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Research article

Assessing the suitability of the SLEUTH cellular automata model for capturing heterogeneous urban growth in developing cities: A case study in Northern Nigeria

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ABSTRACT

Cellular automata (CA) models like SLEUTH (an acronym for slope, land use, excluded area, urban extent, transport-network and hill shade) have predominantly been developed and applied in developed countries. Modeling can serve as a tool to guide policy measures in facing urbanization challenges. However, developing cities have peculiar differences (heterogeneity, poor planning, and low infrastructure) thus the existing modeling approaches may not be able to apprehend heterogeneous urban growth. This research will use selected cities with similar spatial extents as controls but disparate urban extents, and growth indices to analyze the performance of SLEUTH simulations. Presumably, a comparison of the model simulations of the cities would display some significant differences, due to these variations and the scale of observation that has to be used for the model simulations. The results for the successfully calibrated cities (Kano/Funtua couple: 0.48/0.02. Katsina/Kaduna: 0.48/0.83 respectively) showed that in each city couple, the more expansive city with the most compact urban settlement pattern had a higher prediction accuracy, also predicted images of the cities showed underestimation of the urban areas over the years with the exception of Katsina city. The study further showed the model's effectiveness in modeling cities in developing countries, such as Nigeria. It is recommended that the type of urban growth experienced by cities be taken into consideration when implementing SLEUTH. Limitations of the study are centered on the inherent limitations of the model, the possibility of the occurrence of errors in data preparation, the scale and urban settlement type, which play an important role in the success of the calibration. Future research could be focused on adding other relevant inputs to the model and creating a metric that ascertains the best satellite image resolutions for a particular study area's growth coefficient values.

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1. Introduction

Urban dynamics can be studied and forecasted with urban modeling tools providing a futuristic view on the potential importance of urban growth and development [1]. Over the years, many urban growth models have been developed and used in developed countries for forecasting growth patterns [2–4]. In developing countries however, there are few studies showing the application of these models and their performances [5].

Models also have an element of uncertainty as tools, in that models are abstract in the way they represent reality, and urban growth simulation is peculiar [1]. The variables represented in urban modeling are hard to simulate as they deal with human systems which are usually fractal in nature [1]. Thus, the indices that govern urban systems are difficult to predict [1]. Compared to other social systems, urban systems are more difficult to simulate due to their stochastic nature [2].

In the context of the developing world where this research takes place, many of the problems identified by Lee [6] still serve as hindrances for the application of models. Implementation of these models in developed countries has been moderately successful [7–11]. This may be attributed to their homogenous nature [12–17]. However, few studies have reported using CA simulations for relatively more heterogeneous (in terms of varied construction, lack of planning, and inadequate infrastructure like roads) urban areas and smaller unit-size developments as in this study area, which is quite common in developing countries [18–20]. Also, because field-based validation data and the necessary Geographic Information system (GIS) knowledge needed to develop and implement such models, not many models have been developed for African cities [19,20].

Cellular automata urban expansion models are now the most popular modeling technique. This is due to their simplicity, flexibility and ability to incorporate the spatial and temporal dimensions of urban processes [21–24]. SLEUTH is a modified CA model that predicts the spread of urbanization over an area based on its historical urban growth [25]. Their near universal popularity has made them the model of choice to study many cities in the world [26,27]. However, the fragmented urban growth of cities has rendered it less effective as a model due to its sensitivity to fractured urban growth [16]. Forms of CA have been widely tested in developing countries as well, including Lagos City in Nigeria by Baredo and Demicheli [28]. Few studies have been made with the model where the housing units are very small and fragmented [18] which again is common in developing countries like Nigeria. There are also differences in factors that modify urban growth and complicates modeling and the different contexts of modeling in developing countries [29].

Techniques including artificial intelligence have been used by researchers to calibrate urban cellular automata models or to define the transition rules of the models [21,30]; others have concentrated on the effects of modifying the different parameters that are part of the model such as neighborhood type and size [31,32]. Researchers have also experimented with the modified cell size parameter [33–35], while Ménard and Marceau [36] focused on both cell size and neighborhood. Dietzel and Clarke [37] looked at land use classes whereas Childress et al. [38] and White et al. [39] focused on the choice of transition rules. Liu and Andersson [40] examined the effects of temporal dynamics on the behavior of a CA-based urban growth model. In summary there are some aspects that require further research in the application of CA; namely differences in spatial extent (size of the study area), resolution (cell size), thematic classification (number of land uses), and time step (discrete interval in time).

The CA's ability to see the variables that drive land-use changes is influenced by the scale of observation. That is, interactions may vary from one spatial scale to another and behave in a non-linear fashion [41–43]. The implication is that the behavior of CA models in their quantification of urban patterns is modified by the spatial extent of the study area and by extension the data resolution of the image. Scale problems and scale influence are part of the modifiable areal unit problem [44,45]. Spatial units are modifiable in several ways. The units can be combined to form units of various sizes or spatial arrangements [46]. Research that is dependent on modifiable and arbitrary units should always be questioned to a degree [44].

There are considerable differences among Nigerian cities in their spatial extent, extent of built-up areas, population size, and other indices [47]. For instance, some cites that might have a similar area size may have significant differences in their overall built-up area. Some cities have mega-status population figures [47], and spatial extents of several hundred square kilometers in places such as Lagos and Kano, while other cities like Katsina and Daura have less than a million inhabitants each [47] and so far less built-up extent. Funtua for instance, with a population of 225,156 [47], has an administrative and functional area of 384.1 km^2 which is commensurate to the area of Kano of 573.24 km^2. But the population of Kano City of 2,826,738 persons is almost eight times the population of Funtua City [47]. The density of these two cities likely varies considerably and it is to be expected that a comparison of the model simulations of these two cities would display some significant variations due to these differences and the scale of observation that has to be used for the model simulation.

The three city comparisons (Kaduna 116.4 km^2/Katsina 133.8 km^2, Kano 573.24 km^2/Funtua 384.1 km^2, Bakori 736.5 km^2/Malumfashi 890.1 km^2) were chosen for this study based on their functional areas, and similar administrative sizes. They also exhibit varied scales (built-up extents, densities, populations, economic size, and growth factors). It is logical that the model would be influenced by different scales, thus a simulation of each city pairing with the SLEUTH model would display differences in the simulation results and would help answer the research question: Does the scale/size of a city play any role in the efficacy of the SLEUTH model?

This study will thus attempt to explore the performance of the SLEUTH urban growth model and how it is affected by the city scale in a developing country, using selected similar sized city pairings in Nigeria as a case study. To achieve this, congruently sized city pairs with similar spatial areas as a control but disparate sizes will be simulated with the model. The differences manifested in the simulations of the city pairs would allow for comparisons and further analysis.

1.1. Model constraints and strengths

The reliance of SLEUTH on purely physical factors, disregarding socio-economic and political factors, is a limitation of its functionality; as other factors influence land-use changes, and longtime cycles also affect its predictive efficacy. This is a result of its inability to capture variations in development trends. Localized differences and sudden changes in growth are also not well captured by the model, because it assumes symmetric growth. Dispersed urbanization is also poorly captured. Lastly, future scenarios might not be perceived by its simulations with low resolution input data and is another limitation especially in its applicability in developing urban policy development and planning. Future researchers should focus on modifying the model to accommodate regional differences and local variations.

The strengths of the model are its ability to generate simulations for long periods of time, even decades. It is also clearly detailed and quite accurate in its simulations of future growth of areas, and current spatial patterns and growth directions can be used to predict growth. This in turn strengthens policy making and planning for development and environmental protection. SLEUTH also has a wide range of useable indices that allow for a better understanding of the urban growth landscape and in scenario analysis.

2. Methods overview

The case studies comprise three city pairings which are congruently-sized administrative and functional areas, and involves comparisons of the model simulations for each one of the pairs to its counterparts. The case study method is suitable for the pattern of question ('how') that this study investigates: how do city scale factors affect SLEUTH efficacy if the resolution of the city input cell image is the same and the administrative extent and city functional area is congruent or very similar? As SLEUTH modeling has shown to be context dependent a case study design is appropriate. Case study approaches are advantageous for researching unique or unusual circumstances and generate ideas for further research. Real-world scenarios can also be investigated as opposed to contrived or hypothesized experiments. Its disadvantages are that there is the risk of bias, difficulty for other researchers to replicate and restricted control over variables, and finally the tendency to span longer time periods.

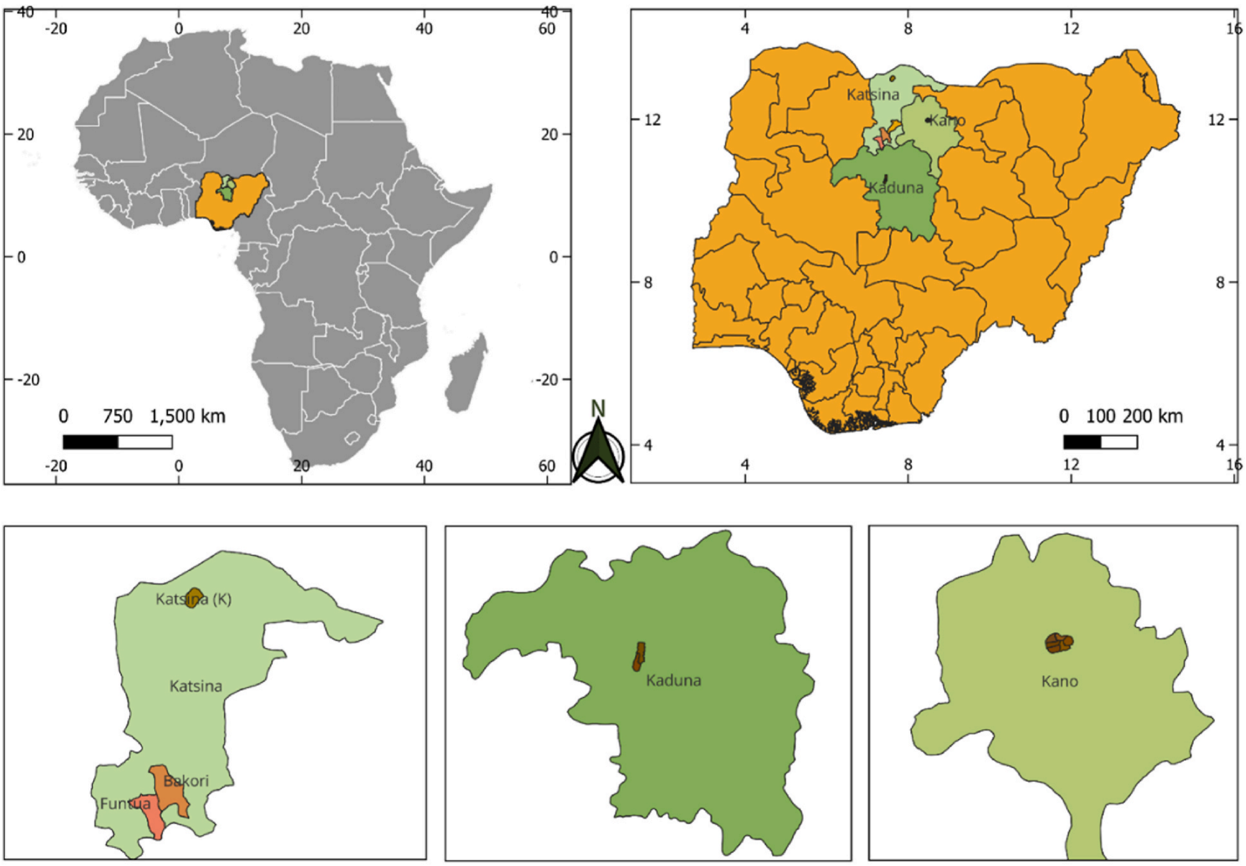

Fig. 1. Map of study areas.

2.1. Study area

Three city pairings in northern Nigeria (Kano/Funtua, Kaduna/Katsina, Malumfashi/Bakori), (Fig. 1), which have a congruent administrative spatial extent and functional area, have been chosen as the paired cities to analyze SLEUTH simulations. The similarity and administrative size of the spatial extent of these cities will serve as a control for the simulation. The Kano/Funtua pairs have administrative areas of over 573.24 km^{2}and 384.1 km^2 respectively. Kano, however, is the most industrialized city in Northern Nigeria and has a much greater built-up extent than its pair Funtua. The Katsina/Kaduna pair both have an administrative extent of 133.8 km^2 and 116.4 Km^2 respectively (Table 1). Kaduna is the former capital of Northern Nigeria and the second most industrialized city in the northern region; it too has a much greater built-up area and larger economy. The Malumfashi/Bakori pair have administrative areas of 890.1 Km^2 and 736.5 Km^2 respectively. Here, Malumfashi has a significantly greater built-up extent. These differences in physical characteristics are expected to manifest in the simulation patterns of the cities using the SLEUTH model.

2.2. Data used

The data used in the study is entirely secondary data in the form of satellite images and the global elevation files downloaded from the United States Geological Survey (USGS), a United States scientific agency. Other secondary data in the study are shape files of roads, cities, and areas not suitable for, or precluded from physical development. The data was processed in ArcGIS 10 [48] software to make it suitable for the SLEUTH implementation.

The six input data layers were all modified into suitable vector and raster formats to suit the model. The SLEUTH model uses six input data layers [14] derived from its acronym and of which five can be used for a study: slope, exclusion layer, urban extent, transportation, and hill shade layer, see Fig. 2. Multispectral Landsat 7 and 8 images of four time periods were used as required by the model. The following years with a four-year gap were used: 1999, 2013, 2017, and 2021 respectively. The year 2009 image was not used due to an error developed by the Landsat 7 satellite in 2003. See Table 2 for details. The data sets were obtained from the United States Geological Survey (USGS), a web-based repository which also provides 1 Arc-Second Global elevation data sourced from the Shuttle Radar Topography Mission (SRTM) for all Landsat and other sensory imagery [49].

The SLEUTH input layers provide the model with vital spatial information about the circumstances that govern land-use changes in an area and is based on those factors that the model simulates anticipated possible scenarios as to what urban landscapes will possibly manifest in the future. The slope layer helps SLEUTH guide development away from areas with steep slopes, while the exclusion layer provides information on which areas are entirely unsuitable for future developments and maintain a semblance of being realistic. The transportation layer provides information about transportation networks which influence the direction and type of development that occurs as growth mostly occurs around transport nodes. The urban layer provides information on the existing urban extent; this helps the model evaluate the current trend of urbanization in the area and how it might grow outward or inward. The hill shade layer guides the model on topographic influence on the development of the area, and the land use layer provides information on the extant land uses in the area and helps the model predict how the land uses may change in the future.

2.3. Dataset preparation

Data preparation mainly involves the use of GIS and remote sensing techniques that include data conversion, data import/export, classification and reclassification [50]. All Landsat 7 and 8 images for the four time periods were atmospherically corrected to remove the effects of atmosphere on reflectance values [25]. In addition, as the study area falls within WGS_1984_UTM_Zone_32, all satellite images were projected into this zone. The study areas were clipped from the satellite images using ArcGIS 10 [48] software and city shape files [48]. To extract the built-up area, the interactive supervised classification algorithm was utilized in ArcGIS software. Image classification involves categorizing the pixels from remotely sensed images into a schema. Supervised classification uses the spectral signatures obtained from training samples to create an image. The statistics for each class in every band are considered to be normally distributed and the algorithm estimates the probability of a pixel being in a specific class. The class with the highest likelihood is assigned the pixels. From the classification, the pixels were categorized into one of the following categories: water surface, built-up land, non-built-up land (grassland, bare land). Roads, parking lots, commercial areas, residential areas and industrial buildings are considered as built-up. Visual interpretation of color composites of Landsat imagery was used to delimit the training sites for the cover classes [48].

2.3.1. Sampling frame and ground-truthing

A specific number of accuracy assessment points were generated in ArcGIS using stratified random sampling for the classified image

Table 1
Relative sizes, growth rates, and populations of city pairs.

City couple	Local government administrative Area (Km^2)	Population (NPC 2006)	Population density (Km^2)	Growth rate (%)
Kaduna/Katsina	116.4/133.8	767,306/318,132	6,591/2,377	2.5/3.7
Kano/Funtua	573.24/384.1	2,826,738/225,156	4,931/586	2.6/3.7
Bakori/Malumfashi	736.5/890.1	149,516/182,891	203/205	3.7/3.7

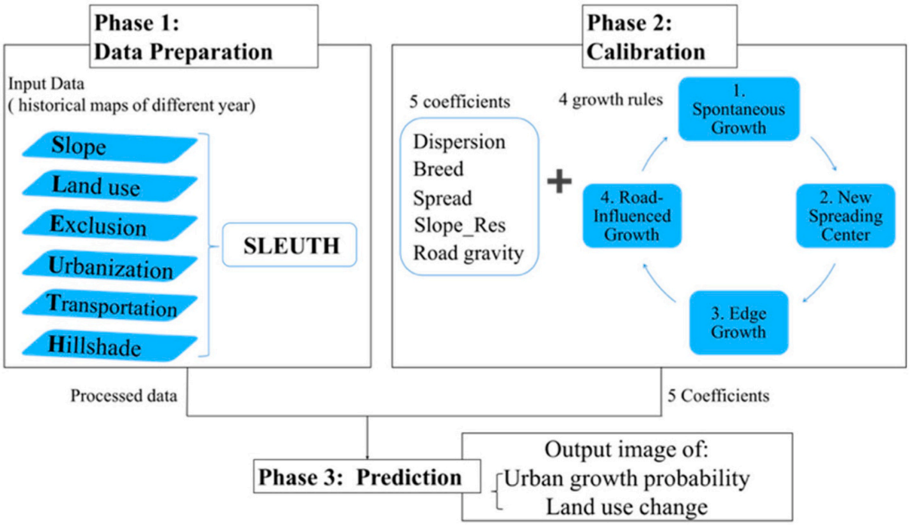

Fig. 2. SLEUTH model structure (Source: [33]).

Table 2
Satellite images collected for the extraction of built-up areas.

Cities	Satellites	Dates of acquisition	Representative years
Kaduna	Landsat 7, landsat 8 OLI	Feb.2017, April 2017, May 2017, May 2021	1999, 2013, 2017, 2021
Katsina		Feb.2017, April 2017, May 2017, May 2021	
Kano		Feb. 2017, April 2017, May 2017, May 2021	
Funtua		Feb. 2017, April 2017, May 2017, Oct. 2017	
Bakori		Feb. 2017, April 2017, May 2017, Oct. 2017	
Malumfashi		Feb. 2017, April 2017, May 2017, Oct. 2017	

as part of the accuracy assessment process. The number of points generated for each land cover type was ten times the number of land cover classes of the image (for instance, 40 points for each land cover class for a classified image with 4 land cover types/classes, totaling 160 points), and each land cover type was given points proportional to its area. Ground truthing involved comparing the accuracy points of land cover types and their associated land cover types with Google Earth images, true color, and false color composite images of the same area in an error matrix to determine the accuracy of the land cover classification. An acceptable level of accuracy is eighty percent [51].

2.3.2. Data layers

For each period, urban layers were derived by extracting the urban pixels from the classified image. The seed year, or start date used for the model was 1999. It is the initial state from which further conditions for growth will occur. The classified images were then recoded into urban/non-urban categories in the ArcGIS software and turned to grayscale GIF images to make the data suitable for SLEUTH operation [51].

ArcGIS was used to convert the images into the suitable format for the model. The data for the excluded area (water bodies, parks, hills, etc.) was derived in vector format. It was then merged and rasterized. Null values were given to developable areas while a unitary value of 100 was used for the excluded areas. The road layers of 2018 and 2020 derived from shape files were formatted and utilized for the purpose of this study. ArcGIS was used to convert the shape to raster files for SLEUTH operation. A binary format was used for the road layer, zero represented non-road features while values above zero up to 255 (100 recommended) represented road features. Both the slope and hill shade layers were generated from one Arc-Second Global elevation data and formatted in GIS software [49].

2.4. SLEUTH model implementation

Specific procedures need to be followed in order to implement SLEUTH [49]. The procedures are applied in a prescribed sequence and the parameters set first. This determines the simulation output [49]. The model then executes its functions with the suitable variables and the expected modeling results are generated. The SLEUTH model has three primary modes: *test, calibrate,* and *predict* functions. The modes are executed from a file called the Scenario file; from it the user can execute a multiple of model parameters [52].

2.4.1. Calibration

The most significant step in the SLEUTH modeling process is calibration (Clarke et al., 2002). Calibration aims to determine the best set of values for the growth parameters (breed, diffusion, spread, slope and road-gravity) that optimally reproduces historic land cover change within the study area. These parameters range from 0 to 100 and govern the systems behavior; they are set at the beginning of each calibration run [12,14,53]. Calibration is mainly done in three steps: coarse, fine and final calibration. In coarse calibration a 'brute force' method is employed. Steps are taken in units of 25 through the whole coefficient range for all the coefficients. The coefficients are narrowed down step by step up to the final calibration stage. In the coarse calibration step the input image was re-sampled to a quarter of its resolution as the input, then the input data was re-sampled to half in the fine calibration state and back to the full resolution at the final calibration stage. Resampling is vital for spatial alignment of the input data layers as SLEUTH is based on a grid framework. And for the resolution of input data to coincide with the required modeling resolution. In each calibration stage the most suitable parameter ranges are identified and used in the subsequent stage with lesser intervals.

Some metrics are produced in the control_stats.log file by the model after each calibration [52]. Several methods have been suggested to identify the best coefficients for calibration from the statistical control log file [49]. Therefore, it is at the discretion of the user to choose the method to calibrate the model. For the purpose of this study, the coefficients were selected using the Lee Sallee metric. It measures the degree of spatial match between the modeled and input data for each combination of variables [52]. Using the control_stats.log file the Lee Sallee metric from the coarse calibration was sorted in descending order to find the 'top 3' best fit values. This was repeated for the next phases of the calibration. For the 'Start'_ value the minimum was selected and for the _'Stop' value the maximum was selected for each coefficient. An appropriate interval between the two aforementioned values was taken as a 'STEP' value. With the calibration complete the best metrics are implemented in SLEUTH to generate urban area images that predict the urban land cover map in 2021.

2.4.2. *Goodness of fit*

Subsequent to each calibration process the real growth and simulated values can be gauged with the model's least squares regression metrics [16]. The indices serve the purpose of assessing the goodness of fit of the model for the study area. Table 3 describes the subset of the metrics that can be used.

2.5. *Prediction accuracy*

Evaluating prediction accuracy takes place after a successful calibration and is determined by making comparisons of a predicted urban map with an actual reference map of the same area and temporal dimension [54]. In theory, this is valid if the actual map is highly accurate [54,55]. The observed map itself is subject to classification errors when compared to ground truth data. Several studies have attempted to give explanations for errors in observed maps [54]. Classification accuracy is mostly around 80 percent in remotely sensed data due to the mixed pixel problem. Accuracy assessment is important as it helps to determine the accuracy of simulated maps and give reasons for the estimates of errors.

There are several methods that are used to make comparisons of predicted maps and actual maps to assess the accuracy of the predicted maps [54–58]. Several map comparison techniques and software are currently available. They, to name a few, include: The Kappa technique and its variations, K-simulation and its variations, and quantity disagreement and allocation disagreement [56]. This study will use the Jaccard coefficient and mean squared method to determine the accuracy of the prediction maps. The Jaccard coefficient can be used to assess the correlation of two raster files, that is, how strong the overlap between them is. The MSE measures the quality of a raster in comparison to a reference raster. These calculations can be done in ArcGIS using the raster calculator tool.

3. Results and discussion

3.1. *Urban extent from 1999 to 2021*

It is important to discuss the urban extent from the classified input images from 1999 to 2021, this will help show how city extent has changed over the years and so will provide a context for comprehending the prediction results. This is shown in Fig. 3.

From the classified images of city urban extent, it appears that over the past twenty odd years, the extent of the cities has increased significantly for all the cities in the study. The increase is greater in the larger cities, as illustrated in the figures below. The red colored areas represent new growth from 1999 to the year 2021 while the black areas represent urban areas that have remained relatively unchanged or experienced less significant urban growth over the period of analysis, and the green areas represent areas where relatively no growth has taken place. Kano, as can be seen has experienced extensive and sprawled growth, this is as expected as it is

Table 3
SLEUTH least squares regression metrics.

Index	Description
Product	A composite index that is the result of all indices multiplied together.
Compare	Makes a comparison of modeled final extent with the real final extent.
Population r^2	Least-squares regression score of the modeled urbanization compared with the actual urbanization for the modeling period.
Edges r^2	Least-squares regression score of modeled and actual urban edge pixel count for the modeling period.
Xmean r^2	Least-squares regression value comparison of average X values for modeled urbanized cells and actual urban extent urbanized cells.
Lee Sallee shape index	A shape index that measures spatial fit between the modeled and actual extent for the modeling period
R^2 cluster	Least-squares regression score of modeled urban clustering and actual urban clustering for modeling period.

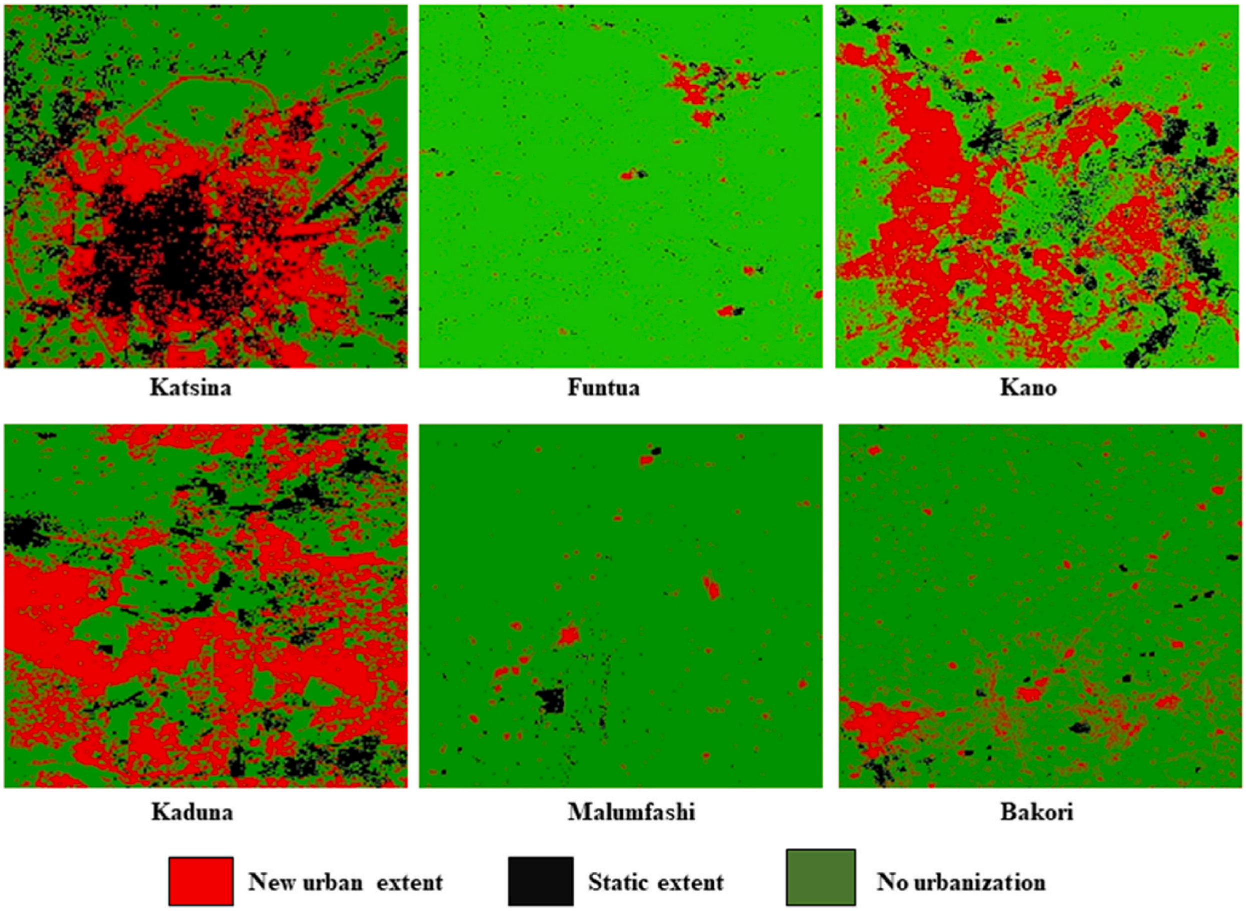

Fig. 3. Map of urban sprawl of cities.

the most industrialized and populous city in northern Nigeria and also the distribution hub of local products and exports to other parts of the country and neighboring countries. Kaduna is also an industrialized city, second only to Kano in northern Nigeria in population and industrialization, and as shown in the figure, it too has witnessed extensive growth in a similar fashion to Kano. Katsina's growth on the other hand shows a different pattern from Kaduna and Kano and is more compact and less sprawled than the other two cities. Known factors affecting the growth of Katsina may have caused this pattern. The hinterland of the city has been exposed to security challenges due to banditry in recent years so may be a plausible explanation for the lack of broad outward and sprawling growth towards the outskirts of the city center as shown in the other cities. Lastly, Malumfashi, Bakori and Funtua show extensive sprawl compared to the first three cities mentioned. This can be attributed to the economic characteristics of these cities, that they are virtually non-industrialized and mostly serve as markets for farm produce from the hinterland of their respective areas. See the figure below for a map of the urban sprawl of the cities.

Table 4
Accuracy assessment of city pairs for years 1999, 2013, 2017 and 2021.

City	Satellite image year							
	1999		2013		2017		2021	
	Kappa statistics	Accuracy percentage	Kappa statistics	Accuracy percentage	Kappa statistics	Accuracy percentage	Kappa statistics	Accuracy percentage
Bakori	87.80	92.50	80.40	90.10	92.0	95.40	96.00	97.40
Funtua	93.20	96.20	99.10	99.20	91.40	96.10	68.40	84.70
Kaduna	95.60	97.32	95.10	97.50	94.50	97.20	75.30	89.90
Kano	94.10	96.10	89.70	92.90	75.30	82.10	89.30	92.90
Katsina	98.90	99.30	86.10	90.30	94.10	96.10	96.40	98.20
Malumfashi	82.90	98.40	86.90	90.40	86.70	91.90	89.30	92.20

3.2. Accuracy assessment of land-cover classification

3.2.1. Classification accuracy

Table 4 shows the accuracy assessment results of the land cover classifications for the four periods. The Kappa statistics for all classifications were over 75 percent in most images and total accuracy was at least 80 percent and above. This level of accuracy is considered satisfactory and suitable for further analysis.

3.3. Calibration results

The culmination of the calibration process is to determine the optimum coefficient values that best simulate historical growth patterns. The best fit calibration values are shown in Table 5.

The table shows that the best-fit coefficient calibration values of some of the cities play an important role in the growth trends of the cities; breed, slope and road gravity for instance in Bakori. In other cities the coefficients play a moderate role as in Kano and Kaduna city. Katsina and Funtua coefficient values show little significance in the growth trends of these cities; with the exception of slope for Katsina which is important in the urbanization trend of the city. For those cities whose growth trends appear to be influenced by only a few of these coefficients, the cities' growth trends appear to be influenced by other factors like economic, or population dynamics.

3.4. Prediction metrics

The least-square regression metrics for the three city pairs are comparatively similar in their output, in that the cities with larger built-up areas appear to show a greater goodness of fit (Table 6). Several of the metrics can be used to measure the goodness of spatial fit. The Lee Sallee metric, as stated previously, is a metric that determines the amount of spatial fit between the modeled and actual extent in the modeling period. It is the metric used to gauge the performance of spatial fit in this study. With it, a value of 1 would indicate a perfect spatial fit, getting high values for this is however challenging [14].

In each of the three city pairs, the city with the most expansive urbanized built-up area had the highest degree of fit with regard to the calibration using this metric. This calibration obtained the following Lee Sallee values for the city pairs as shown in the results section: Bakori/Malumfashi – 0.12 and 0.01 respectively; Kano/Funtua – 0.26 and 0.10 respectively; Katsina/Kaduna – 0.34 and 0.40 respectively.

Modeling results from other studies provide a context for the results. Silva and Clarke [16] obtained a value of 0.35 in Lisbon (Portugal) and 0.58 in Porto (Portugal). Hakan et al. [59] obtained a value of 0.51 for Texas (U.S.A), Clarke and Gaydos [14] obtained a value of 0.30 in San Francisco Bay (U.S.A), while Hua et al. [60] in Jimie district (China) obtained a value of 0.48. From these results it can be concurred that the calibration results are relatively successful for all the city pairs with the exception of the Bakori/Malumfashi pair which had a Lee Sallee metric of 0.12 and 0.01 respectively, as the Lee Sallee scale has a range of 0.1 for least fit to 1.0 for perfect fit [13]. These abysmal values of the Lee Sallee metric for Funtua, Bakori, and Malumfashi can perhaps be attributed to the fragmented growth of their urban settlements and relatively small housing units [16], and the expanse of the built-up areas of the cities. Thus, the calibration for these cities is a poor fit and not suitable for getting good prediction simulations.

3.5. Model prediction images compared to actual/reference images

The results of the successfully calibrated urban landscapes predicted and generated by the simulations are shown in Figs. 4 and 5. Figures with caption A represent the actual urban landscape while B represents the predicted simulated urban landscape of the particular year per city.

The visual images of the model predictions are highly illustrative of the model's sensitivity to local conditions. These images can be used to qualitatively assess and describe the changes and direction of urban extent over the years and degree of similarity of actual versus predicted images. They are also important for quantitative analysis. All of the predicted images of the cities show an underestimation of the urban spread over the years with the exception of Katsina cities which show overestimation in the north-western part of the city.

Table 5
Best-fit calibration values for the SLEUTH prediction stage.

Coefficient type	City					
	Kaduna	Katsina	Kano	Funtua	Bakori	Malumfashi
Dispersion	1	0	2	0	6	0
Breed	55	0	17	0	100	1
Spread	15	0	18	0	100	0
Slope	3	76	55	6	1	6
Road gravity	25	1	20	0	100	1

Table 6
Least square regression metrics for the city pairs.

Least-square regression metrics	City couple		City couple		City couple	
	Bakori	Malumfashi	Kano	Funtua	Kaduna	Katsina
Product	0.00000	0.00000	0.00454	0.00000	0.00026	0.00000
Compare	0.25775	0.72234	0.69073	0.73609	0.51420	0.66654
Population r^2	0.88196	0.37846	0.99438	0.81837	0.99164	0.77868
Edges r^2	0.80197	0.43378	0.81536	0.66607	0.05610	0.50643
Xmean r^2	0.88417	0.86151	0.35165	0.01597	0.11121	0.72862
Lee Sallee shape index	**0.11710**	**0.00700**	**0.25898**	**0.08204**	**0.39719**	**0.34330**
R^2 cluster	0.84025	0.66431	0.18570	0.18961	0.77335	0.47861

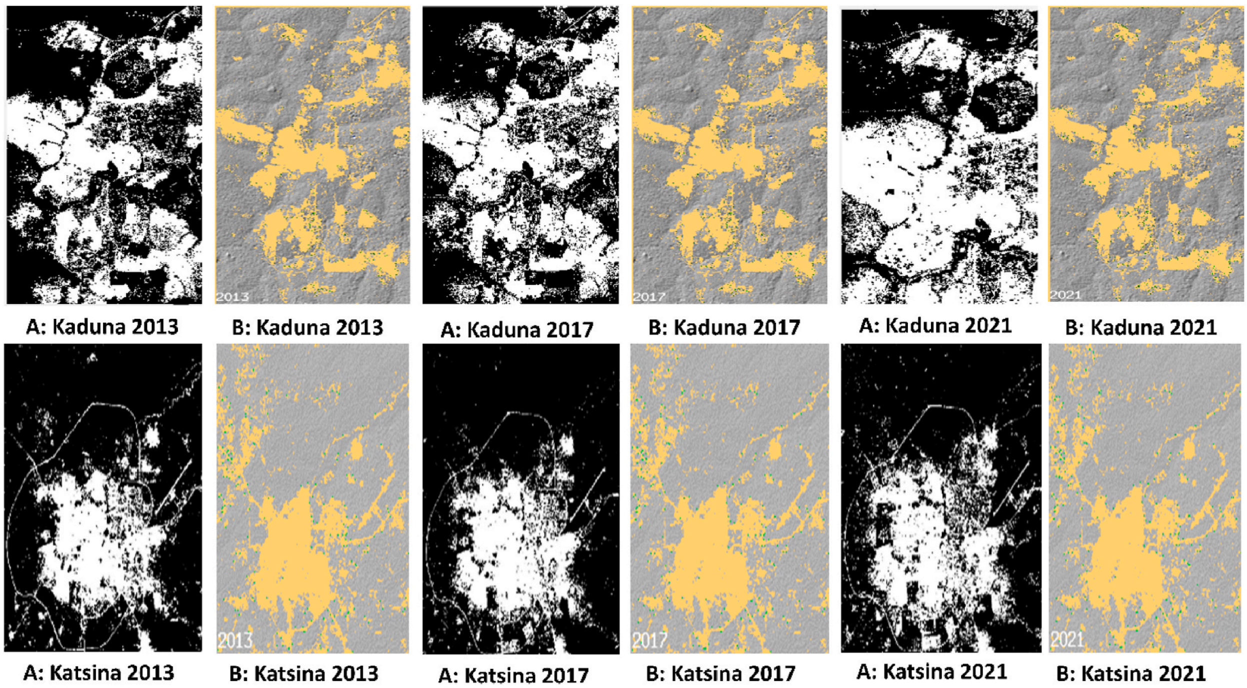

Fig. 4. Fig. 4: Comparison between the actual urban landscape (A) and simulated urban landscapes (B) for Kaduna and Katsina.

3.6. Jaccard coefficient results

There are two coefficients in the index, and they are the intersection – which refers to the quantity of elements common to the sets being compared. These are the elements that appear in both sets. The other coefficient is the union –this is the total quantity of discrete elements that appear in both sets combined. The limitations of the index are the size of the two sets being compared. That is, the quantity of elements in the intersection of the two sets cannot be greater than the smaller of the two sets, and the quantity of elements in the two sets cannot be smaller than the larger of the two sets. An illustration of Jaccard coefficient is shown in Fig. 6.

For the successfully calibrated city pairs, a prediction accuracy can also be evaluated with the Jaccard coefficient. The Jaccard values for the successfully calibrated cities are shown in Table 7 (Funtua was included for illustrative purpose only despite failing calibration).

The Jaccard accuracy tables in the result as presented in the tables showed that, for each city-couple, the city with the most expansive, urbanized built-up extent and more compact urban areas had a relatively higher Jaccard coefficient. This suggests underestimation by the model as a result of small unit size fragmented urban growth in the smaller city-pairs and heterogeneity of building materials. Unlike the larger, compact and more urbanized cities where buildings are more homogeneous and plot sizes larger, which is better captured by the spatial resolution of the satellite image used for the classification. Some studies [16,62] have found similar results.

The predicted maps presented in Figs. 4 and 5 also manifest a common theme. They mostly show underestimation of the urban areas when compared with the actual images of the urban landscapes. This is more pronounced in the sparsely populated parts of the cities. A number of factors could account for this. The inherent limitations of the model: disregarding non-physical factors, inability to perceive sudden policy changes, fixed parameters and mono-cell type. This could lead to wrong assumptions about the growth

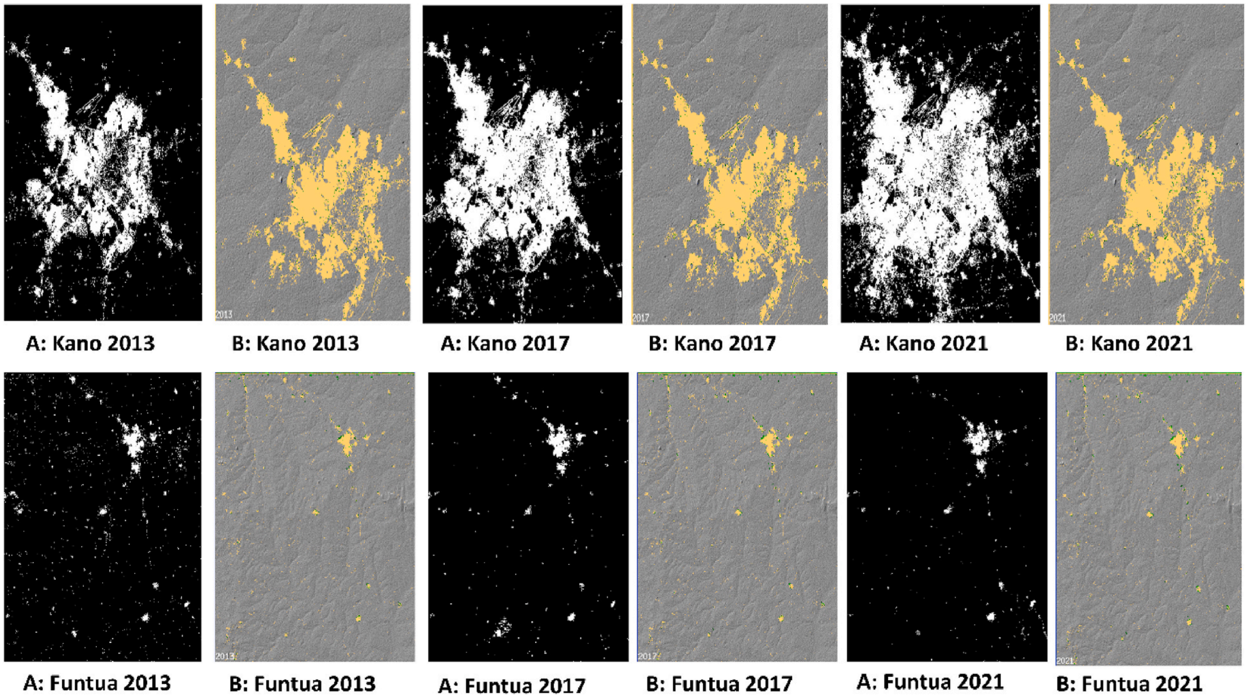

Fig. 5. Comparison between the actual urban landscape (A) and simulated urban landscapes (B) for Kano and Funtua.

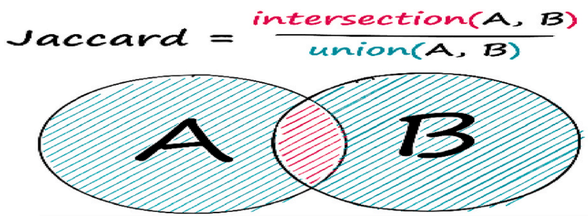

Fig. 6. Jaccard coefficient overlay (Source: [61]).

Table 7
Jaccard coefficient for city pairs.

Actual map year	Predicted Map							
	Kano		Funtua		Katsina		Kaduna	
	Jaccard coefficient	Average	Jaccard coefficient	Average	Jaccard coefficient	Average	Jaccard coefficient	Average
2013	0.25	0.48	0.03	0.02	0.43		0.78	
2017	0.44		0.02		0.44	0.48	0.99	0.83
2021	0.76		0.02		0.57		0.72	

projections of the cities. Also, the regulations governing land-use in cities of developing countries are often inapt. Lack of homogeneity of the cityscape, common to the study area could also mislead the model to behave in an unusual manner. Parameterization errors also factor in the model simulations; if the parameter settings do not represent the most accurate growth patterns of the cities errors in the simulation results occur. A lot of the developments that occur in these cities are not master-plan compliant, they're mostly informal, this too leads to mismatches between predicted and actual growth. Despite this the overall accuracy of the predicted maps is relatively high when the Jaccard coefficient is used to measure it. This accuracy is much higher in Kano and Kaduna cities which are the larger of their respective pairs and are relatively big cities.

The similarity between rasters is carried out by comparing their pixel values and other indices to gauge their similarity. Many methods can be used to do this as done with the Jaccard in the previous section, however the objective of a study will determine the best to use. It's important to use other evaluation metrics to ensure that the model results within the goals of a study are giving out valid results. The mean squared error will be used in the subsequent section to do this.

3.7. Mean squared error results (MSE)

This is another of the numerable techniques available to measure the differences between two rasters. The MSE calculates the average squared difference between corresponding pixel values in a predicted raster and the reference raster, while the Jaccard calculates the similarity between sets of pixel values in the predicted raster and the reference raster. The MSE's strong point is its ease of use and disregard for often times subjective human perception in its results. It is a quantification of how accurately a predicted raster mimics a reference raster. This is beneficial for this type of study. It is calculated by squaring the mean of the difference between the reference raster and the modeled raster in any order and squaring the result. This is then divided by the total number of pixels in the combined rasters. A value approaching zero indicates a greater fit between the two rasters and the converse indicates a lesser fit between the reference and modeled raster. Table 8 shows the results obtained.

The results of the mean squared error showed that Kano had a better fit between the reference raster and the modeled predicted raster with regard to its paired city, Katsina had a better fit than Kaduna, and the Bakori/Malumfashi both showed extremely low values. This is what was expected for the Kano and Funtua pair, as the Jaccard coefficient, and Lee Sallee metric also showed a better fit for Kano than Funtua in the previous sections. The mean squared error for Katsina and the Kaduna pair, however, diverged from the result pattern of Kano versus Funtua of which Katsina the less expansive and dense of the two pairs produced a lower value in the MSE showing a lower error. This is possible as a result of the fundamental differences in the indices the two metric measures. The MSE as stated in the previous section calculates the averaged squared difference between corresponding pixel values in two rasters in a 'pair-wise' manner, while the Jaccard calculates the similarity between 'sets' of pixel values. As for the Bakori/Malumfashi and Funtua results, it can be said that while low values are the desired outcome in MSE, the extremely low values for the three cities indicate overfitting. This suggests that for these three cities with these extremely low MSE values the model was likely subverted by random variations and noise. Also, as stated earlier, SLEUTH does not do well with dispersed settlements, which is characteristic of these three cities compared to the other cities.

From the above findings, it can be implied that there are limits in city size and density of urban form with which the SLEUTH model generates unsatisfactory calibration and prediction results. It is essential therefore, that the calibration has a high goodness of fit and the city to be relatively dense and compact for successful prediction purposes, otherwise modeling results cannot be reliable as a model's predictive power is what gives it value [16]. This signifies the model's unsuitability for some Nigerian cities and developing countries in general with these types of cities. All models by their nature have limitations; however, SLEUTH can still be used for many cities in Nigeria if certain city indices are suitable, that is, the expanse of the city, compactness of the urban settlements and the scale.

3.8. Factors influencing urban growth patterns in northern Nigerian cities

There is a clear relationship between the indices that govern the transport system, economic forces and population dynamics of northern Nigerian cities. Increasing population leads to greater demands on urban services and growth of informal settlements, while economic forces can also attract population groups around industrial and commercial activities [63]; transportation hubs are also a pull-factor for the development of urban areas and economic activities. Social services and facilities play a critical role. Finally, government policies and regulations play a distinct role in molding the direction of urban growth of cities [64].

The nature and scale of growth between the cities varies due to differences in factors such as investment potential, availability of infrastructure and services, education and manpower, resource availability and governance [65,66]. Kano and Kaduna are both relatively industrialized and older cities; Kano lies on the path of the old Trans-Saharan route and is presently a budding trading center, while Kaduna is the former capital of the defunct northern Nigerian region. These peculiar factors have influenced their growth patterns. The other cities-Katsina, Bakori, Malumfashi and Funtua are less industrialized, as such their growth trajectories will be different from the former two and of a slower dynamic. But Katsina is a state capital, and this will ultimately play a role in growth pattern compared to the other cities. Thus, a multitude of factors will play a role in how each city develops.

3.9. Limitations and future research

The limitations of the study are constraints arising from limitations in accuracy levels of the classified images used to derive the urban extent images, inaccuracies could occur too in the processing of the input data layers in GIS software to make them amenable for implementation in the model. Calibration may also be sub-optimal and may have not captured the best growth patterns and accurate trend of development of the cities over the study period. Further, the calibration process is computer resource intensive as the fine and final calibration phase can run for more than the better part of a day or even several days depending on the speed of the processor.

Future research should focus on more robust calibration methods. Methods to incorporate other factors in the SLEUTH model, such as socio-economic indices, should be explored further, as they may be a factor in the output of the results simulations. Including the ability to input real-time data and policy changes in the SLEUTH model, could also be explored by other researchers in the future.

3.10. Recommendations

It is recommended that urban modelers take cognizance of city size, type of urban growth, and resolution when modeling with SLEUTH in some cities that are similar to the cities used in this study, that had sub-optimal results. It is best to use high resolution images to get better classification results. Also, it is important to ensure that parameterization captures the growth trend as accurately as possible during the calibration process, especially the parameters related to dispersion to accommodate the scattered type of growth

Table 8
Mean squared error for city pairs.

Actual map year	Predicted Map											
	Kano		Funtua		Katsina		Kaduna		Bakori		Malumfashi	
	Mean squared error (MSE)	Average	Mean squared error (MSE)	Average	Mean squared error (MSE)	Average	Mean squared error (MSE)	Average	Mean squared error (MSE)	Average	Mean squared error (MSE)	Average
2013	0.08	0.12	0.0003	0.001	0.16	0.17	0.28	0.27	0.005	0.004	0.0004	0.0003
2017	0.11		0.0004		0.30		0.30		0.005		0.0003	
2021	0.16		0.003		0.17		0.23		0.002		0.00005	

in such urban areas.

4. Conclusion

The findings of this study showed that less developed cities can successfully be modeled with SLEUTH just like the developed cities around the world if the size of the cities and spatial resolution are taken into consideration. The limitation of the model is centered on the scale and urban settlement type, which play an important role in the success of the calibration of the model. The lack of consideration of size and spatial resolution of cites would lead to unsatisfactory prediction by the model as seen in Funtua, Bakori and Malumfashi in this study.

CRediT authorship contribution statement

Umar Ali Saulawa: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yahaya Ibrahim:** Writing – review & editing, Supervision, Project administration. **Abubakar Bello:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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