Brains vs. Brawn – Comparative strategies for the calibration of a Cellular Automata – Based Urban Growth Model

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Abstract

The need for good modelling tools to simulate urban growth are a planning tool necessary in today's age of widespread urban growth and the natural and human disasters that quickly follow. The SLEUTH urban growth model is a CA-based urban change model that simulates urban growth according to a calibrated set of parameters. The following work compares two methods of calibration. The first, "Brute Force" method uses a predetermined order of stepping through the "coefficient space". The second method, fully introduced here, uses a Genetic Algorithm (GA) to search through the coefficient space in an adaptive manner. This work compares the computational speed and modelled accuracy of the two methods, using the city of Sioux Falls, South Dakota (US) as a testbed. The results show that the GA method of calibration is superior to the Brute Force method, because of improved model fits, as well as superior computational needs. The forecasted model runs, to the year 2015 show different results from the GA and Brute Force methods, possibly due to the data used in model preparation. Improvements on the GA method of calibration are suggested as well as a hybrid approach to SLEUTH calibration.

1. Introduction

1.1 Urban Modelling and SLEUTH

It has been recognized that humanity's spread of cities has and will have severe consequences to both human society and to the natural world. From the large shantytowns and slums of the third world, to the thousands killed by natural disasters, cities grow with dire consequences. It is no wonder that we appear to be moving into a period of many approaches to modelling the spatio-temporal phenomenon of urban growth. This has been aided by the increased availability of computers, both in their ubiquity and increased affordability.

One popular urban growth model is the SLEUTH, created by Dr. Keith Clarke at UCSB Geography (Clarke et al., 1997; Clarke et al., 1996). SLEUTH is composed of a series of growth rules, which form modified Cellular Automata (CA). When running SLEUTH, the rules of the CAs (the growth rules), are calibrated to historical urban spatial data. SLEUTH can then be used to forecast urban extent under different scenarios. Due to its scale independence, transportability and transparency, SLEUTH has become a popular tool in modelling the spread of urban extent over time, be it recreating the past or forecasting growth into the future (Yang and Lo, 2003). Yang and Lo also cite the ability of SLEUTH's growth rules to self-modify as it models a region into the future, deviating from monotonically increasing, line-fitting urban growth models. Lastly, SLEUTH can be used as a powerful planning tool by incorporating different human perceptions into the data used for forecasting the future footprint of a city.

SLEUTH has been used to model a growing number of geographical regions. These cities include Porto Alegre City, Brazil, where the model was used to assess the potential demand of refuse disposal (Leao et al., 2001), and Chester County, Pennsylvania, where SLEUTH was loosely coupled to a groundwater runoff model (Arthur, 2001). Other cites include Porto and Lisbon, Portugal (Silva and Clarke, 2002), San Francisco (Bell et al., 1995; Clarke et al., 1997) the Mid-Atlantic United States (Bradley and Landy, 2000), and the Washington-Baltimore metropolitan region (Clarke and Gaydos, 1998). Santa Barbara, California has been the focus of many SLEUTH modelling experiments. These include the loose coupling of SLEUTH to a systems model of population and economics (UCIME, 2001), and the comparison of SLEUTH and spatio-temporal interpolation to re-create historical urban extent (Goldstein et al., 2003). Herold et al (Herold et al., 2003) used SLEUTH's back-casting ability to measure how Santa Barbara and the surrounding cities' urban form and shape have changed since 1929.

Like many geographical models accounting for real, data-rich regions, as opposed to simulated regions, SLEUTH is computationally expensive. For SLEUTH it is the calibration stage of the model, when the rules of CAs are parameterised with calibration coefficients, that is the most computationally expensive, taking close to 15 days of CPU time to completion (Yang and Lo, 2003). With the increased availability of free remotely sensed products and publicly available GIS data, the geographical extent, and along with it, the array sizes of SLEUTH modelling will increase. Currently Dr. Clarke and his colleagues recommend using what is called the "Brute Force" method of calibration, which entails a slow, yet methodical exploration of the possible values of the coefficients for the growth rules. What is presented here is an alternative to Brute Force calibration, one that takes advantage of a Genetic Algorithm to be the "Brains" to Brute Force's "Braun".

1.2 An Overview of Genetic Algorithms

Genetic Algorithms, developed by Holland (Holland, 1975) as a method of mimicking meiosis in cellular reproduction to solve complex problems, were later adapted as a mechanism of optimisation (Goldberg, 1989). GA's have been used to calibrate urban growth models as exhibited by Wong et al, (2001), who revisited the primordial Lowry model in an attempt to choose the parameters of household and employment distributions for Hong Kong. A GA was employed as a search tool to find the optimal set possibilities of land use planning for Provo, Utah (Balling et al., 1999). Colonna et al (1998) used a GA as a method of generating new rules for a CA in a landuse modelling exercise of Rome, Italy. GA clearly offers a utile alternative in urban model calibration

The use of GAs as a tool has expanded considerably since their inception. Their strength lies in their ability to "exploit and explore" the search space in a non-random, yet improving way. This is done by evaluating a suite of potential solutions, then allowing the fittest members of that population of solutions to recombine to form successive populations of solutions. What follows is a generic description of a GA and how it works. For this example, it is assumed that the problem to solve, be it an equation, a model or a set of solutions, is clearly defined. In addition, it is assumed that the representation schema for that problem is well defined.

First, the Seed Population is initialised, and the initial group of "chromosomes" to be evaluated is chosen (Figure 1). A chromosome is a set of characters that encode solutions to the problem. They are the solution's "genotype". Initialisation can be done by random, stratified random, or non-random methods. The Initial Population is then evaluated by the problem. The evaluation process tests every chromosome in the population and assigns each potential solution a metric of fit. If the criteria for stopping are met, then the GA ends, presenting the best solution. There are a number of different methods for determining the stopping criteria for a GA, including a set number of model runs, a shrinking variance in the solutions presented, or, ideally, the obtaining of the sole, optimal solution. However, if the stopping criteria are not met, the fittest members of the population, the chromosomes, are selected to "breed" to create the next generation of chromosomes. There are a number of strategies for selection, including elitism, which promotes the best performers, tournament selection, which allows pairs of chromosomes to compete based on their fitness; and roulette-wheel selection, which also judges chromosomes based on their fitness, allowing the better performers better odds of progressing. For review and analysis of selection criteria, see (Goldberg and Kalyanmoy (1991).

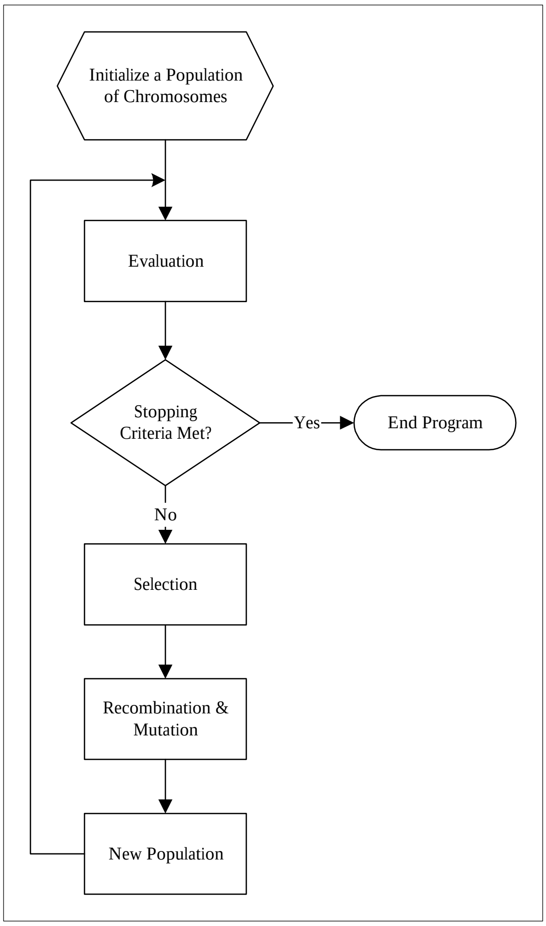

Figure 1. Flowchart of a generic Genetic Algorithm

The chromosomes chosen for selection are then recombined and mutated, in a process aping meiosis in cellular reproduction. Chromosomes undergo crossover and replacement, allowing bits of information, or “genes” from one chromosome to be transmitted to another. An example of crossover will be demonstrated below. In mutation, genes in individual chromosomes are randomly perturbed to change their individual, and therefore chromosomal characteristics. The resulting new population of chromosomes is then evaluated by the “problem” and the cycle begins again, until the stopping criteria are met.

2. The SLEUTH Urban Growth Model

2.1 General description of SLEUTH

The urban growth model SLEUTH, uses a modified CA to model the spread of urbanization across a landscape (Clarke et al., 1997; Clarke et al., 1996). Its name comes from the GIS data layers that are incorporated into the model; Slope, Landuse, Exclusion layer (where growth cannot occur, like the ocean), Urban, Transportation, and Hillshade. For complete documentation of SLEUTH, see the Gigalopolis website, where the source code (in the C programming language) is available for download (Gigalopolis, 2003).

SLEUTH is an urban growth model that employs Cellular Automata to represent the change in the system. It deals exclusively with urban shape and form, as opposed to demographic or economic models of urban change. In modelling the change of urban form over time, the other factors that drive urban change are subsumed and therefore not explicitly necessary. SLEUTH results have been compared to the results systems models of economics and demographics and have been shown to yield comparable results of urban change over time (UCIME, 2001). The calibration stage of running SLEUTH is of import in the work presented here. SLEUTH trains the four growth rules to their parameters. The growth rules, described below, are separate CAs that operate on one urban landscape. The coefficients of the growth rules are Dispersion, Breed, Spread, Slope, and Road Gravity. The following is a description of the four growth rules which occur in the order presented, as summarized from the Gigalopolis website.

1) Spontaneous Growth Rule
Spontaneous Growth determines if a random pixel in the urban lattice will be urbanized. The Dispersion and the Slope coefficients are used in this rule.

2) New Spreading Centres Rule
The New Spreading Centres Rule determines if a newly urbanized pixel (from the Spontaneous Growth Rule) will be a new urban centre and if so, will urbanize land. The Breed and Slope coefficients factor into this growth rule.

3) Edge Growth Rule
The Edge Growth Rule adds new growth adjacent to existing urban pixels. The Spread and Slope coefficients determine the amount of Edge Growth.

4) Road-Influenced Growth Rule

This final growth rule determines the extent the road (or transportation) network contributes to the urban growth of a city. New urbanized pixels "travel" on the road network and urbanize available pixels. This rule is determined by the Dispersion, Breed, Slope, and Road Gravity coefficients.

The five calibration coefficients are all integers and range from 1 to 100. By running SLEUTH in Calibration Mode, the different combinations of coefficients are used to model the historical urban growth of a geographic locale. Deviation from the city's real extent and shape, (as indicated by the historical, or control, years) determines the best, and worst combination of the calibration coefficients. The goal of calibration is to determine which of the 10^{10} (or 100^5) possible combinations of coefficients gives a specific urban region the best fit. The term for all the possible coefficient combinations is called the c*oefficient space*. It is unknown, but assumed that the coefficient space is a complex surface, due to the unique properties of individual urban extents, the spatial scale and resolution chosen for the modelling, but most interestingly, because of the combinatory effects of the calibration coefficients with each other. Current research is underway at UCSB Geography to explore the coefficient space and to examine if some coefficients have systematic, as opposed to chaotic reactions to each other.

SLEUTH calibration makes available 12 metrics, each a different spatial metric of the calibration's fit relative to the control years. In addition a 13th, the product of the 12 metrics is provided. Most SLEUTH modellers use the product metric to determine the fitness of the coefficients (Arthur, 2001; Bradley and Landy, 2000; Clarke et al., 1997; Clarke et al., 1996; Silva and Clarke, 2002; Yang and Lo, 2003). Candau (Candau, 2002) has presented calibration results using only the Lee-Sallee index (Lee and Sallee, 1970). The Lee-Sallee index is a shape index measuring the union of the model estimation of growth, as compared to the known data years' urban growth.

In a typical SLEUTH run (see Figure 2), the geospatial data for a region is first organized in the required manner. The model requires that all data be in the GIF data format and that the domain of the data (as well as the pixel count) be identical for all data layers. The geospatial data can include many historical urban extents (four required), one to many historical transportation layers, one hill shade layer, one slope layer, and one excluded layer. Calibration, the focus of the work presented here, is described in more detail below. However, regardless of the method of calibration, Brute Force or Genetic Algorithm, the final stage is identical. In Parameter Self- Modification, the parameters are calibrated once again, allowing the model to change the value of the coefficient due to over- or under-estimates of simulating an S-curve, a common growth signature of many US cities (Clarke et al., 1996). The S-curve pattern is that of slow growth for long periods, a short period of extremely fast growth, followed by a tapering of new urban growth. Following calibration, the modeller then uses SLEUTH to forecast the future urban growth of the region. Both statistical products are available, as are graphical outputs, which can then be returned to a GIS for further geographical analysis.

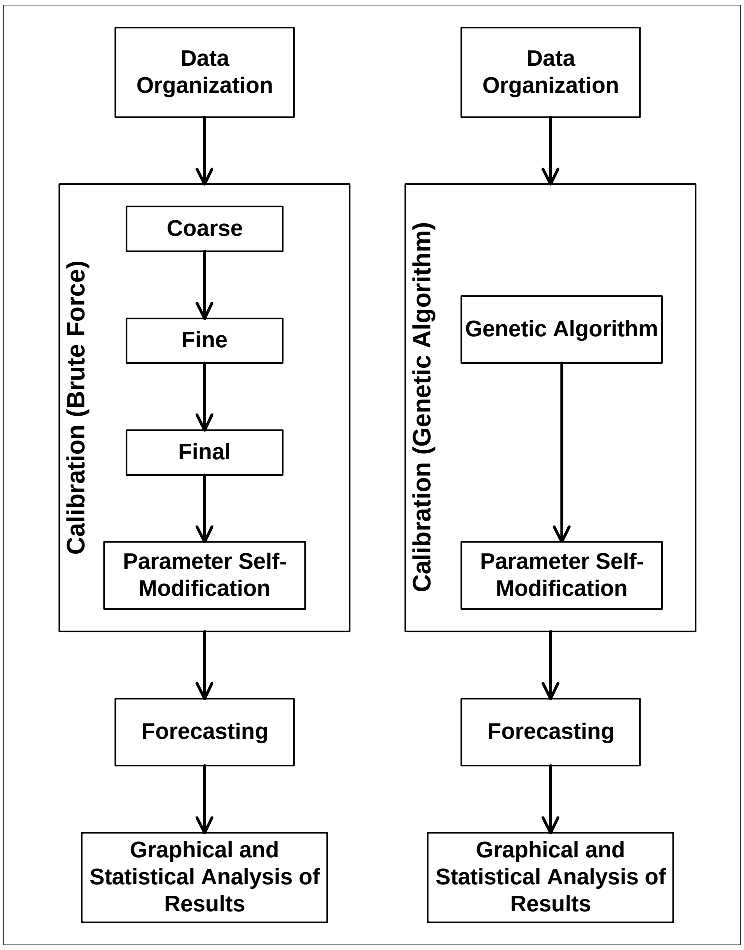

Figure 2. General outline of a SLEUTH model run and the two calibration approaches examined in this work.

2.2 Brute Force Calibration

The recommended method of coefficient calibration is the Brute Force method, which steps through the coefficient space in large, and then increasingly smaller steps (Gigalopolis, 2003). The first step, Coarse Calibration, takes steps of 25 units through the entire coefficient space, for all coefficients. The second step, Fine Calibration, takes steps of 5 or 6 units through the coefficient space and the third, Final Calibration, takes steps of 1 (ideally) to 20 units through the coefficient space.

The following is a sample run-through of Brute Force calibration, and the decisions that go along with it. The Coarse calibration takes steps of 25 units through the coefficient space, with a range of 1 to 100. Table 1 shows the top 15 performers, according to a specific metric of fit. In this example, the set with the ** is the best performer, with the sets with the * just behind it.

Table 1. Coarse Calibration - Steps of 25 units over all the coefficient space [0 to 100]. The Sets contain the values of the calibration coefficients, Dispersion, Breed, Spread, Slope, and Road Gravity

15 Sample calibration sets of 3125 (5^5):		
{1 - 1 - 1 - 1 - 1}	{25 - 25 - 25 - 25 - 1}	{1 - 1 - 75 - 1 - 1}
{25 - 1 - 1 - 1 - 1}	{25 - 25 - 25 - 25 - 25}*	{25 - 25 - 75 - 25 - 25}
{51 - 1 - 1 - 1 - 1}	{25 - 25 - 25 - 25 - 50}	{50 - 50 - 75 - 50 - 50}
{75 - 1 - 1 - 1 - 1}	{25 - 25 - 25 - 25 - 75}**	{75 - 75 - 75 - 75 - 75}*
{100 - 1 - 1 - 1 - 1}	{25 - 25 - 25 - 25 - 100}	{100 - 100 - 75 - 100 - 100}

* Indicates the top three coefficient sets
** Indicates the top coefficient sets

Next, the range is narrowed, to 20 units plus or minus each of the best Coarse calibration, with a step of 5 units. This process, of Coarse to Fine resolution necessitates some "feel" for the direction and the performance of the calibration coefficients. The range could have been smaller or larger, as could be the step. Table 2 shows the results of the Fine Calibration, again showing the best and close performers.

Table 2. Fine Calibration - Steps of 5 units "around" top performers
[range of 20 for each coefficient]

15 Sample calibration sets of 3125 (5^5):		
{15 - 15 - 15 - 15 - 75}	{25 - 25 - 25 - 25 - 65}	{25 - 15 - 15 - 25 – 75}*
{20 – 15 - 15 - 15 - 75}	{25 - 25 - 25 - 25 – 70}*	{25 - 20 – 20 – 25 – 75}
{25 –15 - 15 - 15 - 75}	{25 - 25 - 25 - 25 - 75}	{25 – 20 - 15 – 25 – 75}
{30 -15 - 15 - 15 - 75}**	{25 - 25 - 25 - 25 – 80}	{25 - 15 – 20 – 25 – 75}
{35 - 15 - 15 - 15 - 75}	{25 - 25 - 25 - 25 - 85}	{25 - 15 - 25 – 25 – 75}

*Indicates the top three coefficient sets
** Indicates the top coefficient sets

Again, the modeller is forced with a decision. In this case, looking at the first coefficient, Dispersion, the best coefficient set had a value of 30, the next two, a value of 25. When the modeller decides to focus the search on the 30, instead of the 25, potentially better results could be missed.

Table 3. Final Calibration - Steps of 1 unit "around" top performers
[range of 5 for each coefficient]

15 Sample calibration sets of 3125 (5^5):		
{30 –13 - 15 – 16 - 75}	{30 –13 - 15 - 15 - 75}	{28 -15 - 15 – 18 – 73}
{30 –14 - 15 – 17 - 75}	{30 –14 – 16 - 15 - 75}	{29 -15 - 15 – 18 – 74}
{30 –15 - 15 – 18 - 75}	{31 –15 – 17 - 15 - 75}	{30 -15 – 16 – 18 – 75}
{30 –16 - 15 – 19 - 75}	{30 –16 – 18 - 15 - 75}	{31 -15 – 16 – 18 – 76}
{30 –17 - 15 – 20 - 75}	{30 –17 - 19 - 15 - 75}	{32 -15 - 16 – 19 - 77}

Table 3 shows sample Final coefficients. In this example, 9375 (3125 x 3) different coefficient sets were evaluated. Recent SLEUTH calibration of the Atlanta region (Yang and Lo, 2003) used only 4268 different coefficients due to computational constraints.

The Brute Force method is efficient in searching through the coefficient space in a complete, regular, and reproducible manner. However, it has three major shortcomings. The first is that it is computationally expensive. It takes at least 9,375 runs of SLEUTH (as suggested by the model's guidelines) in three calibration modes for each dataset. The second shortcoming is that due to non-linearity in the model for coefficient combinations, the Brute Force method may get trapped in a local maximum, missing a better coefficient set at a global maximum. As seen in the example above in the Coarse calibration, one of the three best calibration sets {75 - 75 - 75 - 75 - 75} is very different from the other two calibration sets. This set, though potentially closer to the global optima, will be in essence discarded in favour of the more popular {25 - 25 - 25 - 25 - *} sets. For more detail on the Brute Force calibration of SLEUTH, refer to the Gigalopolis web site.

2.3 The Calibration of SLEUTH using a Genetic Algorithm

This work presents a new and novel method of calibrating SLEUTH to the historical urban extent data. This method takes advantage of a GA's ability to explore the entire coefficient space in an innovative and systematic way. What follows is an overview of the terminology used for the GA as applied to SLEUTH, and the SLEUTH GA methods.

A string of SLEUTH calibration coefficients is called a *chromosome*, also called a calibration set, above in the Brute Force description. Again, the calibration coefficients are always in the same order: Dispersion, Breed, Spread, Slope, and Road Gravity. Each individual calibration coefficient is referred to as a *gene*. A set of chromosomes, evaluated at one time is a *population*. The first population used at the beginning of the experiment is the *seed population*, described below. Each successive population is also referred to as a *generation*.

One common issue in constructing a GA is the issue of encoding the process of representing a gene's value in the parlance of the computer program. A common approach is to use binary encoding, whereas all genes' values are translated into their binary value. For example, the number 5 becomes the string 0101 or the number 38 becomes 100110. Since SLEUTH's calibration coefficients (or genes) are already numerical values between 1 and 100, SLEUTH-GA uses natural coding, whereas the numerical values are used as their "raw" value, or 5 is represented as 5 or 38 is 38.

2.3.1 Population Initialisation

There are three strategies employed in determining the Seed Population. These are Stratified, Partial Random, and Random. For the initial population of 18 chromosomes, 6 were Stratified, 4 were Partial Random, and 8 were Random (Table 4). The Stratified chromosomes (1-6) were segments of the coefficient space, spread out over all possible solutions. These can be seen in Table 4. The Partial Random (7-10) chromosomes were alternating low or high values of genes interspersed with randomly chosen genes. The Random chromosomes (11-18) are indicated by an X in Table 4. Lastly, the Random chromosomes are composed of completely random genes, drawn from a random number generator.

Table 4. Schema of Seed Population for GA-SLEUTH.
An X indicates a random number between 1 and 100.

Chromosome number	Method of Choice	Dispersion	Breed	Spread	Slope	Road Gravity
1	Stratified	1	1	1	1	1
2	Stratified	25	25	25	25	25
3	Stratified	50	50	50	50	50
4	Stratified	75	75	75	75	75
5	Stratified	100	100	100	100	100
6	Stratified	10	90	10	90	10
7	Partial Random	10	X	10	X	10
8	Partial Random	X	10	X	10	X
9	Partial Random	90	X	90	X	90
10	Partial Random	X	90	X	90	X
11	Random	X	X	X	X	X
12	Random	X	X	X	X	X
13	Random	X	X	X	X	X
14	Random	X	X	X	X	X
15	Random	X	X	X	X	X
16	Random	X	X	X	X	X
17	Random	X	X	X	X	X
18	Random	X	X	X	X	X

2.3.2 Selection Strategies

Two Selection methods were employed in the selection of chromosomes from P_n to be bred into P_{n+1}. The first was Elitism. Elitism promotes the best-performing chromosome to the next generation. While this has the benefit of ensuring the increase of fit of the populations over time, it can be responsible for the premature arrival of a (false) optimal solution through continual self-promotion (Goldberg, 2002; Liepins and Potter, 1991). In Tournament selection, pairs of chromosomes are randomly chosen and the best performer out of the pair is allowed to breed. This is done twice to obtain pairs of chromosomes for breeding. A sample selection is presented in Table 5.

Table 5. Sample Results from SLEUTH calibration

ID	Coefficients	Metric of Fit
C 1	10-10-14-14-15	0.13
C 2	2-5-1-43-88	0.34
C 3	75-75-75-75-75	0.55
C 4	100-90-100-9-10	0.34
C 5	3-5-35-35-99	0.05
C 6	6-6-6-6-6	0.24

The first pair of tournaments for the population in Table 5 randomly chose C5 vs. C3, and C1 vs. C6 to compete. The "winners" will be C3 and C6, according to their higher fit in each tournament, both of which will proceed to Crossover due to their higher metrics of fit. In some cases, the Tournament may tie (as in the case of C2 vs. C4). In this case, the first-drawn chromosome will be selected for breeding.

2.3.3 Breeding methods (Crossover)

After the chromosomes are selected, they are then used to determine the successive generation's population through meiosis-like processes called crossover. For the SLEUTH GA, Uniform crossover was used to breed the winners of the Tournament Selection. In Uniform crossover, each gene in a chromosome has an equally good chance of being chosen to compose each "child". The advantage of this method is that the gene pool can be "shaken, not stirred", exploring the coefficient space in an extreme manner (Syswerda, 1989). A disadvantage of uniform crossover is that chromosomes can be thoroughly disrupted and can produce few beneficial combinations (Davis, 1991).

Take for example the breeding of C3 and C6, from above.

C3:	75-75-75-75-75
C6:	6-6-6-6-6

After random drawings of either a 1 or a 0, the following "template" is created:

"Template of crossover":	1-0-0-0-1

This then results in the following prodigy:

Child 1:	75-6-6-6-75
Child 2:	6-75-75-75-6.

Crossover is an effective method of exchanging generic material between two chromosomes. In the GA used here, another form of crossover was used to explore the coefficient space. Self-crossover is the process of one chromosome "looping back" on itself (Pal et al., 1998). For example, C2, from Table 5, will be self-crossed on the second position, between the 5 and the 1:

Original C2:	**2-5-**1-43-88
Self-crossed C2:	1-43-88-**2-5**

While self-crossover has few biological homologues, it provides an entirely different mechanism for the genetic material to be exploited, without being lost (as in crossover). Further research on the utility of self-crossover is needed to see if it actually contributes to the path of the optimal solution.

2.3.3 Mutation

The final stage of the genetic algorithm is mutation. In the mutation routine, each gene has the potential to be changed by the addition or subtraction of a random number. The mutation rate used was 10%, though there were many instances of no mutation in a chromosome. After mutation, the entire new population is scanned and all identical chromosomes are subjected to mutation a second time. Since there is a maximum and minimum value for a gene, values greater than 100 and less than 1 were "looped" back to a valid value. This was by either subtracting 100 (for values greater than 100), or taking the absolute value of the number, (for values less than zero).

The GA used for SLEUTH calibration was comprised of 18 chromosomes changing over 200 generations. The new population, $P_{n+1,}$ can be traced back to P_n as shown in Table 7.

Table 7. Summary Table of Breeding of P_n to P_{n+1}

Chromosome number	Method of Selection	Crossover	Mutation
1	Elitism (best)	None	No
2	Elitism (best)	None	Yes
3	Elitism (best)	Self	No
4	Elitism (2nd best)	Self	No
5	Tournament	Yes	Yes
6	Tournament	Yes	Yes
7	Tournament	Yes	Yes
.	"	"	"
.	"	"	"
.	"	"	"
18	Tournament	Yes	Yes

2.4 The Sioux Falls Study Area

The Sioux Falls, South Dakota urban region was used to compare the calibration techniques. Sioux Falls is located in the Southeast Corner of the Mid-Western State (Figure 3). Since the last ice age, Native American had been living in the region, renown for its large waterfalls and arable land. Westerners first settled Sioux Falls in the late 1850's as a part of the great American Westward Expansion, bringing the railroads and industry with them. The Population of Sioux Falls has grown considerably from 10,300 people in 1900 to over 124,000 people in 2000, according to the US Census Bureau. The Metropolitan region of Sioux Falls lies mostly within Minnehaha County yet has expanded into Lincoln County since the 1940's. Since 1979, Sioux Falls has implemented a growth plan called "Sioux Falls

2015” that has been attempting to focus and control growth in an intelligent manner (www.siouxfalls.org/planning). Their efforts have been focusing on infill and development in designated areas, trying to avoid the infamous “urban sprawl” of many American and increasingly European cities.

Figure 3. Location of Sioux Falls, South Dakota

The terrain of the Sioux Falls region is mostly flat with some moderately sloped areas and some extreme slopes around the waterfalls. Figure 4 shows the historical growth of urban extent of Sioux Falls. Over time, the urban extent had expanded into the flat regions in the region, avoiding the low, yet steeper sloped to the North. Sioux Falls lies at the intersection of Interstates 90 and 29, which are major transportation routes in the Midwest, connecting Sioux Falls to other major US cities.

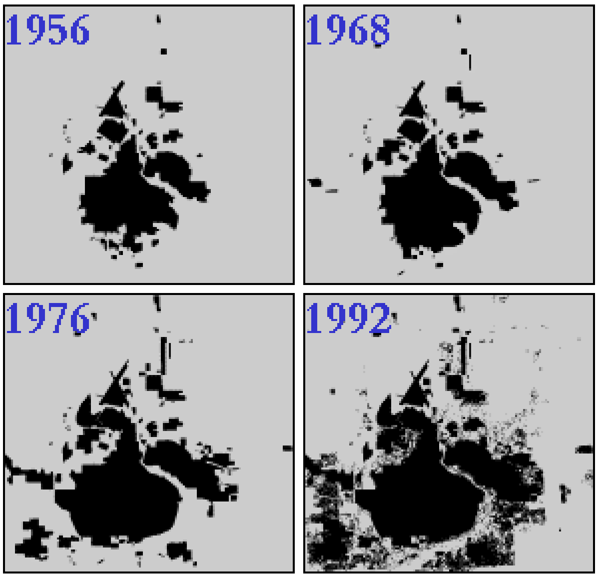

Figure 4. Sioux Falls historical urban layers

2.4.1 Sioux Falls Data

The geospatial data of Sioux Falls was created from USGS GIS polygon coverages of urban extent, transportation networks, parks and protected lands. All data was rasterised at 30m resolution, and clipped to a grid of 486 by 465 pixels, or 14,580m East-West by 13950m

North-South.

SLEUTH uses binary urban/not urban data layers to represent the domain of anthropogenic influence on land. For the Sioux Falls urban layers from 1956, 1968, and 1976, urban extent was determined as areas which were indicated in USGS coverage as "urban/built-up lands" or "urban other/open spaces, parks, etc...". These coverages were created from black and white aerial photography. The resolution of the photography was approximately 3 feet.

The 1992 urban extent was obtained from the National Land Cover Database, a product of the 30-meter Landsat Thematic Mapper and USGS (www.usgs.gov). For the Sioux Falls region, the polygons that had the value corresponding to “Developed” were converted to urban. This included “Low Intensity Residential”, “High Intensity Residential” and “Commercial/Industrial/Transportation” land use classes. Note in Figure 4 how the remotely sensed data products led to a very “speckled” texture of the new urban growth.

The historical Transportation Layers were created from the USGS 1:100,000 scale Digital Line Graphs (DLG’s). The roads and railroads were classified by use type (major, minor roads, or railroad) and rasterized to a 30m resolution. Only major roads and railroads were used for this study. More information on DLG’s can be found at http://edcwww.cr.usgs.gov/glis/hyper/guide/usgs_dlg. The dataset contains transportation layers for the years 1956, 1968, 1976, and 1984.

The Exclusion layer is composed of areas in which a city cannot grow. These include parks, natural reserve areas, and bodies of water. The Sioux Falls excluded layer was made from a parks coverage, acquired from the City of Sioux Falls Planning and Engineering Department in Arc/Info coverage format. This was combined with the hydrography coverages taken from the USGS 1:100,000 scale DLG’s.

The Slope layer of Sioux Falls was created from the USGS Digital Elevation Model of South Dakota, compiled at a 30m resolution. The Arc/Info SLOPE routine was used to calculate the city’s slope, in units of percent rise.

3. Method of Comparison

To compare the different calibration methodologies, a single metric of fit was calculated for each run of calibration coefficient combinations. For this calibration exercise, the metric of fit was comprised of the product of three spatial metrics; number of urban pixels (Pop), number of urban clusters (Clusters), and the Lee-Sallee (LeeSallee) index. While SLEUTH affords a diverse number of spatial metrics to be used in calibration, the three chosen represent the most challenging components of an urban model, as well as being simple enough to explain and observe.

The Brute Force and Genetic Algorithm methods of SLEUTH calibration were performed on the Sioux Falls dataset in the following ways. The Brute Force method was run through once, at coarse, fine and final resolutions (resulting in 9375 calibration runs). The Genetic Algorithm was run for 200 generations, for 18 chromosomes in each population (resulting in 3600 calibration runs). Both the GA and the Brute Force methods were run for only one Monte Carlo iteration, as opposed to 10-100 Monte Carlo iterations, as suggested by the current Gigalopolis protocol. This was done because of the author’s suggestion that in using multiple Monte Carol runs for calibration, SLEUTH only uses the mean response of the calibration coefficients to the model, and does not account for the variance or the stochasticity in the model for true urban growth behaviour. The exploration of the use of multiple Monte Carlo runs will be presented in upcoming research.

The GA was implemented on a cluster of 12 SGI O2's, running Irix release 6.5, running R10000 MIPS processor at 195Mhz with 128MB of RAM. The Brute Force calibration was carried out on a PC running Redhat Linux release 8.2 on a 700 Mhz Pentium III processor with 384MB RAM.

To compare the different calibration methods, Sioux Falls was calibrated by each method, Brute Force once, the GA method ten times. Calibration included parameter self-modification, for the preparation for forecasting. For parameter self-modification, all coefficient sets were calibrated for 10 Monte Carlo iterations. Following calibration, the Brute Force coefficient set and the top two GA coefficient sets were used to forecast Sioux Falls urban extent to the year 2015. Analysis and comparison of the two calibration techniques include the calibration metric of fit, the number of iterations needed for calibration, and the overall forecasting behaviour.

4. Results

4.1 Results of the Brute Force Calibration

The Coarse calibration was initialised to explore the entire range of the coefficient space, at steps of 25 units (Table 8a). This resulted in 3125 combinations and took close to 8 hours of CPU time to evaluate. The results of the Coarse calibration show that low values of the Dispersion and Breed coefficients are good, and that the Slope coefficient seems to vary a lot (Table 8b). The top two performers seem slightly better than the following performers.

	Dispersion	Breed	Spread	Slope	Road Gravity	
Start	1	1	1	1	1	
Step	25	25	25	25	25	
Stop	100	100	100	100	100	Possible combinations
Possible units	5	5	5	5	5	3125
					Elapsed time	7:46:59

Rank	Pop	Clusters	LeeSallee	Dispersion	Breed	Spread	Slope	Road Gravity	Metric
1	0.99037	0.99743	0.60125	1	1	50	25	25	0.59393
2	0.98809	0.99915	0.59965	1	1	50	1	50	0.592005
3	0.97925	0.99699	0.60068	1	1	50	75	50	0.586445
4	0.98806	0.97829	0.60447	1	25	1	100	1	0.584286
5	0.98396	0.98886	0.60033	1	1	50	75	1	0.58412
6	0.99124	0.97461	0.60426	25	25	1	100	25	0.583759
7	0.99693	0.96079	0.60774	1	1	25	1	1	0.582118
8	0.98388	0.98238	0.60033	1	1	50	100	25	0.580245
9	0.98415	0.98578	0.5974	1	1	50	75	25	0.579571
10	0.98422	0.99886	0.58709	1	1	75	50	1	0.577167

Tables 8a and 8b. Table 8a is the parameters of the **Coarse** calibration as well as the elapsed time to completion. Table 8b is the 10 best coefficient sets from Coarse Calibration and their related statistics.

The results of the Coarse calibration show that the range and step of the Dispersion and Breed coefficients should be shrunk, in favour of exploring low coefficient values (Table 9a). The Spread and Road Gravity coefficients of the best performers of the Coarse calibration appear in Table 8b to have widespread coefficient values. A path for searching the wide coefficient values was used, as demonstrated in Table 9a. The Slope coefficient, still widely variant in the Coarse calibration did not largely reduce in range and step for the Fine calibration run.

	Dispersion	Breed	Spread	Slope	Road Gravity	
Start	1	1	35	1	20	
Step	5	5	5	20	10	
Stop	25	25	60	80	60	Possible combinations
Possible units	5	5	6	5	5	3750
					Elapsed time	7:46:59

Rank	Pop	Clusters	LeeSallee	Dispersion	Breed	Spread	Slope	Road Gravity	Metric
1	0.99928	0.99988	0.60418	1	5	35	80	50	0.603673
2	0.99366	0.99339	0.60668	1	1	35	60	30	0.598849
3	0.98701	0.99959	0.60691	1	1	35	1	60	0.598781
4	0.98851	0.99514	0.60727	1	1	35	20	20	0.597375

5	0.98426	0.99842	0.60783	1	1	35	20	30	0.597318
6	0.98431	0.99831	0.60783	1	1	35	20	40	0.597282
7	0.9835	0.99959	0.60671	1	1	40	40	30	0.596455
8	0.98178	1	0.60622	1	5	35	1	20	0.595175
9	0.98713	0.99342	0.60614	1	1	40	1	30	0.594402
10	0.98126	0.99977	0.60573	1	10	35	20	20	0.594242

Tables 9a and 9b. Table 9a is the parameters of the **Fine** calibration as well as the elapsed time to completion. Table 9b is the 10 best coefficient sets from Coarse Calibration and their related statistics.

For the Final calibration, the Dispersion, Breed, and Spread coefficients' ranges were narrowed, due to the nature of the best performers of the Fine calibration. The Slope and Road Gravity coefficients still varied considerably across the domain. For the Final calibration, the ranges of the Dispersion, Breed, and Spread coefficients were narrowed, and their step reduced to one unit (Table 10a). For the Slope coefficient, the range was still large (1 to 80) with a large step of 20 units. The range of the Road Gravity coefficient was kept large, from 30 to 60, with a moderate step of 5 units. This resulted in 5250 runs of the program, taking over 10 hours to evaluate.

	Dispersion	Breed	Spread	Slope	Road Gravity	
Start	1	1	32	1	30	
Step	1	1	1	20	5	
Stop	5	5	37	80	60	Possible combinations
Possible units	5	5	6	5	7	5250
				Elapsed time		10:27:08
				Total Number of Runs		12,125
				Total Elapsed Time		27:05:05

Rank	Pop	Clusters	LeeSallee	Dispersion	Breed	Spread	Slope	Road Gravity	Metric
1	0.99998	0.99959	0.60498	1	3	33	80	45	0.60472
2	0.99546	0.99988	0.60652	1	2	36	80	50	0.603694
3	0.99928	0.99988	0.60418	1	5	35	80	50	0.603673
4	0.99457	0.99997	0.60651	1	1	35	60	35	0.603199
5	0.99941	0.9993	0.60384	1	4	34	80	50	0.603061
6	0.99888	0.99999	0.60374	1	1	35	80	45	0.603058
7	0.99819	0.99959	0.60399	2	1	35	80	35	0.60265
8	0.99938	0.99787	0.60402	1	2	36	80	35	0.60236
9	0.99661	1	0.60406	1	2	32	60	60	0.602012
10	0.9982	0.99655	0.60493	1	2	35	80	55	0.601758

Tables 10a and 10b. Table 10a is the parameters of the **Final** calibration as well as the elapsed time to completion. Table 10b is the 10 best coefficient sets from Coarse Calibration and their related statistics.

The Final calibration honed in on some good performers. Most notable is the best performer, while not having the best LeeSalle metric, was an improvement over the following coefficient sets (Table 10b), with a Metric of 0.60472. It should be noted, however, that the first-ranked coefficient set from the Fine calibration was ranked third in the Final calibration run, and only two other sets performed better.

Results of Parameter self-modification for the Brute Force calibration resulted in the following coefficient set: 1-2-24-83-45.

4.2 Results of the Genetic Algorithm Calibration

The Genetic Algorithm approach to calibration resulted in seven chromosomes that outperformed the Brute Force calibration, and three that did not (Table 10b and Table 11). The general trend of all the GA chromosomes after 200 generations was that low values of the Dispersion and Breed coefficient are desirable and the Spread coefficient was relatively stable around values in the high 20's. However, both the Slope and the Road Gravity coefficients are highly variant with relatively large ranges. This could have been due to the complex interactions among the coefficients in the growth rules, or due to the flat nature of Sioux Falls (other than the steep ravines, surround by parklands). In addition, the transportation layer used for Sioux Falls included only the major (interstate) roads and railroads. A more detailed transportation layer including minor roads may have given different results. The average time it took for the GA calibration was 5.364 hours, one-fifth the time of the Brute Force calibration, on a much slower processor.

Rank	Dispersion	Breed	Spread	Slope	Road Gravity	Metric	Time (Hours)
1	1	1	27	16	31	0.608151	5.35
2	1	3	27	17	29	0.60642	5.23
3	2	1	29	24	3	0.606047	5.52
4	2	1	29	24	4	0.606047	5.21
5	1	1	27	24	20	0.605818	5.21
6	1	1	31	70	55	0.605118	5.47
7	1	1	31	77	24	0.603935	5.35
8	1	7	27	31	37	0.603886	5.34
9	1	4	28	29	27	0.599125	5.45
10	3	2	41	25	32	0.598816	5.51
					Average Time		**5.364**

Table 11. Results of ten independent Genetic Algorithm calibration runs. All used the same Seed Populations and ran for 200 generations of 18 chromosomes.

When plotted out over time, the general asymptotic behaviour of all the GA's is clear (Table 5). This may be due to the relative high amount of elitism in the GA itself. Most of the GA runs exhibited a large step to a higher metric value, and then slowly stepped up after that.

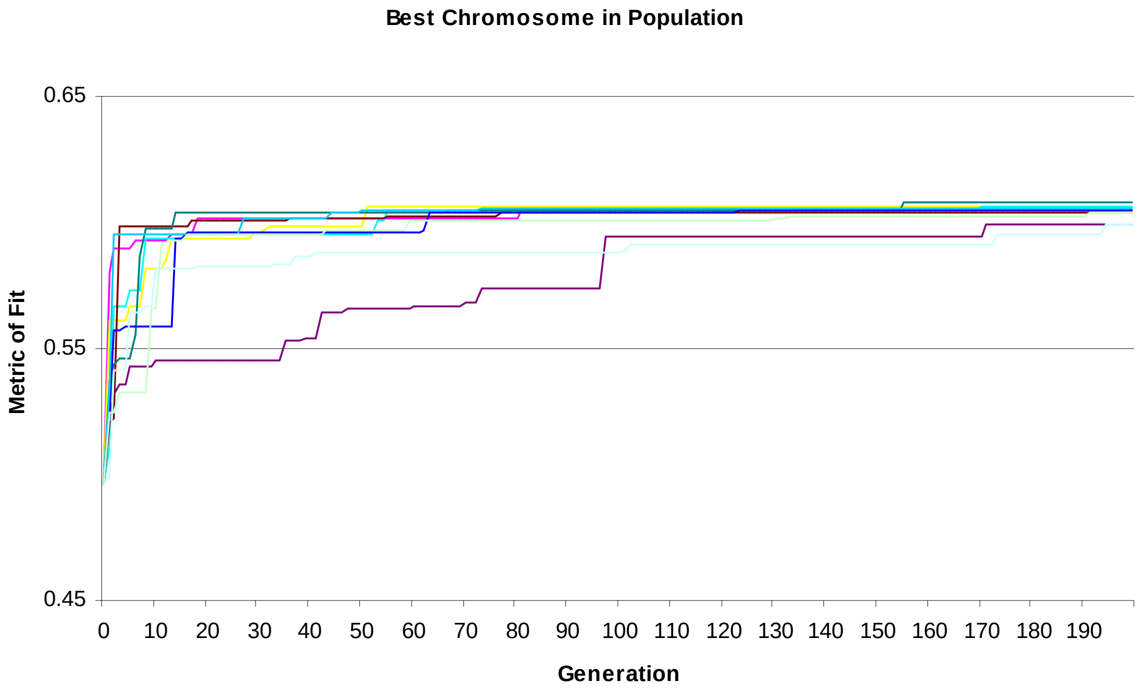

Figure 5. Performance of ten individual GA calibrations

The self-modification of the top two GA calibration coefficients resulted in the following prediction coefficient sets (in order of rank): 1-1-12-34-29 and 1-1-21-26-3.

4.3 Comparison of forecasting results

According to the forecasted urban extents, Sioux Falls will either grow very little or not at all (Figure 6). Most of the growth was focused near the 1992 urban extent, showing that Sioux Falls grows from its edges, rather than “spotting” out new urban centres. The best GA calibration run, forecasted a minute amount of urban growth in the 23 years between 1992 and 2015. This warrants further investigation.

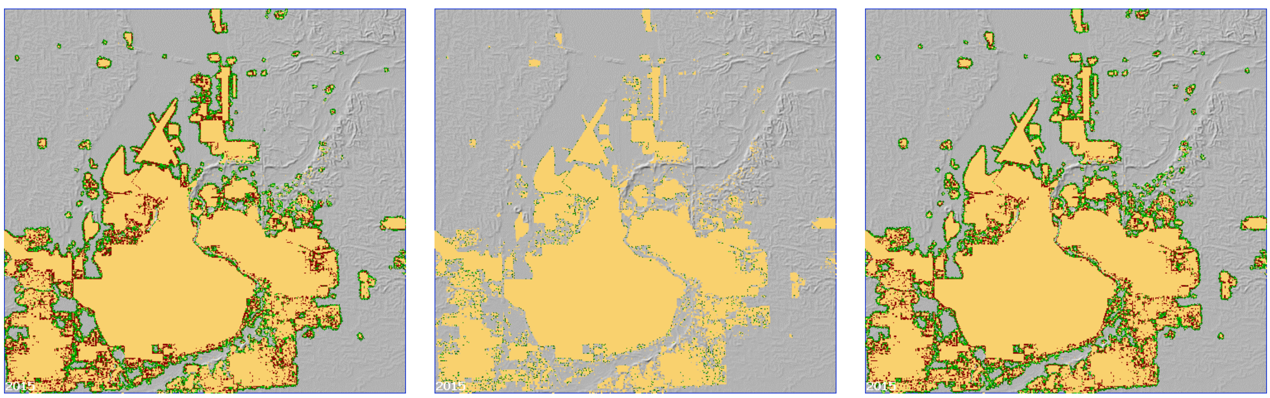

Figure 6. Forecasts of Sioux Falls urban extent from 1992 to 2015. From left, 6a, Using Brute Force coefficients. 6b Using best GA coefficients. 6c Using second-best GA coefficients. Yellow is urban extent in 1992. Red was urbanized in 90% of the runs. Green was forecasted in greater than 50% of the runs.

All three forecasting runs exhibited most of their growth from Organic Growth that occurs at the city edges (Table 12). This mirrors the Sioux Falls planning department's plans to incorporate adjacent lands into the city as residential and commercial centres (www.siouxfalls.org/planning). However, Sioux Falls is itself expecting the urban extent to grow at a rate of 2.5% to 2015 and SLEUTH at its best does not forecast similar growth.

	Organic Growth	Total new Pixels	Number of Pixels as Urban	Clusters	Growth rate
Brute Force	1000.9	1005.8	97342.2	611.4	1.03
Best GA	91.8	92.8	76691.9	987.5	0.12
2nd best GA	915.3	918.8	97323.8	580.9	0.94

Table 12. Statistics from the three forecasting runs. Ten Monte Carlo iterations were used to forecast to 2015.

Other than the Best GA run, the forecasts are very similar in visual and statistical measures. The Best GA run had a much greater number of clusters than the other two, indicating two components. First, the Best GA run was sending out more and smaller urban clusters than the other two. Second, and more likely, the other two runs filled in urban extent where the best GA run could not, merging many clusters together.

5. Discussion and Conclusion

The Brute Force method of SLEUTH calibration does a good job at finding the coefficient set that fits the historical urban data layers well. It hones in on a suite of solutions, and is very good at parsing the coefficient space up into smaller and smaller pieces. However, the Brute Force method leaves much room for subjectivity. Human input is necessary twice in the process, from the Coarse to the Fine resolution, and from the Fine to the Final resolution searches. It is up to the user to determine what the domain of the successive search will be, and what size the steps will be through that space. For Sioux Falls, it was evident from the Coarse calibration that Dispersion and Breed were to be kept low, with a range of 1 to 25, with a step of 5, this was not the case for the Slope coefficient, which necessitated a larger range, from 0 to 80, with a step of 20. However, the decision of coefficient range and step is up to the modeller and their own "feel" of the data, so a different modeller would have potentially obtained different calibration results with a slightly different approach to the calibration process.

This is not the case with the GA method of SLEUTH calibration. The three components to be decided upon are the mutation rate, the number of chromosomes in a generation, and the number of generations. All three are chosen beforehand, but many combinations can, and should be tested. In fact, given the UCSB Geography computing constraints, a modeller can afford to test four different GA combinations of mutation rate, population size and number of generations, in the same amount of time of doing one Brute Force calibration.

However, as the GA method of Calibration did not always out-perform the Brute Force method, getting stuck in local maxima, there is room for improvement to the GA. The first area of exploration is the mutation rate. The mutation rate used in this GA was %10, which is considered very high in the GA community. Both lowering and rising the mutation rate will change the GA, and in doing so may speed up or slow the selection process. Similarly, the GA tends to get stuck on high-performing (elite) chromosomes for many runs (Figure 5). This can be improved by allowing for greater mutation and de-emphasizing elitism when such local maxima are reached. The most interesting and obvious developments in the GA for SLEUTH calibration will occur in the modification of the number of generations, possibly creating some stopping criteria, and the population size. This issue will be a balance between the computational speed provided by the GA and casting a wide-enough net in the coefficient space to find the best chromosome.

When comparing the GA and the Brute Force calibrations in terms of computation time, the success of the GA is impressive. For the array size used for Sioux Falls, 486 by 465 pixels, the GA method outpaced the Brute Force by from 4 to 5 times as fast, even though the Brute Force calibration was running on a faster computer. The close to six hours to run the GA for Sioux Falls indicates that Yang and Lo (2003) could shrink their 15-day Brute Force calibration considerably as well.

According to different coefficient choices, Sioux Falls will look either very similar or somewhat different in the year 2015. While the model showed growth in all three of the coefficient sets tested, it is not clear which, if any of these are a representation of the truth, as we have 12 years to go to 2015. The model forecasts could be validated to the current Sioux Falls urban extent, either from the Ikonos satellite or vector-based data sources. The question, then of “What is Urban”, becomes of import as the urban landscape looks very different from a satellite relative to a cadastral map of land use.

The discrepancies between the forecasts of Sioux Falls’ growth in 2015 are possibly due to a number of factors. First, the use of the LeeSallee metric in the metric of fit can be a harsh judge of model fit. The LeeSallee metric judges overlap and any deviations from the overlap are penalized. This may have led to the best GA coefficient set as being the best reproducer of the 1992 urban extent and yet not a good estimator of what comes next, especially in the Parameter self-modification stage of calibration. In the self-modification stage, the model had to account for a “phase change” in urban form – from the solid globular form of Sioux Falls in 1976 to the speckled 1992 urban layer. The speckled pattern is hard for a model to calibrate to, especially since the earlier data layers were not speckled. The issue of speckled data will have to be resolved, as the use of remote sensing products will surely increase in urban modelling, not decrease.

The two methods of calibrating the SLEUTH model presented here, Brute Force calibration, and a modified Genetic Algorithm (GA), illustrate the potential advances of incorporating evolutionary computing methods into spatial modelling. The Brute Force method is just that – it throws the hammer of computation at the problem of searching the complex coefficient space of the SLEUTH coefficients. On the near horizon are computers with enough computational power to manage the large data sets and lengthy routines used in SLEUTH and the complete exploration of the search space will be possible. The recent development of cheap CPU’s and home-grown Beowulf parallel computing clusters echoes this sentiment. However, in the present, when there are still computational constraints put on the SLEUTH model user, the GA method of calibration provides a viable and welcome alternative to Brute Force.

The alternative of the GA method posits the question, "how good of a fit really matters for SLEUTH?" Is finding the "best" set of coefficients going to make a difference when running SLEUTH? Is the benefit of the GA dependent on the spatial resolution or the urban region in focus? These questions indicate the path of future exploration of the influence of calibration on the SLEUTH model. Research by Candau (2002) showed that a longer time scale is not necessary for a more accurate calibration of a region. Instead, the most recent urban geospatial data are the most important to obtain in order to calibrate effectively. However, since Sioux Falls was largely formed by 1956, the first control year, it is possible that older historical data would improve the projections.

The primary advantage of the GA is that it slows the arrival of a solution, and therefore prevents the process of getting stuck in a local maximum, as opposed to a more global optimum, as illustrated in this modelling exercise. The strength of the Brute Force method is to carefully explore the coefficient space in a regular way. A hybrid method of calibration could be advantageous. This would entail using the GA to get a good estimate of a set of good solutions, then using the Brute Force approach to consistently "step" around those in a regular manner. This would be an improvement on Brute Force, in terms of speed and accuracy.

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