simulate and forecast patterns of urban development. (Jantz *et al.*, 2003). This particular model utilizes, on a conceptual level, the suitability of land for development, and a set of growth rules that are used to simulate a variety of urban environments (Clarke, Gaydos, Hoppen, 1997). A summation of how the SLEUTH model works will be discussed later in this paper. The SLEUTH urban land use model allows researchers utilize to model future land use scenarios to forecast urban land use changes. It has been used in a variety of regions to examine possible future land use change patterns such as San Francisco, California (Clarke, Gaydos, Hoppen, 1997) and the Baltimore, Maryland area (Jantz *et al.*, 2003) as well as the upper Delaware River Watershed (Jantz and Morlock, 2011). SLEUTH has seen adoption due to its ability to be coupled with Geographic Information Systems (GIS) technology (Jantz and

Morlock, 2011) through data inputs and to process the SLEUTH model outputs. This allows the SLEUTH model to be effective as a planning tool, that interested parties, such as the National Park Service, can utilize to identify high risk areas and areas that have the potential for high amounts of growth.

Personal communication with park managers at the C&O and Antietam revealed that they would be interested in using SLEUTH model results to guide land protection decisions around the park, often in parcel level form (Carter, M, Hitchcock, J, Personal Communication, January 13, 2012). However, it is unclear how effective the land use model is at predicting local level land use changes (Jantz, Goetz, and Shelly, 2003) and the model is not effective at predicting pixel level changes. Typically, the model is used to forecast large land areas, such as the entire region of the Delaware River Watershed (Jantz and Morlock, 2011). However, an evaluation of the model at near parcel-level analysis is not yet prevalent in the literature. Because of these gaps in the literature, this study will utilize the modeling capabilities of the SLEUTH model to predict observed land use in the Chesapeake and Ohio Canal and the Antietam National Battlefield Area. This study seeks to address that gap in the literature about the effectiveness of the SLEUTH model on smaller scales as compared to larger scales.

Based on collaboration with National Park Service personnel at the C&O canal, concerns over the acquisition of individual parcels of interest were a primary interest when considering the capabilities of the SLEUTH model (Carter, M, Hitchcock, J, Personal Communication, January 13, 2012). These personnel were specifically interested in utilizing the model to predict, based on past and possible growth patterns, which parcels will be developed in about twenty years to use as supplementary material when submitting proposals for land acquisition around the park premise for future additions to the park (Carter, M, Hitchcock, J, Personal Communication, January 13, 2012). However, most of the research which has used the SLEUTH model has not focused on such small, parcel level analysis (e.g. Jantz and Morlock, 2011, Jantz, Goetz, and Shelly, 2003). As such, researchers have surmised that the model may be sufficient to predict land use change at a regional level (Jantz and Morlock, 2011).

SLEUTH can be used as a planning tool to assist land use managers to make informed decisions in a variety of ways. For instance, the SLEUTH model has been used successfully to recreate urban patterns in the Delaware River Watershed and to forecast the urban growth in that area into the future (Jantz and Morlock, 2011). This area of the United States is similar to this study's area of interest in that the Delaware River Watershed has within its bounds many protected lands and other sensitive areas, including the areas which provide New York City, which is one of the most influential and vulnerable cities in the world, with its water supply. This model is appropriate for this kind of research because it allows the modelers to input several growth scenarios to predict different levels of urban expansion in any particular area. This feature would allow the land use managers to predict for different future scenarios such as high growth (e.g. boom cycles in the economy) or bust cycles (e.g. recessive cycles in the economy) and, perhaps, for significant changes in zoning.

The SLEUTH model can be used as a tool to inform policy makers and decision makers about different possibilities in future land use if current trends are allowed to continue. The model's results could potentially be used to target vulnerable areas and/or areas at risk for urban change, and then to plan accordingly to minimize the impact of those changes (Jantz, Goetz, and Shelly, 2003).This potential use matches closely with the goals of the National Park Service Personnel that were interviewed at the outset of this project (Carter, M, Hitchcock, J, Personal Communication, January 13, 2012). However, those officials expressed interest in utilizing the model to predict parcel level changes and to use those predictions to inform policy and other land management strategies.

For instance, the model has been used to provide land use managers in the Delaware River Watershed with land use change estimates based on a variety of factors, such as soil types and general growth pressures. Jantz and Morlock (2011) suggest that the model's results can be used to predict, based on different scenarios, which policies would be best for sensitive land preservation. While the SLEUTH model has these sorts of functions, the model has not yet been proven to provide the sort of accuracy that would inform detailed estimates of at risk parcels for land management purposes. As such, this study will seek to add a more insight into that side of the SLEUTH model's results and to ultimately determine at what geographic scale the model's results become more reliable.

SLEUTH Model Overview:

The SLEUTH model is a cellular automata model (CA) which analyzes data that is divided into cells in a regular grid (Jantz, Goetz, Donato, and Claggett, 2009). The model utilizes a set of mathematical and spatial rules to determine when a change in state can occur (i.e.non-urban to urban land) and these rules are determined by parameters which are determined by user input and by the datasets chosen (Jantz, Goetz, Shelley, 2003, Candau and Clarke, 2011). The SLEUTH acronym stands for

Slope, **L**and Use, **E**xcluded areas, **T**ransportation, and **H**illshade, which correspond to the five basic inputs that the model requires.

SLEUTH simulates four types of urban growth. These are best described as initial rules for the model to follow in assigning new urban growth in an area (Candau and Clarke, 2011). These growth rules specify to the model the conditions that must be met for the model to predict urban growth in an area (O'Sullivan, 2001). These growth rules are applied sequentially in a step by step manner during an annual growth cycle (Candau and Clarke, 2011). The specific characteristics and list of these growth rules are as follows and more information about these rules has been compiled and posted online by Candau and Clarke (2011).

- Spontaneous growth – this growth rule is a function of SLEUTH to model the occurrence of random urbanization. In a CA model this idea can be described as each cell on the grid having a designated probability of becoming urbanized at any time (Candau and Clarke, 2011).
- New spreading center growth – This function of SLEUTH describes the model's ability to assign spontaneously grown urban cells to become a new spreading urban center or, in general, new urban areas (Candau and Clarke, 2011).
- Edge growth – determines growth that spreads from existing urban centers. These cells are determined by cells present in both established urban centers or in urban centers spawned from the new spreading center growth step described above (Candau and Clarke, 2011).
- Road-influenced growth – for this type of growth and its associated rules, the model uses distance from urban areas to transportation networks (i.e.: roads) to assign new urban cells. (Candau and Clarke, 2011). Thus, the model

preferentially assigns urban cells near road networks where that infrastructure exists.

Each of these four types of growth is controlled through five growth coefficients: *dispersion, breed, spread, road gravity*, and *slope*. These five coefficients determine the probability of any given cell becoming urbanized. Each growth coefficient will have a value of 0-100, with 0 meaning no influence from that coefficient and 100 meaning the coefficient has its maximum impact on the urban growth in the area (Jantz, Goetz, and Shelly, 2003). A more detailed explanation of each of these coefficients follows in this section (Sources: Candau and Clarke, 2011, Clarke, Hoppen, and Gaydos, 1996):

- Dispersion: The dispersion coefficient is the primary controlling coefficient for the spontaneous growth parameter described above. This coefficient controls how often a cell will be selected for random urbanization. It also works in conjunction with the road-influenced growth parameter to determine how far away from a road feature the model will keep or discard randomly assigned urban growth cells.
- Breed: This coefficient determines the likelihood of a spontaneously grown cell becoming a spreading center (or, in other words, new spreading center growth, as previously described). The breed coefficient also determines how many times the model will search for spontaneously grown urban cells next to existing road features in determining which of those cells will become urbanized land.
- Spread: This coefficient determines the likelihood that a cell which is part of a spreading center (defined by the model as a cluster of urban cells > 2 in a

3x3 cell neighborhood) will generate additional urban cells around the clusters.

- Road gravity: Road gravity describes how far the model will look from existing urban areas for road networks to assign new urban areas. The accessibility of these locations due to proximity to roads makes them attractors for development (Clarke, Hoppen, and Gaydos, 1997).
- Slope: This coefficient is based on the assumption of the model that steeper slopes act as a deterrent for development. Thus, a critical slope is determined that acts as a barrier for development. However, the model determines the likelihood of development on each particular cell in a nonlinear fashion. If a high slope coefficient is entered into the model, steep slopes are considered less likely to urbanize. As this coefficient approaches zero, higher slopes in the area have less effect on the probability of urbanization (Clarke, Hoppen, and Gaydos, 1996, Candau and Clarke, 2011).

The SLEUTH model utilizes these growth coefficients to simulate how an urban area grows. These values are calibrated by comparing the modeled urban extent values to the observed urban extent values.

Study Area:

The focus of this study is centered in four counties in Maryland which contain the two national parks in question: Washington, Frederick, Allegany, and Montgomery Counties (See Figure 1). These two national parks are two National Park Service (NPS) landholdings: the C&O and the National Battlefield at Antietam. The C&O Canal and the Battlefield both have a storied past, and are key links to the past in terms of both historical and societal significance. The next two sections will give a context on some significant details of these two National Parks and their surrounding counties.

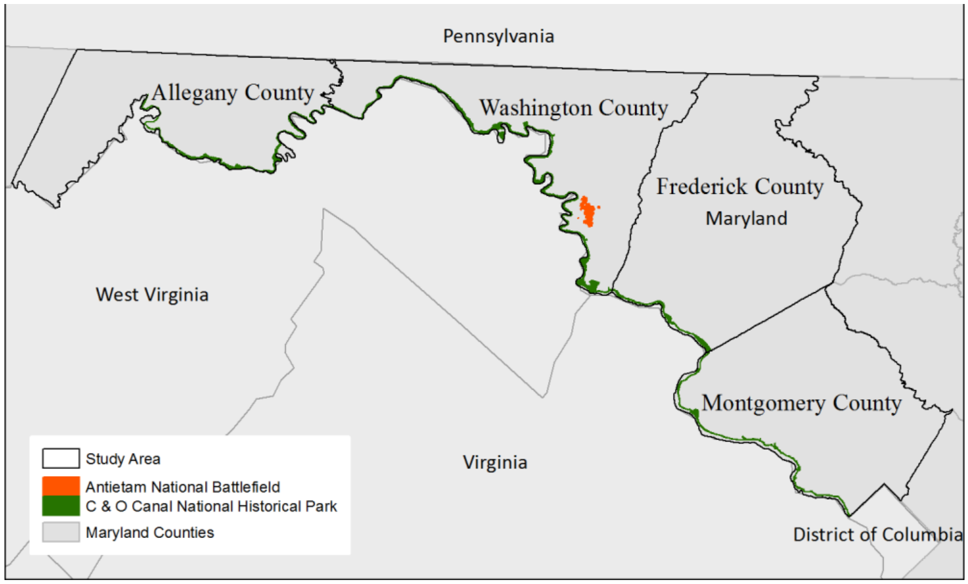

Figure 1: This map portrays the study area used in this study. The extent of the Chesapeake and Ohio Canal (C&O) and the Antietam National Battlefield are shown in green and orange, respectively.

The Chesapeake and Ohio Canal:

The Chesapeake and Ohio (C&O) Canal is a unique National Park Service landholding with both a unique past and unique geographical properties. It was built between 1828 and 1859 and remained in operation from 1831 to 1924 (Mackintosh, 1991). It runs along the largely unnavigable Potomac River (U.S. Dept. of the Interior, 2012), and thus gave communities, including Washington, D.C., along that river easy access to trade goods, including coal (C&O Canal Association, 2011). The C&O Canal remained in operation until 1924 when flood damage made repairs to the Canal too expensive (US Dept. of the Interior, 2012). Also leading to the demise of the Canal was the nearby Chesapeake and Ohio Railway, which, due to the relatively faster speeds of railway locomotion, made canal transport a thing of the past (C&O Canal Association, 2011).

Antietam National Battlefield:

The Antietam National Battlefield resides at the site of one of the most notorious battles of the United States Civil War. The battle took place as the final set piece in the Maryland Campaign of 1862, and was the first incursion into the Northern States by General Lee of the Confederate forces (United States Dept. of the Interior, 2012). The twelve hour battle began on September 17th, 1862 and resulted in about 23,000 casualties cumulatively from both sides out of about 100,000 servicemen (United States Dept. of the Interior, 2012). The Battlefield was turned into a National Park in 1978.

These two National Parks are examples of American culture and history through a century of struggles and growth in the country. They both represent cultural changes in the United States; the Civil War represented a struggle for human rights and the Canal representing huge leaps forward in technology and the changes in people's ways of life that technology brought with it. These lands are valuable for their open space and educational benefits, as well as their historical significance.

Study Area Growth Trends:

This region of Maryland has been growing in the past three decades. According to the United States Census Bureau, the total population in this area has increased from about 887,000 residents in 1980 and 1,427,000 residents in 2010 (U.S. Census of Population and Housing, 1980, U.S. Census of Population and Housing, 2010). This increase is mirrored by a similar increase of employment opportunities in the study area as well, with about 480,000 employees in 1980 (based on those paying unemployment insurance), which increased to about 809,000 employees in 2000 (MDP, 2010). However, this growth has not been uniform over the entire study area.

Washington, Montgomery, and Frederick Counties all experienced population growth during this time period, while Allegany County experienced relatively little change (see tables 1 and 2). Total population and employment in the study area seems to decline with distance from the Washington, DC-Baltimore area. The growth characteristics of these four counties will be discussed individually in this section. These changes in employment and population were used to manipulate the model to produce more accurate results. This will be discussed later in this document.

Table 1: This table summarizes the employment and population trends in the Study Area. Data Sources: (Urban Area Source: Irani and Claggett, 2010. Population Source: United States Census, 1980, 1990, 2000, and 2010. Employment Statistics: Maryland Department of Planning. (MDP, 2010)).

1980s			
County	Urban Area (km^2) (1984)	Employment (1980)	Population (1980)
Allegany	50.48	27,992	80,548
Frederick	122.15	30,391	114,792
Montgomery	372.25	276,808	579,053
Washington	101.68	42,025	113,086
1990s			
County	Urban Area (km^2) (1992)	Employment (1990)	Population (1990)
Allegany	53.21	27,682	74,946
Frederick	148.06	50,970	150,208
Montgomery	409.41	382,357	757,027
Washington	106.41	51,300	121,393
2000s			
County	Urban Area (km^2) (2001)	Employment (2000)	Population (2000)
Allegany	53.74	30,186	74,930
Frederick	165.71	77,323	195,277
Montgomery	439.74	447,314	873,341
Washington	108.68	63,037	131,923

Table 2: This table details how the urban area, population, and employment growth rates have changed over time in the study area. Data Sources: Data Sources: Urban Area Source: Irani and Claggett, 2010. Population Source: United States Census, 1980, 1990, 2000, and 2010. Employment Statistics: Maryland Department of Planning (MDP, 2010).

	Urban area changes		
County	1984-1992	1992-2001	2001-2006
Allegany	5.13%	0.98%	0.16%
Frederick	17.50%	10.65%	3.14%
Montgomery	4.44%	2.10%	1.11%
Washington	9.08%	6.90%	0.53%
	Changes in Population		
County	1980-1990	1990-2000	2000-2010
Allegany	-7.47%	-0.02%	-2.91%
Frederick	23.58%	23.08%	18.47%
Montgomery	23.51%	13.32%	12.21%
Washington	6.84%	7.98%	12.04%
	Changes in employment		
County	1980-1990	1990-2000	2000-2010
Allegany	-1.12%	8.30%	2.52%
Frederick	40.37%	34.08%	13.47%
Montgomery	27.60%	14.52%	8.77%
Washington	18.08%	18.62%	1.63%

Allegany County

Population changes:

The population in Allegany County, Maryland has been relatively stable since 1980. It saw a decline in population from 1880 – 1990, but it saw a slight increase of about .1% from 1990 to 2010 (U.S. Census of Population and Housing, 1980, 1990, 2000, 2010).

Employment change:

Allegany County experienced very little employment gain in the study timeframe. This poor economic growth is due to the decline of the manufacturing industries within the county before 1980. However, recent employment growth is attributed due to the slight rise in the mining industries within the county (Allegany County Department of Planning, 2002).

Urban area change:

Allegany County had the lowest concentrations of urban areas among the four counties. Allegany County experienced less than 1% urban area growth from 1984 to 2006, with the total surface area of urban areas amounting to about 53.66 km^2 out of 1,115.40km^2 of total urban area within the county (Irani and Claggett, 2010). Typically, population and employment growth is a catalyst for urban growth (Bhatta, 2011, Brueckner, 2001, Farahmand et. al., 2011) but this county experienced very little of both of those during the study time period. However, this urban growth may be attributable to the rise of the mining industries in the county (Allegany County Department of Planning, 2002). Urban growth continued in areas in which this industry remained prevalent (Allegany County Department of Planning, 2002).

Frederick County

Population changes:

Frederick County has seen significantly more growth than Allegany County, and has seen higher rate of positive change than the three other counties during the study time period. Population growth in Frederick County increased by 23% between the censuses from 1980 to 1990 and 1990 to 2000, with a 17% growth recorded from 2000 to 2010 (U.S. Census of Population and Housing, 1980, 1990, 2000, 2010).

Employment change:

Frederick County has experienced the highest percentage gain in employment over the study time period. This is due to the County's location near Montgomery

County and the subsequent proximity to the Washington, D.C. Metro area (Frederick County Department of Planning, 2010). This proximity has brought job growth into the county and is expected to cause an increase in housing construction demand into the future (Frederick County Department of Planning, 2010).

Urban area change:

This County has also seen a substantial gain in total urban area during the study time period as well. From 1984 to 2006, the surface area of the urban expanses increased a total of about 43.5km^2 (Irani and Claggett, 2010).

Montgomery County

Population changes:

Montgomery County has seen population growth that is similar to Frederick County, but less pronounced - although it has the largest population in the study area. It grew about 23% from 1980 to 1990, and growth has been declining since, with 13% from 1990 to 2000 and 10% from 2000-2010.

Employment change:

Montgomery County has seen lower employment growth from 1990-2000 than Frederick County experienced (see table 1) (MDP, 2010). Montgomery County also sees a large influence from the D.C. area and is often considered a suburban county of that city (Hanlon, Short, and Vicino 2010, Shen, 2007, Short, 2007). This county also has the largest number of total jobs within the study area as well (Shen, 2007, MDP, 2010).

Urban area change:

This county saw the largest total growth in urban area from 1984-2006 among the counties in the study area, with a total of about 67.5km^2 of urban growth during the time period (Irani and Claggett, 2010).

Washington County

Population changes:

Washington County has seen slower growth than Frederick and Montgomery Counties, but much higher growth than Allegany County. It grew in population by about 6.8% from 1980-1990, about 8% from 1990 to 2000, and 10.5% from 2000-2010 (U.S. Census of Population and Housing, 1980, 1990, 2000, 2010).

Employment change:

Much like Montgomery and Frederick counties, Washington County has seen employment growth (MDP, 2010) and has seen fairly low unemployment rates throughout much of the study time period (Washington County Department of Planning, 2002), although the Washington, D.C. area has less influence on this county than Montgomery and Frederick Counties. Also, Washington County has seen steady growth in housing demand and a fairly low unemployment rate in the 1990s (Washington County Department of Planning, 2002)

Urban area change:

Washington County is considered primarily rural (Shen, 2007) and the changes in urban extent and total urban extent corroborates this observation. This county saw the second lowest growth in urban extent among the study counties, with only about 7.2km^2 of urban growth occurring during the study temporal extent (Irani and Claggett, 2010).

Growth Trends and the SLEUTH Model:

These changing population and employment trends in the study area were used as a basis to modify the SLEUTH model inputs (explained later). Population and employment are two of the most basic drivers of urban expansion over time (Bhatta, 2011, Brueckner, 2001, Farahmand *et al.*, 2011). However, the relationship between population and employment change and urban expansion is not a linear relationship. Within these four counties in Maryland, particularly Frederick, Montgomery, and Washington Counties, population and employment have outpaced urban expansion (see figure 2), suggesting that development within these four counties has occurred as infill development to fulfill Smart Growth policies within the State of Maryland (Shen, 2007) or simply that the development that has occurred has resulted in higher density development, such as less dwelling space per person (Otis, 2012). While some of the cited and examined causes of urbanization within the reviewed literature are exceedingly complex and range from ecological change, cultural factors, economic factors, physical and biological attractors (Nelson *et al.* 2006), the concentration of population and employment in an area is an easily quantifiable reason cities grow and expand (Sabbagh, 2001, cited in Farahmand *et al.*, 2011, Bhatta, 2011). As such, the trends of population and employment were integral to the execution of the SLEUTH model and the results. This will be further detailed in the methods section of this document.

Research Questions:

Due to the available literature and the needs of the National Park Service personnel interviewed, two major research questions manifested themselves. These objectives are as follows:

1. Can the SLEUTH model be used to accurately predict urban changes at the local level? If not, does the accuracy of the model improve at larger scales?
2. Can the SLEUTH model be improved to predict, at smaller scales, urban growth based on outside factors such as employment and population changes?

Methods:

Due to the suggestions of the National Park Service officials with whom this author communicated with as part of this project and the lack of literature which suggested that the SLEUTH model could meet those suggestions effectively, this study examined the effectiveness of the SLEUTH model when predicting urban land use change around the National Park Service landholdings. This section will outline the data sources and data processing, and then the methods used for calibrating and validating the SLEUTH model at multiple scales.

It should be noted that this study utilize the SLEUTH "3r" model, which is a vastly improved version of the model. The improvements in the model are described in Jantz, Goetz, Donato, and Claggett (2009).

Data Sources and Data Processing:

A multitude of different geographic information systems (GIS) data were utilized to create the inputs for the SLEUTH model. Each of these data sources were manipulated and processed using ESRI's ArcMap software and its extensions (ArcMap version 10.X software) (ESRI, 2011). Each dataset was taken from its original source and projected into the UTM zone 18 North (NAD 1983) for input into the SLEUTH model. Afterwards, they were converted to raster datasets with 30 meter cell sizes.

Finally, they were transformed from raster datasets into a .gif format which the SLEUTH model utilizes for its processing. The rest of this section will describe those data that were utilized in this study with each particular input of SLEUTH described separately.

Overall, two major sources of data were used during this study. These two are the Maryland Department of Natural Resources (Maryland DNR) and the Chesapeake Bay Land Cover Data (CBLCD) series. The Maryland DNR makes a multitude of datasets (in ESRI shape file format) which designate different land areas available to the public for free. Conversely, the CBLCD is a Landsat-derived dataset which classifies land use by the Anderson level 2 classification system (Irani and Claggett, 2010) and is available at a 30 meter resolution. These two data sources are described in their particular uses in this section.

Slope:

The slope input later was derived from publicly available USGS Digital Elevation Model (DEM) datasets (Gesch, 2007, Gesch *et al.*, 2002). These data were transformed from a raw DEM dataset that recorded only elevation above mean sea level into a raster file that displayed percent slope instead of the default elevation values in a GIS environment. However, this data set, via processes used in the ESRI ArcMap (ESRI, 2011) toolsets, calculated values that were greater than 100% slope. This was caused by the way that slope angles (in degrees) are converted into percentage slope. As the slope angle approaches 45 degrees, rise = run, which results in a slope of 100%. For slope angles > 45 – 90 degrees, slope percentage approaches infinity, which is the origin of the slope values greater than 100% (ESRI, 2011).

Excluded Areas (AKA exclusion/attraction layer):

The exclusion/attraction layer is one of the most important inputs when utilizing the SLEUTH model. This layer designates which areas of the study area are more or less likely to attract development, both in reality and in the model space. As discussed later, this study tested two exclusion/attraction layers: one that only represented lands excluded from development and one that took population and employment trends into considerations.

The exclusion/attraction layer functions by classifying each cell in a study area by the level of attraction or exclusion that the user wishes to assign to each cell of land cover. At its most basic level, this layer can be used to designate what land areas are off limits for development and which areas can be developed on. Furthermore, the exclusion layer can be modified to attract or exclude development at a varying scale by manipulating cell values. Specifically, the layer operates on a 0-100 scale, where 100 = total exclusion, 0 = strongest attraction, and 50 = neutral (Jantz and Morlock, 2011). At the most basic level, this layer is used to designate areas that cannot be developed on, such as water or protected lands, such as those which are the focus of this study. However, this layer can be modified to reflect areas which attract or preferentially exclude urban development (Jantz and Morlock, 2011) and this has been performed in this study. The details of those modifications will be discussed in a later section.

In this study, the inputs for the excluded areas into this study were derived from a variety of inputs available from the Maryland Department of Natural Resources (Maryland DNR). These inputs all incorporate a variety of excluded area land designations that were compiled by the Maryland DNR in ESRI GIS spatial file formats. These include private conservation properties, rural legacy properties, forest conservation easements, federal lands, environmental trust easements, Maryland DNR lands and conservation easements, and county lands. All of these datasets are provided as-is from the Maryland DNR and no guarantees as to the accuracy of these datasets is implied or specified by the DNR. These are the most complete datasets pertaining to the protected and other lands within Maryland that this author is aware of during this study's timeframe. The following list describes all of the datasets that are categorized as being completely excluded from development, and include data from the Maryland DNR and the Chesapeake Bay Watershed Land Cover Dataset (CBLCD series) (Irani and Claggett, 2010). These following land areas were assigned values of 100 in both the unmodified and modified versions of the exclusion layer used in this study. This signified that these areas are off limits to development. It is also important to note that all land areas outside of the four counties used in this study area were assigned values of 100 to preclude all chance of urban growth outside of the study area. This method resulted from a lack of spatial data for areas outside of the study area.

- Private conservation properties: this dataset contained spatial data that recorded the locations within Maryland that are protected from development via private stakeholder groups. These data were checked using current tax records within the Maryland Department of Planning resources, and may contain errors resulting from different digitizing methods depending on the data authors (Maryland DNR, 2010).
- Rural Legacy Properties: these properties are the areas in Maryland that are protected by Maryland's Rural Legacy Program. These land areas are considered Maryland's most pristine remaining rural areas. Lands within this dataset are essentially easements on property that are purchased with grants via Rural

Legacy Program funding. Data in this set was cross checked with Rural Legacy Program documents and verified with Maryland State tax parcel information (Maryland DNR, 2011).

- Forest Conservation Easements: this dataset contains data from the 2011 submittal year about lands protected by Maryland's Forest Conservation Act (Maryland DNR (2), 2010). This program was enacted in 1991 to help conserve sensitive forested areas within Maryland.
- Federal Lands: this dataset contains the lands that are run and maintained by United States government agencies and authorities. However, United States postal properties were not included in this dataset. It was cross checked in 2005 to tax parcel information for accuracy (Maryland DNR, Wildlife and Heritage Division, 2002).
- Environmental Trust Easements: this dataset refers to lands associated with the Maryland Environmental Trust (MET) that preserves open land between a non-intrusive agreement between the landowner and the MET. The primary method of controlling land use change on these parcels is easements, or agreements for preserving the land and not developing it (Maryland DNR (2), 2011).
- Maryland DNR lands: this dataset contains information about the lands owned and maintained by the Maryland Department of Natural Resources (Maryland DNR (3), 2010).
- County lands: lastly, this dataset represent all of the lands that county and municipal authorities in Maryland own and maintain (Maryland DNR (3), 2010).

The Maryland DNR notes that this dataset may contain omissions if the data were of a sensitive nature or if the underlying records were incomplete.

- Water features: the inputs for was derived from the Chesapeake Bay Land Cover Dataset (CBLCD series) (Irani and Claggett, 2010) by extracting the land cover class that denotes open water and adding it as an input into the excluded layer.

Urban Areas:

The urban extent for four time periods (1984, 1992, 2001, 2006) within the study area were derived from the CBLCD series (Irani and Claggett, 2010) using the land use classes that best described total urban area within the study area. These land use classifications that are available within the CBLCD series are: developed open space, low intensity urban, medium intensity urban and high intensity urban land use classes (Jantz, C.A., personal communication, December 5, 2011). The aforementioned classifications best represent the total lands impacted by urban extent within the study area. For input into SLEUTH, this dataset was transformed into a binary raster dataset, with 1 representing urban areas, and 0 representing everything else.

Transportation:

The transportation input layer was derived from the publicly available United States Census TIGER road dataset (U.S Census, Geography Division, 2011) from 2010. The road input used in this study reflects the major roadways in the study area.

Hillshade:

The hillshade input was not used in this study, as it is simply a tool for the display of data after the model makes its predictions (Jantz, C., Personal Communication, 2012). This was found to be unnecessary for this research.

SLEUTH Model Implementation:

This study utilized the processes of calibration and validation to explore the model's effectiveness when predicting local scale urban growth around the two NPS landholdings. These two steps assess the model's effectiveness at capturing total urban growth, urban growth patterns and locations of change during a specific time period (calibration) and its effectiveness at "forecasting" to a known year based on the trends in the calibration step. This section will detail how these two steps were used to assess the model's accuracy at different geographic scales.

Calibration utilizes the model parameters described above to find parameter values which best fit the historical urban growth in an area (Clarke, Hoppen, and Gaydos, 1996, Candau and Clarke, 2011). In this study, the time period from 1984-2001 was used as the calibration time period. The model is calibrated to identify which combination of urban growth parameter values described previously best recreated the urban characteristics of a study area.

Validation utilizes the calibrated parameter values to project growth between 2001 and 2006, which is then compared to the observed growth in 2006. The primary purpose of validation is to determine the ability of the model to recreate the local level growth around the C&O and the Antietam National Battlefield. This study does not make forecasts beyond 2006, since the focus of this study is on assessing model performance across scales.

Modifications to the Excluded Layer:

This section explains the rationale behind the modifications made to the excluded layer input for this study. The primary function of the excluded layer input is to designate which areas of the study area are off limits or more attractive for development in the model. However, the functionality of the excluded layer can also be enhanced to better reflect the actual urbanization patterns in an area (Jantz, Goetz, and Shelly, 2003). We tested two exclusion/attraction layers (a "basic" and "advanced") so these methods are separated into two separate calibration and validation procedures.

The "basic" SLEUTH model iteration utilized a basic excluded layer which simply excluded all of the protected lands and water within the study area and specified them to the model as off limits for development. Conversely, the advanced model run and respective excluded layer in this study was modified to reflect the effects of population and employment growth on urban growth, which are two of the major drivers of urban growth (Bhatta, 2011). Over the study time period (1984-2006), Maryland experienced changes in population, employment, and urban growth which made modifying the excluded layer to reflect those changes in demographics and landscape relatively easy. The main goal of modifying the excluded layer in this way was to promote more rapid urban growth in areas with a higher proportion of population and employment growth and cause less urban growth in areas with slower population and employment growth. Based on feedback from SLEUTH model expert Dr. Claire Jantz, we determined exclusion layer values to either attract or discourage the model to develop or not develop certain urban areas of the study area.

Based off of the observed trends in the study area, we assigned default exclusion values to the counties based on historical population and employment trends to reflect the low population/job growth in Washington and Allegany Counties and the high population/job growth in Montgomery and Frederick Counties. Another one of the contributing factors of these modifications was the observation that the influence of the D.C. metropolitan area significantly drops off in Washington County (Washington County Department of Planning, 2002). Based off of these simple observations, Allegany and Washington Counties were assigned a value of 90, which resulted in a lower probability of urban development, and Frederick and Montgomery Counties were assigned an exclusion value of 25, which resulted in a higher probability for urban development within the model.

These values were based off of the basic observations of the current conditions of population, employment, and urban extent in the study area. Frederick and Montgomery County benefit from the economic influence of the D.C. and Baltimore areas. Indicative of this economic influence is the fact that commuters have been reported to travel great distances to work within these two counties (Frederick County Department of Planning, 2010) sometimes even to the D.C. area. These effects are lesser in the two outer counties; Allegany and Washington. Thus, we opted to stimulate urban growth in Montgomery and Frederick Counties to approximate the growth effects of the D.C. area and to slow the urban growth in the other two counties to approximate the relatively slower growth trends in those two counties.

In summation, two excluded layers were used to examine whether or not using a more robust exclusion/attraction layer improves SLEUTH's performance at different scales. The basic exclusion layer without any alterations to account for population and employment growth will hereafter be referred to as the basic results, and the results for the excluded layer which took population and employment into account will hereafter be referred to as the advanced results.

Model Calibration:

The first step in utilizing the SLEUTH model was the initial calibration of the model. Calibration allows the SLEUTH model to calculate goodness of fit statistics to help the users determine which of the five parameters discussed previously best explain the growth trends in the study area (Candau and Clarke, 2011). This step involved using brute force calibration to coerce the model to test all possible variations of the parameter value combinations (which were 3,125 different combinations in this study) (See the *"SLEUTH Model Overview"* section) within a study area (Jantz, Goetz, Donato, and Claggett, 2009). The model was calibrated as a result of setting base values for each of the five parameters in the previous section in increments of 25 (0-100).

After initial calibration, four parameter sets were chosen for this study's analyses (see table 3 in the results section). These four results were then used to run the model in predict mode from 1984 to 2001, with the model predicting 2001 urban conditions. These results were then compared to observed conditions in 2001, and are referred to as the calibration results in this study. This term may be slightly misleading in this case, as the results of the calibration were not used to in turn modify the model's input parameters. Instead, they were used to add further data to the analysis in the form of the model predicting to two different years using two different start points. Validation, in the case of the SLEUTH model, allows the user to utilize the input parameters deemed to be best fit by the initial calibration and compare them to observed values. The model was validated by running the model from 2001 to an independent time point, 2006, which was not used in the initial calibration. The validation process was completed using the same model parameters as presented in table 3, four times for each respective run number. These model runs were subsequently compared to the observed conditions in 2006.

Model Results Processing

In order to answer the research questions, arrays of three different grid sizes were used to evaluate the model's effectiveness at different scales. Three "fishnet" grids were created that consisted of 150m, 300m, and 600m cell sizes to create a range of scales at which to compare percent developed of both modeled and observed urban extent during the 2001 and 2006 data years. These particular resolutions were used to simulate a range from a scale that would be more analogous to a large parcel of land to over a half a square kilometer of land, while still fitting a uniform number of 30*30 cells. The 150*150 meter fishnet grid size was chosen for the smallest resolution to evaluate the SLEUTH model for this study for two reasons: 1: it approximates the size of a large parcel of land which the NPS or other land management agency/organization might desire to acquire to protect the park, as each grid cell represents approximately 5 acres of land. 2: A smaller grid size may have exceeded the computational ability of the hardware available to handle all of the grid cells when calculating their *zonal statistics*, as it would have created significantly more records for the software and hardware to process. The other two grid sizes were used to give a comparison of the accuracy of the model at different resolutions.

Next, I created subset of those fishnet grids to only contain cells within 2.5km of the C&O canal and the Antietam National Battlefield. The 2.5 km study area was appropriate for this study, as the intent of this study was to examine at which geographic scale the SLEUTH model could predict urban growth around national parks. The 2.5km study area was used over a smaller geographic extent to create more records with which to create statistics, as a smaller extent, such as a 1km extent would have resulted in smaller sample sizes. Additionally, ESRI software encountered errors when a larger extent which contained more records were used with the *zonal statistics* tool, which was used to calculate the total (sum of) predicted and observed urban area within each cell. In short, the ESRI ArcMap software could not calculate the statistics for the entire study area (i.e. all four counties) on the available hardware and this necessitated a smaller sample size.

Finally, I subset the fishnet grids to only contain polygons which either intersected the four study area counties or which were within the counties. This step was to avoid and statistical errors which would be introduced by 0 values, as all exclusion values outside of the four counties to were set to 100 to automatically preclude growth outside of the counties (Jantz, Goetz, and Shelley, 2003). This would have resulted in no growth outside of the county boundaries, resulting in 0 percent growth in both observed and predicted values, resulting in erroneous values.

Finally, I calculated Zonal Statistics using ESRI ArcMap software (ESRI, 2011) to calculate the sum of the cell values from the calibration and validation results from SLEUTH. I then calculated the percentage of urban land per fishnet grid cell by using the following formula:

$$\left(\frac{\left(\frac{Sum\ of\ cells\ with\ a\ probability\ assigned}{100}\right) * 900\frac{m}{cell}^{2}}{Area(m^2) of\ each\ fishnet\ cell}\right) * 100$$

I examined the four different calibration and validation runs of the SLEUTH model (with a total of 8 result datasets), thus this formula was repeated twenty-four times, eight times for the results of each grid size. The results of this formula represented how much, in percent, of each grid cell was predicted by the SLEUTH model to be urban area. The SLEUTH model records results in a .gif image that reports urban area by probability (in percent) of development. Thus, the formula divides the total sum by 100 to derive, in percent of total urban 30x30 pixels in each fishnet grid cell, was predicted to be to have a probability of being urbanized in either 2001 or 2006.

Conversely, I also calculated the percent of each fishnet grid cell was urban area in 2001 and 2006 as per the CBLCD series by utilizing a similar formula, as follows:

$$\left(\frac{(Sum\ of\ all\ urban\ cells) * 900\,\frac{m}{cell}^{2}}{Area(m^2) of\ each\ fishnet\ cell}\right) * 100$$

This formula differs from the first in that the original observed urban area was derived from the CBLCD series to represent urban areas as a value of one and everything else as zero values. Thus, there was no need to convert the probability sums as in the last formula into a total number of developed cells.

These two formulas produced two statistics: the percent developed as predicted in the calibration and validation runs, and the percent of developed land as observed in 2001 and 2006. In order to assess the accuracy, the modeled results were compared to the observed results by subtracting the modeled values from the observed values.

The results of comparing modeled values to predicted values were then used to gather basic statistics, including mean error (specifically, over/underestimation), minimum error, maximum error, and standard deviation. These are reported for each of the eight calibration and validation runs for each of the three geographic scales examined in this study (see the results section). In addition, regression statistics were also produced which compared the percentage developed per grid cell as modeled and observed. A regression analysis was used as per a similar study by Jantz and Morlock (2011). Normally, regression is used to predict a value based on an independent variable. In this case, however, this method used the regression analysis (R^2) to classify the goodness of fit between one sample set and another in an easy to interpret number (Jantz and Morlock, 2011). This made it an effective tool to assess how well the modeled values matched the observed values for urban extent in each different grid size.

In addition to the basic statistics and the regression statistics, a basic distribution of errors was also produced. These statistics, displayed in tables 6 and 7, were produced by simply counting how many grid cells were within different ranges of values using Microsoft excel. These statistics show how many grid cells had < -5%, -5% - 0%, 0% - 5%, and > 5% over and underestimation (Jantz and Morlock, 2011). These results were then mapped to present a visual representation of these results as well.

Results:

First, the results of the brute force calibration process which derived the base parameters used for this study will be presented. Next, the results of the fishnet-based statistics will be discussed. Finally, the results of the distribution of error will be presented.

Brute force calibration results:

All 3,125 results of the brute force calibration are too numerous to list in this paper. However, the results of the brute force calibration process that were used to produce the results of this study can be examined in table 3. These results were chosen based on their fit statistics on how well the model matched area and clusters, and from suggestions from Dr. Claire Jantz, (Jantz, C, Personal Communication, 2012), and were chosen on the assumption that they would produce acceptable results in this study. These input parameters (see table 3) were used to produce the results for both the calibration and validation steps of this study.

In table 3, there are several indicators about which model runs predict different aspects of urban growth better than the other. For instance, an area fraction value of .05095 means that the model overestimated the total urban area by 5.095%. Conversely, a cluster fraction value of .014 signifies that the model overestimated total urban clusters in the study area by 1.4%. The parameters to the left (e.g. Slope resistance, spread, breed, and diffusion) of those fractions indicate which input parameters the model used to produce those results.

Table 3: This table records the input parameters derived from the initial calibration of the SLEUTH model, and which have been used in each of the four different model results which have been used in this study's results.

Basic Run #	Diffusion	Breed	Spread	Slope resistance	Road gravity	Control year	Area fraction	Cluster fraction
1	0	25	25	75	50	2001	0.05095	0.014
2	50	50	0	25	50	2001	-0.00151	2.040
Advanced Run #	Diffusion	Breed	Spread	Slope resistance	Road gravity	Control year	Area fraction	Cluster fraction
3	0	0	25	100	50	2001	0.042033	0.016
4	50	75	0	75	25	2001	-0.005632	1.697

These four calibration runs represent two from the basic exclusion layer (runs 1 and 2), and two from the advanced exclusion layer (runs 3 and 4) in which the effects of population and employment growth were approximated within the exclusion values. These calibration and their respective validation runs will heretofore be referred to as basic (corresponding to runs 1 and 2) and advanced (corresponding to runs 3 and 4), respectively.

Basic Statistics:

The results of this study are summarized in Table 4 which displays the basic results of this study, and Table 5. which displays the distribution of error within the datasets. These data refer to the four calibration runs (two “basic” and two “advanced” exclusion layer SLEUTH model runs) and four validation runs (two “basic” and two “advanced” exclusion layer SLEUTH model runs). The two “basic” calibrations and validation runs are displayed in table 4. The “advanced” calibration (runs 3 and 4) and validation (runs 3 and 4) runs are displayed in table 5.

Table 4: This table displays the basic statistics of the three geographic grid sizes used in these analyses. These results are for the results of the model after using the basic, unmodified exclusion/attraction layer. These results are derived from the comparison of the modeled results to the observed conditions in each grid cell. Specifically, the calibration results are from comparisons to observed urban extent in 2001 and the validation results are from comparisons to observed urban extent in 2006.

600m Cell size (n= 2951)	Calibration Run 1	Calibration Run 2	Validation Run 1	Validation Run2
Mean Error	-1.47	-1.07	-0.54	-0.42
Minimum Error (%)	-0.23	-4.46	-7.49	-1.44
Maximum Error (%)	54.25	60.87	6.49	5.56
Standard Deviation	4.052	3.263	1.133	0.469
Median	-0.04	-1.09	-0.01	-0.37
R^2	0.9635	0.9673	0.9981	0.9993
300m Cell size (n=10597)	Calibration Run 1	Calibration Run 2	Validation Run 1	Validation Run2
Mean Error	-1.56	-1.14	-0.57	-0.43
Minimum Error (%)	-29.52	-5.21	-9.52	-1.80
Maximum Error (%)	85.00	85.00	25.99	25.10
Standard Deviation	5.284	4.135	1.425	0.687
Median	-0.02	-1.16	0.00	-0.37
R^2	0.9475	0.9575	0.9969	0.9988
150m cell size (n= 39875)	Calibration Run 1	Calibration Run 2	Validation Run 1	Validation Run2
Mean Error	-1.61	-1.18	-0.58	-0.45
Minimum Error (%)	-39.68	-6.36	-13.84	-4.40
Maximum Error (%)	99.96	97.20	60.00	58.36
Standard Deviation	6.60	4.98	1.85	1.01
Median	0.00	-1.12	0.00	-0.32
R^2	0.9304	0.9497	0.9949	0.9979

Table 5: This table displays the statistical error results of the advanced exclusion/attraction layer.

600m Cell size (n= 2951)	Calibration Run 3	Calibration Run 4	Validation Run 3	Validation Run 4
Mean Error	-0.92	-0.46	-0.40	-0.24
Minimum Error (%)	-30.71	-7.80	-10.41	-2.46
Maximum Error (%)	49.56	58.51	6.48	4.88
Standard Deviation	4.236	3.327	1.249	0.517
Median	-0.01	-0.13	0.00	-0.05
R^2	0.9581	0.9657	0.9972	0.9992
300m Cell size (n=10597)	Calibration Run 3	Calibration Run 4	Validation Run 3	Validation Run 4
Mean Error	-0.96	-0.49	-0.41	-0.24
Minimum Error (%)	-39.71	-8.91	-13.29	-2.86
Maximum Error (%)	85.00	85.00	25.99	24.28
Standard Deviation	5.325	4.194	1.481	0.717
Median	0.00	-0.13	0.00	-0.04
R^2	0.9429	0.9561	0.9962	0.9987
150m cell size (n= 39875)	Calibration Run 3	Calibration Run 4	Validation Run 3	Validation Run 4
Mean Error	-0.99	-0.50	-0.42	-0.25
Minimum Error (%)	-54.08	-10.84	-19.28	-4.04
Maximum Error (%)	100.00	99.56	60.00	58.56
Standard Deviation	6.46	5.02	1.85	1.03
Median	0.00	-0.12	0.00	-0.04
R^2	0.9282	0.9487	0.9944	0.9979

Distribution of Error Analysis:

The results of the distribution of errors analysis are displayed in tables 6 and 7. Table 6 displays the results of the basic, unmodified exclusion/attraction layer and table 7 displays the result of the advanced, modified exclusion/attraction layer.

Table 6: This table displays the distribution of errors from the calibration and validation runs which utilized the basic, unmodified exclusion/attraction layer. Again, the calibration results are from comparisons to observed urban extent in 2001 and the validation results are from comparisons to observed urban extent in 2006.

600m (n= 2951)	Calibration Run 1	Calibration Run 2	Validation Run 1	Validation Run2
Percent < -5% Underestimation	12.06%	0.00%	1.02%	0.00%
Percent > 5% Overestimation	1.05%	1.59%	0.03%	0.03%
Percent -5% to 5% error	86.89%	98.41%	98.95%	99.97%
% 0 – (-5%)	54.86%	79.50%	58.18%	79.09%
% 0- 5%	32.02%	18.91%	40.77%	20.87%
300m (n=10597)	Calibration Run 1	Calibration Run 2	Validation Run 1	Validation Run2
Percent < -5% Underestimation	13.48%	0.01%	2.38%	0.00%
Percent > 5% Overestimation	1.00%	1.46%	0.17%	0.19%
% -5% to 5% error	85.52%	98.53%	97.45%	99.81%
% 0 – (-5%)	45.12%	73.66%	43.91%	73.62%
% 0- 5%	40.41%	24.87%	53.54%	26.19%
150m (n=39875)	Calibration Run 1	Calibration Run 2	Validation Run 1	Validation Run2
Percent < -5% Underestimation	12.64%	0.67%	4.09%	0.00%
Percent > 5% Overestimation	0.95%	1.24%	0.16%	0.19%
% -5% to 5% error	86.41%	98.08%	95.75%	99.81%
% 0 – (-5%)	26.73%	65.55%	23.49%	65.36%
% 0- 5%	59.68%	32.54%	72.27%	34.46%

Table 7: This table displays the distribution of errors from the calibration and validation runs which utilized the advanced exclusion/attraction layer.

600m (n= 2951)	Calibration Run 3	Calibration Run 4	Validation Run 3	Validation Run 4
Percent < -5% Underestimation	7.62%	5.08%	2.34%	0.00%
Percent > 5% Overestimation	1.42%	1.83%	0.03%	0.00%
Percent -5% to 5% error	90.95%	93.09%	97.63%	100.00%
% 0 – (-5%)	45.07%	72.99%	47.07%	75.77%
% 0- 5%	45.88%	20.09%	50.56%	75.77%
300m (n=10597)	**Calibration Run 3**	**Calibration Run 4**	**Validation Run 3**	**Validation Run 4**
Percent < -5% Underestimation	7.38%	6.03%	2.85%	0.00%
Percent > 5% Overestimation	1.25%	1.58%	0.17%	0.18%
% -5% to 5% error	91.37%	92.39%	96.98%	99.82%
% 0 – (-5%)	37.02%	67.70%	34.81%	69.43%
% 0- 5%	54.37%	24.69%	62.17%	30.39%
150m (n=39875)	**Calibration Run 3**	**Calibration Run 4**	**Validation Run 3**	**Validation Run 4**
Percent < -5% Underestimation	6.68%	7.38%	3.29%	0.00%
Percent > 5% Overestimation	1.07%	1.29%	0.16%	0.19%
% -5% to 5% error	92.26%	91.33%	96.55%	99.81%
% 0 – (-5%)	22.16%	54.89%	19.49%	52.04%
% 0- 5%	70.10%	36.44%	77.06%	47.78%

The following six maps display the spatial results of the distribution of error tables for the “advanced” model runs presented in table 7. These maps share the same error distribution ranges as were presented in table 6 and 7.

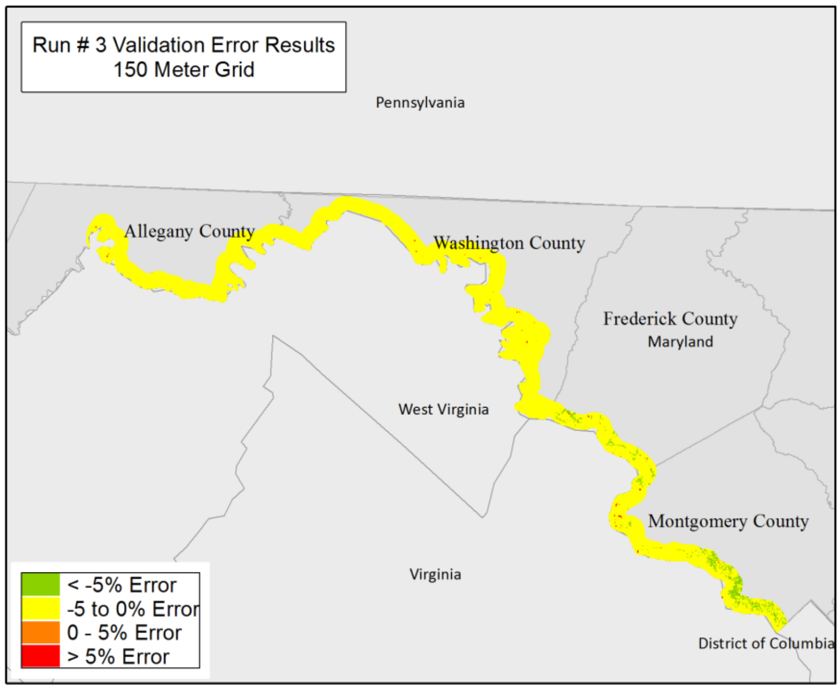

Figure 2: Map of error distribution for run #3 validation at the 150 meter resolution.

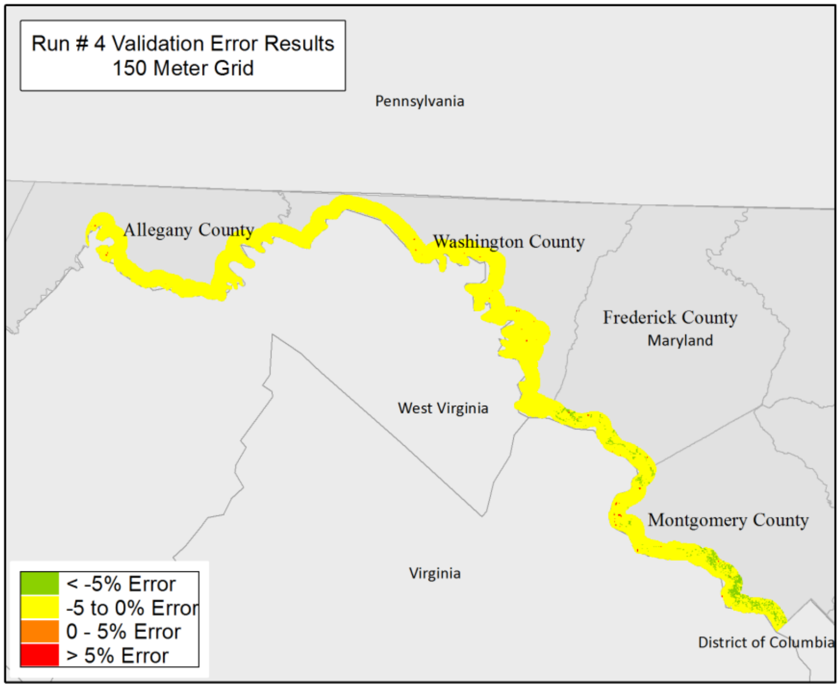

Figure 3 Map of error distribution for run #4 validation at the 150 meter resolution.

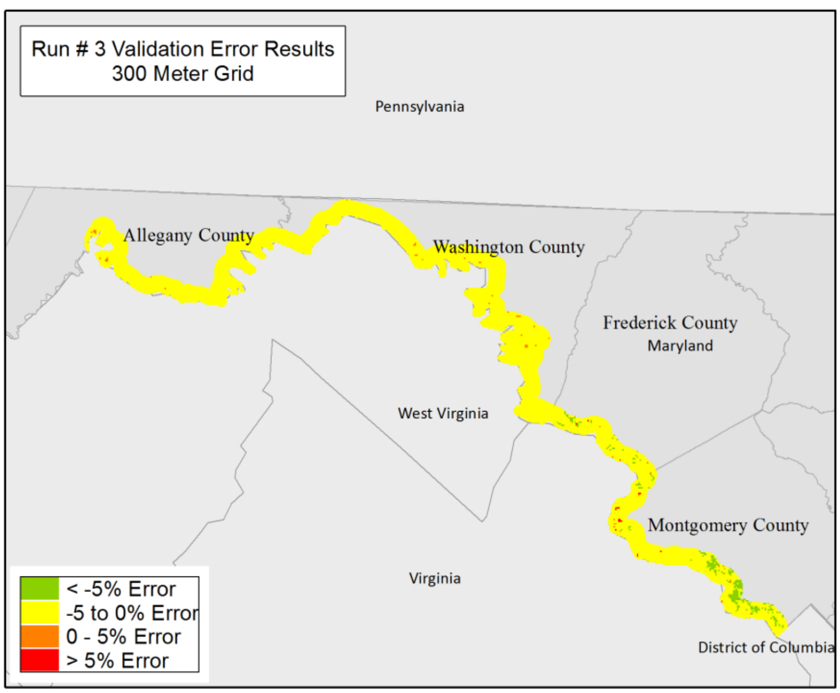

Figure 4: Map of error distribution for run #3 validation at the 300 meter resolution.

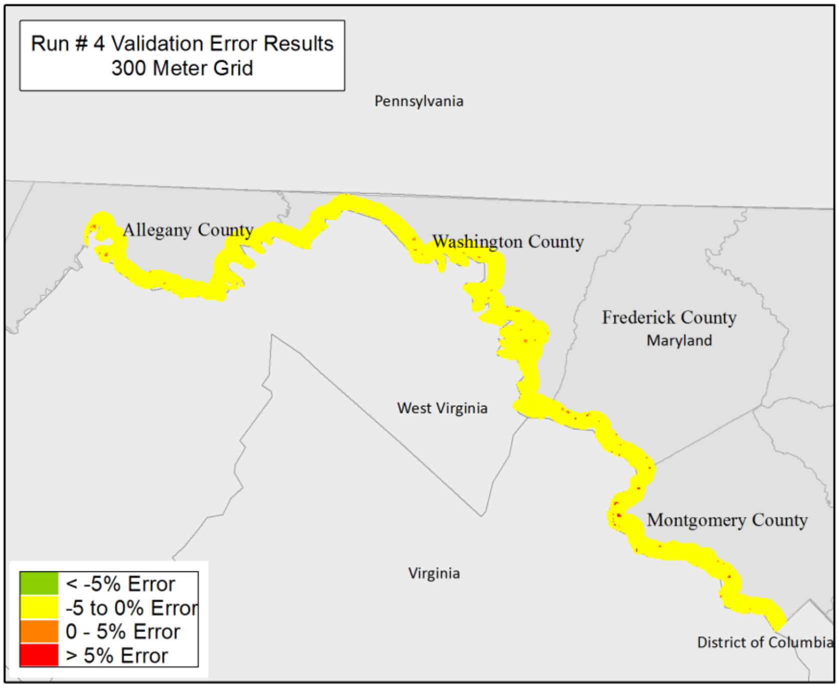

Figure 5: Map of error distribution for run #3 validation at the 300 meter resolution.

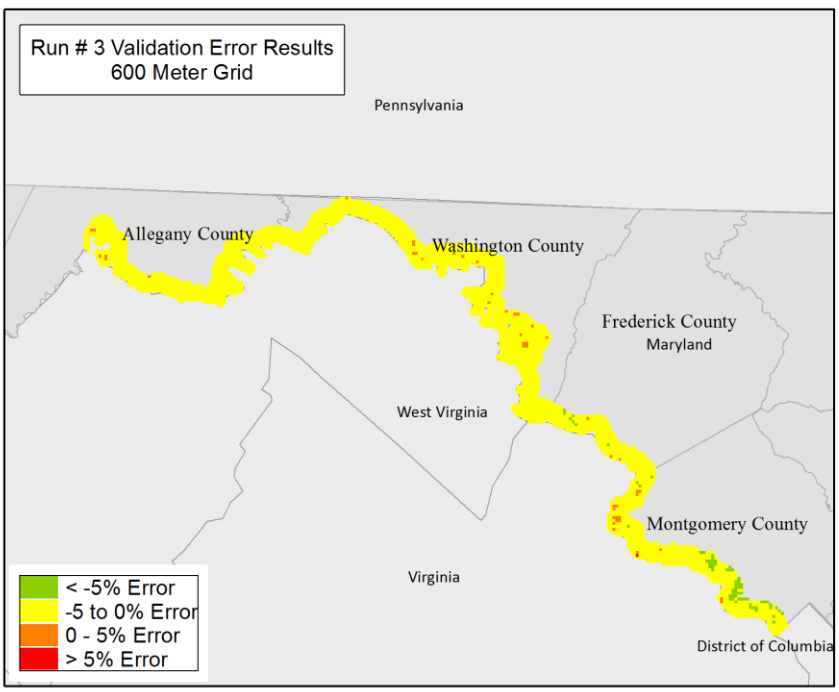

Figure 6: Map of error distribution for run #3 validation at the 600 meter resolution.

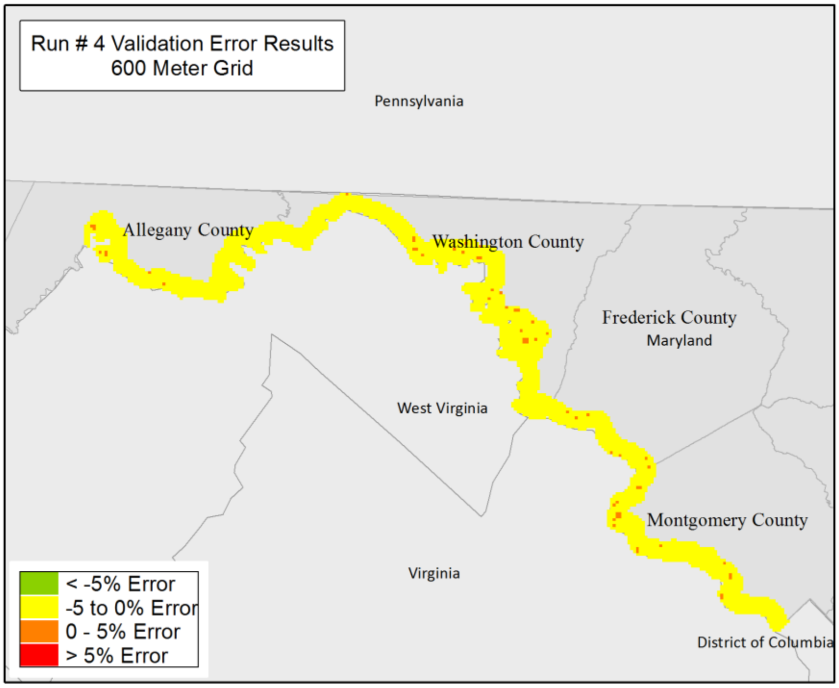

Figure 7: Map of error distribution for run #4 validation at the 600 meter resolution.

Discussion:

This section will discuss the results of this study presented in the previous section in light of the research questions and the general goals of this study. This section will first discuss the results of the brute force calibration, then the basic statistics, and finally the distribution of errors results.

Brute force calibration results:

These eight calibration results (see table 3) were chosen for analysis in this study based on two factors: all four calibration results represented variation in low total urban cluster under/overestimation in one case (base calibration run numbers 1 and advanced calibration run number 3) and low area over/underestimation in the other case (base calibration run number 2 and advanced calibration run number 4).

These two factors of calibration results are two of the most important calibration results to consider when choosing SLEUTH calibration results to use in any analysis that the model creates (Jantz, C., Personal Communication, 2011).

Basic Statistics Discussion:

The results of this study suggest that SLEUTH is more effective at predicting at a courser scale urban changes than it is at finer scale (e.g. parcel level changes) urban changes. The 150 meter “fishnet grid” displayed the highest error across all eight calibration and validation runs. Tables 4 and 5 display the aggregate results of all three scales examined in this study. Basically, the smaller the area of interest is, the more extreme the error in SLEUTH results. In the case of this study, an area of interest refers to an individual fishnet grid cell, but an area of interest can be an area of any geographic size, whether a uniform grid cell or an entire county. For instance, the SLEUTH model itself outputs basic fit statistics which inform the user of the accuracy of the estimation for each calibration run at the regional scale (Jantz and Morlock, 2011), which includes the whole study area which was input into SLEUTH. These numbers are can be fairly accurate, but as the user examines a smaller land area, the potential for error in SLEUTH model’s results increases.

Overall, these results show that the SLEUTH model is more appropriate for predicting where urban expansion is likely to occur over larger land areas. The model better predicts where urban expansion is likely to occur in a larger region rather than at any specific location. Region in this case is analogous to the largest grid size used in this study: 600 meter squares. This is exemplified when examining the statistics present in these tables. This phenomenon can also be observed in the standard deviation statistics, which show that the errors across the study area more closely cluster around the mean value as grid sizes increase.

Modifying the exclusion layer (See tables 3 – 6 and the respective “advanced” results) to better reflect growth catalysts such as population and employment (Bhatta, 2011) do improve SLEUTH’s results, but those modifications do not seem to change the pattern in error over different scales. As can be seen in the results, the error displays similar changes with scale, with the larger grid sizes resulting in less total error in the study area.

Regression statistics were used in this study to examine how the relationship between modeled and observed changed over grid sizes as well. The results of these analyses also suggest that the difference between observed and modeled values also decreases as the grid sizes used to examine the SLEUTH outputs increases. These statistics are presented in the same tables which display the basic statistics for their respective model runs (basic and advanced).

These trends in accuracy over different scales are probably caused because, in places, the SLEUTH model may predict that urban land may become developed in a slightly inaccurate geographic location. For example, perhaps SLEUTH could predict urban expansion in one 150 meter grid cell as being 100% developed. What may have happened in reality, though, could be that the development actually occurred in an adjacent grid cell, which would cause an underestimation value of 100% in that grid cell. These errors would be, in effect, smoothed when a larger grid cell is used which would incorporate those two areas in one cell, like a 300 meter grid cell. The 300 meter grid cell, depending on what other urban development is in that cell, would result in a lower error value for that geographic area. See figure 2 for a visual depiction of this example.

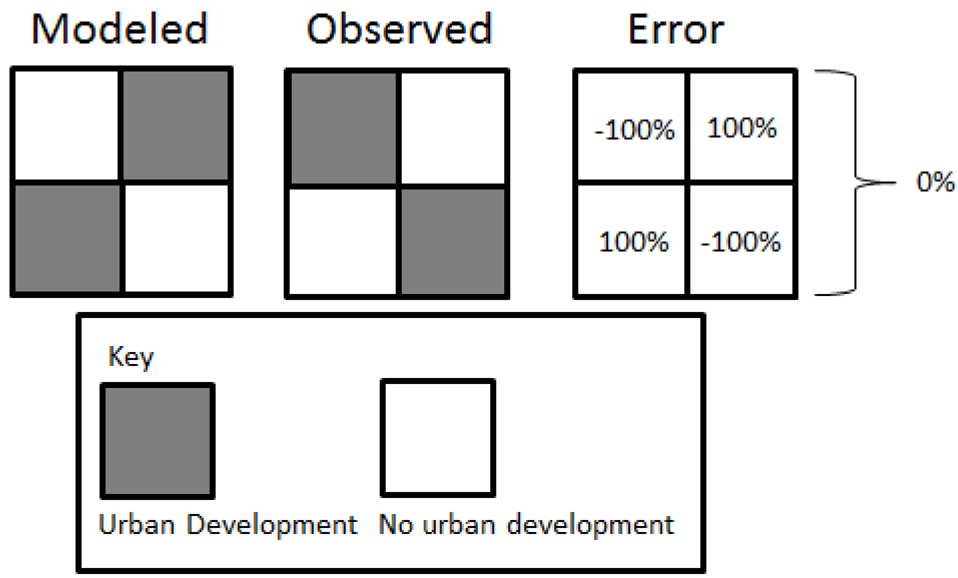

Figure 8: This is a conceptual example of the error that may occur within SLEUTH results. Inside of each larger grid cells (300m, in this case) a conceptual array of smaller grid cells (four 150m grid cells, in this case. This figure shows that the larger grid cells may naturally contain less error because they will contain more erroneously assigned urban area cells that were predicted by SLEUTH a slightly wrong area.

In addition to the accuracy becoming greater as the examined parcels of land become larger, the validation results in this study had overall better accuracy over all three scales, but displayed higher accuracy metrics in the larger grid cells. Table 3 displays the results of those validation runs. This phenomenon is probably due to the shorter time period which SLEUTH was required to predict between, as errors in the SLEUTH model tend to become greater over a longer simulation time period (Jantz, C., Personal Communication, 2012).

Distribution of Error:

The results of the distribution of error analysis (which are displayed in tables 6 and 7) show conceptual similarities to the basic statistics which were previously discussed. However, it is more apparent in these results that the larger grid sizes have more grid cells that are clustered around 0 than the smaller grid sizes. Also, these results also corroborate the observation that the advanced exclusion attraction layer model results also produced a more accurate prediction of 2006 urban extent than did the basic exclusion/attraction layer produced. These results can also be observed in map of the results displayed in figures 2 through 7.

As for those statistics themselves, they reveal that the maximum and minimum values for a single grid cell to are still significantly large (see tables 5 and 6, which are the basic statistics tables), but, as reported in tables 6 and 7, the total number of grid cells with error values greater than or less than 5% over or underestimation are quite small in all of the result datasets. Put differently, the SLEUTH model does not estimate urban extent over or under -5% or 5% very often, and instead stays within the -5% - 5% error range for the vast majority of the grid cells examined. While this is true, the total number of times that the model goes over or under those thresholds decreases noticeably when a larger land area is used for comparison (e.g. the 600m grid cells). In summation, these results suggest that the SLEUTH model has a greater potential to severely overestimate land transition on smaller scales as compared to larger scales, where the differences may be normalized.

As can be seen by the maps displayed in the results section, the geographic distribution of the errors in the courser results datasets (e.g. 600 meter) closely matches that of the finer scale results (e.g. 150 meter). This suggests that, no matter what scale SLEUTH results are processed at, the arrangement of errors would be consistent if a finer or courser scale were used. These maps also suggest that the quality of the input parameters also has a great deal of impact on the geographic accuracy of the results as well. Here it is important to note the difference in the geographic arrangement of the errors between runs 3 and 4 in the validation results: much more underestimation was observed by using the parameters in run #3 as compared to run number 4. Instead, run number 4 displayed slightly more overestimation.

The spatial results displayed in the maps should also be briefly discussed as well (figures 2-7). The spatial distribution of the errors suggests that SLEUTH also encounters more error where more changes in urban area are occurring. In other words, the SLEUTH model calculated more error in Montgomery County, which has experienced more urban expansion than the other counties. This is a phenomena not explicitly analyzed in this study, and certainly could use more examination using different methods than those employed here.

Discussion Conclusion:

Overall, these results suggest that the SLEUTH model would be appropriate to predict future urban conditions in the study area with varying degrees of accuracy, as the error values for both calibration and validation are typically low. However, the SLEUTH urban land use model would be less appropriate to use to pinpoint parcel level land areas for preferential protection as was approximated by the 150m grid cell results. Conversely, the SLEUTH model might be more appropriate to predict future conditions at smaller scales, such as the 600 meter grid size described in this study, or larger. These findings and statistics reinforce the findings and observations made by Jantz, Goetz, and Shelley (2003) where the model was found not to reproduce urban conditions at the pixel level. Overall, the SLEUTH “3r” model’s (Jantz, Goetz, Donato, and Claggett, 2009) results can be used with more confidence for land management purposes at courser scales rather than finer scales, but the ideal scale to use the model for those purposes still remains to be found. Also, the needs of a particular application need to be taken into consideration as well. As can be seen in table 3, the SLEUTH model overestimated urban area by less than 5% in the entire study area after its calibration runs. However, that large of an extent is not conducive to most applications of the SLEUTH model. Thus, what the model will be used to predict needs to be taken into account when selecting the scale at which to examine the results.

In addition to these other observations, it is readily apparent that these results are heavily influenced by the input parameters. Run number 4 (see table 3) showed more accurate results than run number 3 did in this study, suggesting that further iterations of the model calibration to arrive at better initial input parameters (e.g. breed, spread, road gravity) would also create results which more closely approximate observed conditions.

Limitations and possible future studies:

One of the limitations in this study is the lack of input for neighboring states, such as West Virginia and Virginia. Land use policy and urban expansion patterns are undoubtedly different in those other two states, and the fact that these data were not considered in this study's inputs likely changes the outcome of the results in some way. This is particularly true when considering the interdependency of municipalities in the Washington, DC metro area. However, the Potomac River, in this case, likely provides a natural barrier for development on the Virginia side of the C&O Canal. While this remains true, the impacts of bridges into the state of Maryland and development around those bridges were not examined in this study. Perhaps future studies in this area could incorporate inputs into the exclusion/attraction layer which attempt to take these phenomena into account.

This study could have had improved methods with which to produce the results. One example of the possible improvements would be in the calibration stage. Typically, SLEUTH users utilize multiple iterations of initial calibration to arrive at the best possible input parameters (outlined in the "SLEUTH Model Implementation" section of this document) to create the fewest amount of errors in the results of their analysis (Jantz, Goetz, and Shelly, 2003). This step was partly overlooked in this study, as the purpose of this study was to evaluate the effectiveness of the model to predict urban land at different scales. This study attempted to put more emphasis on how the errors change over different scales rather than utilizing multiple initial calibration result datasets to produce the most accurate model parameters. Additionally, no further comparisons of calibration/validation results were used to further evaluate the model to produce the most accurate model parameters. It is unclear at this time whether or not more focus on creating a more in-depth calibration process would have influenced the results. Thus, additional studies which use multiple iterations of the model to produce the most accurate calibration and validation results may produce conflicting results. While this is the case, the results illustrate that processing and interpreting SLEUTH results at coarser scales create fewer opportunities for error as compared to the finer scales.

Another limitation to this study may have been the road network used. The road network used in this study, which was provided by the United States Census Bureau, only detailed the major roads in the study area. A more detailed road network was available, but it was not utilized in this study. It was believed that it would have created errors in the model when it was converted to its binary state for utilization in the model calibration and validation steps. The error may have, if it manifested at all, resulted from the denseness of a more detailed road network input. If the other road dataset was transformed into a SLEUTH input, which contained almost all of the roads in the study area, it would have resulted in large areas of land designated as roads. The 30m by 30m cells that were used as SLEUTH inputs would result in areas much larger than most roads actually occupy, thus overlapping a majority of the urban areas. Because of the uncertainty of the results of this road layer, had it been used, and the limited amount of time to complete this study, the basic major roads layer was used in this study. In addition, this study's purpose was to examine how SLEUTH's accuracy changed over geographic scale. Thus, the importance of the robustness of the data inputs in this study was slightly lessened.

One more limitation presented itself in the methods themselves. The process used to create the grid cells with which data were analyzed were not perfectly nested within one another, which would have been more ideal for this study. This may have introduced slight error in the results. However, due to the large sample sizes which the results are derived from, it is likely that the effect this oversight could have had was lessened a great degree (Langley, 1971).

Conclusion:

Protected lands are an integral part of the American landscape, with the Chesapeake and Ohio Canal (C&O) and the Antietam National Battlefield being prime examples of those protected areas. Recent research has suggested that protected lands attract urban development and population concentrations around those protected areas (Gimmi, 2011). This attraction stems from the desirable aspects of protected lands, which provide benefits such as aesthetic beauty, cultural background, educational opportunities, and historical significance, among others (DeFries *et al.*, 2007).

Several NPS officials at the C&O Canal and the Antietam National Battlefield were interviewed near the onset of this project to assess the possible needs and concerns of those individuals in the context of managing those lands while dealing with the outside pressures. Those NPS officials expressed interest in having supplementary material when considering parcels of land to acquire that may or may not be at risk of being developing, thus adding pressure to the protected lands (Carter, M, Hitchcock, J, Personal Communication, Jan.13, 2012).

Researchers have attempted to use the SLEUTH urban growth model to forecast and thus identify areas of high risk for development in the past (Jantz, Goetz, and Shelly, 2003). However, it was not clear in the literature how the model behaved when predicting possible growth in extremely small areas, such as the parcel level. This examined SLEUTH outputs at the 150 meter, 300 meter, and 600 meter cell sizes.

The results of this study suggests that, with the data and methods used, the SLEUTH model is less appropriate tool for National Park officials to use as an additional source in combination with other methods when considering individual parcels of land to acquire at the parcel level. Alternatively, the model seems to be more appropriate when viewing larger land areas, such as the 600 meter cell size, to evaluate areas at risk of possible development. A larger cell size allows the user to identify risk areas with more confidence, as the observed errors from the SLEUTH methods are lower than smaller scales, such as a 150 meter cell size. However, the user will not be able to pinpoint specific areas to focus land protection strategies on, as the statistical confidence for those specific areas may be much lower than a larger area as predicted by the SLEUTH model.

While the statistics show that, as a whole, the model is more accurate when analyzed at a courser resolution (e.g. the 600 meter grid size), the quality of input parameters also has a great influence on the quality of the results as well. For instance, advanced run number 4 utilized slightly different input parameters than run number 3, and arrived at vastly different results at each of the three analyzed resolutions. This suggests that more detailed methods to arrive at better input parameters may increase confidence at smaller scales than the described methods have produced.

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Finally, I must acknowledge the help of Matthew Krapf and Veronica Woodleif, two of my student colleagues and friends during my coursework at Shippensburg University. Together, we completed a similar project which gave me a good first step when organizing and completing this project, as well as help with the initial knowledge of the SLEUTH model. That project gave me a solid springboard for me to complete this project to finish my degree requirements.

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