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Simulating Urban Growth Using Cellular Automata Approach (SLEUTH)-A Case Study of Praia City, Cabo Verde

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ABSTRACT In recent years, urban growth has become the center of attention and preoccupation for many researchers especially those concerned with urban planning. Some scholars only take into consideration the social dynamism and demographic data of an area of interest while analyzing the urban growth. However, those approaches fail to consider other physical conditions such as the urban extent and exclusion zones (e.g. rivers and forest reserves). This makes it difficult to correctly model the urban expansion as well as simulate for future forecast, which is vital for policymakers and city planners when making informed decisions. This study, therefore, used the Geographic Information System (GIS) to compile the data obtained from a time series of satellite images between 1984 and 2018 for the urban growth model calibration. A modified cellular automata methodology called SLEUTH was then applied to supervise and forecast the urban sprawl in Praia city, the capital of Cabo Verde from the year 1984 to 2050. The forecasted result showed that breed (100) and road (62) coefficients would influence the urban growth in Praia city. This means that there is a likelihood of newly generated detached settlements and many new buildings along the roadside.

INDEX TERMS Urban growth, remote sensing, GIS, cellular automata -SLEUTH and Praia city.

I. INTRODUCTION

Urbanization is a complex phenomenon, which can be assessed and monitored through modeling and simulation processes [1], [2], [3]. A proper urban growth monitoring comes in handy to urban planners by helping them control development in a sustainable way. With advances in technology such as remote sensing and Geographic Information Systems (GIS) [4], new horizons for analyzing spatiotemporal alterations of Land Use Land Cover (LULC) on a regional and global scale [5], urban/regional planning [6], [7] and the analysis of urban evolution through the implementation of specific models [8] can be carried out. In light of that, several urban growth models such as machine learning and statistical methods, cellular automata-based methods, sector-based economic methods, spatially disaggregate economic methods, agent-based methods and hybrid methods [3], [5] have been developed in recent years. These new developments have accelerated a more sophisticated approach to simulating the future processes of the Earth's surface. This is because monitoring and modeling of urban growth and land transitions have become a trend that satisfies the need for policymakers and planners to achieve precise and accurate LULC information [5].

Urban growth is a multifaceted dynamic process related to landscape change driving forces such as the politics, environment, geography and others that affect the city at multiple spatial and temporal scales. Understanding and describing these drivers and their interrelationship is a major task, but the constant reshaping of the landscape has made urban growth a subject of great attention in the last few decades. Moreover, to ensure environmental sustainability for the

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ever-growing urban population of the world, urban changes must be properly managed [9]. It is important to note that, through urban modeling, it is easy to identify the spatial and temporal components of urbanization [10].

Over the years, the different urban growth models [3], [5] developed has helped with the understanding and prediction of urban growth. These techniques can be seen as geospatial and statistical urban growth models that are able to tell the events and actions, and their impact in a specified time-space [11]. Moreover, these models permit the examination and extrapolation of the changing aspects of the city, which is of great value to academicians and developers. Technically, the geospatial and statistical urban growth modeling techniques could be categorized into empirical and Artificial Intelligence (AI) methods, respectively.

In this study, the empirical models refer to the early urban growth modeling techniques applied. Notable among them include ecological approach, social physical approach, neoclassical approach, behavioral approach, and system approach. Some examples of the application of this modeling techniques are: Weber [12], Lösch [13], Isard [14], Alonso [15], Lowry [16], Burgess [17], Harris and Ullman [18], Wilson [19] and Forrester [20] Liu [21]. These empirical methods concentrate on the patterns and processes of urban development by looking at it as an outcome of the combination of human choices and actions, and the wider social processes that placed constraints upon human actions [21]. For example, the ecological approach is centered on ecological principles like succession, dominance, competition and selection determined by human behavior. The defect in this approach lies in its oversimplification of urban ecology and thereby failing to explain much about existing patterns [21]. The social physical approach considers urban growth as human interaction in space by considering it as an analog to Newton's Law of Universal Gravitation. Therefore, there is a limited representation of the behavioral process that leads to an individual's decision in selecting a particular locality to reside [21]. The neoclassical approach, on the other hand, only considers economic activities like the driving force in urban development without considering the human behavior on urban growth. However, these models have been criticized by many researchers because they placed much emphasis on using qualitative analyses in urban growth research. Another disadvantage of the empirical models is that they are static, with little or no regard for the dynamic nature of urban development. The empirical models are also based on assumptions that are far from practical and by no means operational [21], [22].

To circumvent the limitations of the empirical urban growth models, scholars have resorted to the use of AI as a solution approach. This is because AI allows the inclusion of high levels of complex information existing in real-life problems in the modeling process that the empirical models could not represent [23]. Cellular automata (CA) and its different extensions are the AI techniques widely used to model urban growth processes based on the calibration methods and transition rules [24], [25]. Here, the technique can be applied to simulate the spatial pattern of an actual city or an artificial city [26]. CA incorporates LULC maps with neighborhood effects and information about the extent of change expected to predict future changes [27]–[35].

One of the variants of CA known as SLEUTH is the most widely and successfully applied technique for modeling and predicting urban expansion among the various CA models. The SLEUTH is a purely growth-oriented model that stands for its set of input data, namely Slope, Land use, Exclusion, Urban, Transportation and Hillshade. The model was first developed and applied to forecast urban sprawl in San Francisco and the Washington/ Baltimore regions [30] but has since been calibrated and applied to model the urban growth of other regions in the United States and the world. Some examples are, California counties [34], [35], Honolulu, Hawaii [38], Gdansk, Poland [39], Chiang Mai, Thailand and Taipei, Taiwan [40], Tijuana, Mexico [41], Alexandria, Egypt [42], Yaounde, Cameroon [43] Sydney, Australia [44] Adana, Turkey [4], Sana'a metropolitan city, Yemen [45], Tainan, Taiwan [46], Casablanca region, Morocco [8], Lisbon and Porto, Portugal [48] and the most recent Jinan City, China [47]. These studies have shown and reaffirmed the importance of combining SLEUTH, GIS and remote sensing in the study of urban growth at different times and places. The general understanding gathered from the previous works is that:

i. the SLEUTH is an appropriate model for studying urban evolution;
ii. the SLEUTH model is appropriate for coarse resolution and useful in gauging the potential of rural areas to become new urban centers of rapidly expanding cities [49];
iii. the spatial resolution and detail of the input datasets can influence the model while making it more sensitive to local conditions [48];
iv. applying a multistage calibration method can better improve the model parameters to find those that best reproduce the historical growth patterns of an urban system; and
v. the SLEUTH model parameters can be compared across diverse systems [48].

Although there has been an enormous use and implementation of SLEUTH in urban growth modeling, the majority of developing nations, particularly in Africa, are yet to explore and use SLEUTH in their urban studies. This study, therefore, explores the use of remote sensing data, GIS tools and the SLEUTH modeling approach for urban modeling in Cabo Verde for the first time. In view of this, this research applied the SLEUTH model to study the urban growth of Praia city in Cabo Verde.

Cabo Verde has a population of 514 000 inhabitants and 65% of this population is urban [50]. The high percentage of the urbanization is mainly as a result of the rural-urban migration, migration from other islands and neighboring countries to the capital city, Praia [51]. This population growth is increasingly affecting rural areas and the various cities in Cabo Verde. The urbanization has not been followed by political and /or housing programs, which can make available an effective response to demand. The result is the proliferation of unstructured neighborhoods made up of squatting or shattered structures in the suburbs of the capital, where buildings appear overnight, neglecting all kinds of building plans. Moreover, an increase in urban sprawl usually takes a toll on the city's road traffic volumes, increases pressure on local resources and reduces the number of open spaces. These changes in land use have a noteworthy negative influence on the environments and the goods and services that they offer. It also offers opportunities for informal and micro-entrepreneurs by promoting and enlarging their markets. Therefore, the renewal of the country's urban area will be an important driver of structural transformation in the years ahead [51].

For these reasons, the study on urban growth in Cabo Verde especially in Praia city will be very relevant in helping to understand the growth and changes that urban expansion brings. This is critical to agencies who monitor urban expansion and those who are in charge of managing resources and the provision of services in these rapidly changing environments. Modeling and simulation are the common procedures used to understand the complex dynamics of urban systems and evaluating the impact of urban growth on the environment. Therefore, this study will serve as an important document to:

- Geographers;
- Environmentalists;
- Planners, policymakers and everyone concerned with urban growth; and
- Assist as a base for forthcoming research works in this field in Cabo Verde.

The main research questions the study seeks to address include the following.

a) What are the physical characteristics of urban growth in Praia city?
b) Using the SLEUTH model techniques, what may be the future urban growth in Praia city?

To this end, the goal of this study is to model urban growth in Praia city using the power of integrated remote sensing data, GIS tool and SLEUTH model to monitor and forecast the urban growth.

II. STUDY AREA

The Republic of Cabo Verde is a West African country located approximately 450 km west of Senegal in the North Atlantic Ocean between 14° N - 18° N and 22° W - 28° W. It is composed of 10 volcanic islands and 8 islets. It has a land area of 4 033 km^2 and a 700 000km^2 Economic Exclusive Zone (EEZ) [52].

Santiago is the largest island, both in size and in population with an area of 991 km^2. It is the most populated island; accounting for 55% of the total population of Cabo Verde. The capital city, Praia is located in Santiago (Fig. 1).

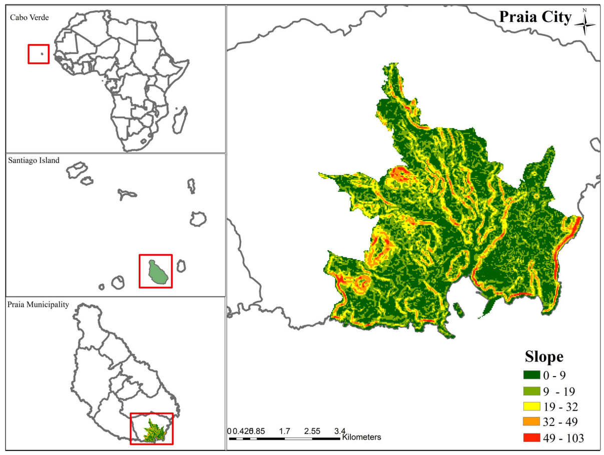

FIGURE 1. Map of the location of Praia city.

Praia is situated at the southern end of Santiago Island where it is bordered on the north by the peak of mountain Antonia and to the south by the limits of the maritime coastline. Praia Municipality covers an area of 102 km^2, which corresponds to about 10% of the entire surface of Santiago Island. However, this study only considered the urban areas of Praia, which covers an area of 33.2 km^2 and is also composed of 42 suburbs or small districts. The most important suburbs for our study are: Platô (city center), Achada Santo Antonio, Palmarejo, Fazenda, Achada Grande, Varzea, Safende, Sucupira (bazaar area), Calbeciera, Terra Branca, Vila Nova, Achadinha, Bairro, Prainha, Monte Vermelho, Achada Mato, Achada Sao Felipe, and other smaller ones.

As mentioned earlier, Cabo Verde's urban population represents about 65% of the entire country's population [53]. There has been a rise in the urban population over the years mainly in the capital city. This achieved urbanization rates around 96.6% and the population looks to continue rising in the future due to urbanization. There are several consequences of this urbanization such as rapid and uncontrolled expansion, inadequate basic services and housing in hazardous locations. Due to these, the present authors were motivated to study, monitor and forecast the urban growth of Praia city.

III. METHODOLOGY

A. INPUT DATASETS AND DATA PROCESSING

For the purpose of our study, a multi-temporal remotely sensed satellite image of the study area (Praia city) was used. The Landsat images used were downloaded from the United States Geological Survey (USGS), 2018, Earth Explorer Data System: U. S. Geological Survey database available online https://earthexplorer.usgs.gov/. (Accessed May 14, 2018). The images were less than 10% cloud-free with a 30-meter resolution. The Landsat images went through image preprocessing, including image enhancement, geometric correction, georeferencing, classification and information extraction. Data from other sources such as GIS digital data and topographic maps were also used.

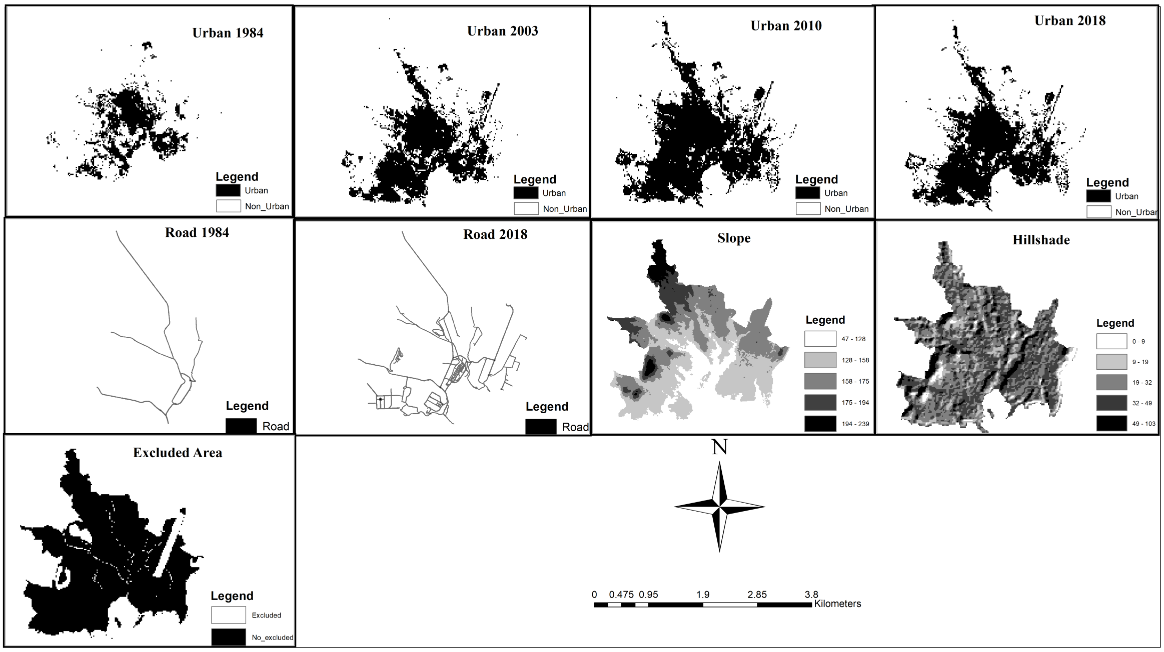

FIGURE 2. Input data layers of the study area.

The input data required by the SLEUTH model included slope, land use, exclusion, urban extent, transportation, and hillshade. The land-use layers are noncompulsory for the SLEUTH model and were therefore left out of the modeling. The input data layers used for the SLEUTH model are presented in Figure 2. The supervised maximum likelihood classification was used to classify the satellite images. According to prior knowledge, a brief reconnaissance survey, additional information from previous research works and general historical information of the study area, two different classes were defined: urban and non-urban from the years 1984, 2003, 2010 and 2018. Here, we considered urban as build-up, public infrastructure, airport and seaport. The urban extent was then extracted from the urban and non-urban defined classes. In order to perform the accuracy assessment, stratified random sampling was used to generate test pixels as presented in table 1. We found the accuracy percentage and Kappa coefficient to be satisfactory as can be seen in table 1. Transport layers were obtained from visual image description, on-screen digitization of the topographic maps and Google Earth image data. The substantial vector layers were converted into a raster with a 30-meter resolution. The excluded layers define all locations that are resistant to urbanization. These include areas where urban development is considered impossible such as water bodies, protected areas, seacoast and airport. Such places are given the value 100 while locations that are available for urban development are assigned a value of 0. The slope layer was extracted from a 30 m ASTER GDEM that was acquired from the USGS and altered to a percentage slope. The hillshade layer was also

TABLE 1. Accuracy percentage and kappa coefficient of classified satellite image.

Satellite image Year	Accuracy Percentage	Kappa Coefficient
1984	82	0.62
2003	90	0.80
2010	88	0.76
2018	90	0.79

generated for the study area from the same ASTER GDEM and subsequently used as the background to model the image output. The input data set for the SLEUTH model are shown in table 2.

A greater part of the data preparation depended on GIS and remote sensing techniques, such as data conversion, reclassification, and data import/export. The Input data were prepared and analyzed using ArcGIS 10.4, ERDAS imagine version 2014 and SLEUTH 3.0_beta run using Cygwin installed on Windows.

For the purpose of model calibration, the input layers were resampled into three spatial resolutions i.e., 200 m coarse, 100 m fine and 50 m final resolutions. All input layers have been enhanced into grayscale GIF images, with the same projection, resolution, and extent according to the naming format specified in the Project Gigalopolis website [54] for application in the SLEUTH model.

TABLE 2. Model data set for the SLEUTH.

Input layer	Prepared through the/source	Format and year
Urban extent	Classified from Satellite images	Raster 1984, 2003, 2010 and 2018.
Transportation networks	On-screen digitization from Google Earth image and image topo sheets.	Rasterized from vector, 1984 and 2018
Excluded layer	On-screen digitization from Municipal plan (Praia PDM)	Rasterized from vector
Slope	DEM generated by USGS	Raster
Hillshade	DEM generated by USGS	Raster

TABLE 3. Correlation among growth types and growth coefficients [57].

GROWTH TYPE	CONTROLLING COEFFICIENTS	SUMMARY DESCRIPTION
SPONTANEOUS	DISPERSION	SIMULATES THE RANDOM URBANIZATION OF LAND
NEW SPREADING CENTER	BREED	SIMULATES THE ESTABLISHMENT OF NEW URBAN CENTERS
EDGE	SPREAD-SLOPE	SIMULATES OLD OR NEW URBAN CENTERS SPAWN ADDITIONAL GROWTH
ROAD INFLUENCED	ROAD-GRAVITY, DISPERSION, BREED, SLOPE	SIMULATES NEWLY URBANIZED CELL GROWTHS ALONG TRANSPORTATION NETWORKS

B. SLEUTH IMPLEMENTATION AND CALIBRATION

The SLEUTH model is very popular among researchers due to its ability to integrate diverse stages of protection for diverse areas. It is also popular because of its success with local-scale modeling and its relative simplicity of computation and implementation.

SLEUTH Model is written in the C programming language and is made up of two inbuilt models; the Clarke urban growth model (UGM) and the land cover deltatron model (LCD) [55]. The UGM was used to simulate the urban growth of the study area. This model uses the standard gnu C compiler (GCC) and the LCD is inserted in the code and driven by UGM [56].

There are three major steps for the implementation of the SLEUTH model and they include test, calibration and prediction. It is important to conduct the test mode before the calibration phase. This is because the test mode model confirms the data sets and their initial response to the input data, including guaranteeing that they conform to data input specifications [48]. The test mode is succeeded by the calibration mode, where past growth patterns are replicated and forecasted [57].

SLEUTH model has five growth coefficients and each individual coefficient has a value that ranges from 0 to 100. These coefficients are dispersion, breed, spread, road gravity and slope. They are responsible for the control and interaction of four types of urban land-use changes which are spontaneous growth, new spreading center growth, edge growth, and road-influenced growth. These four growth types of urban land-use changes are applied consecutively throughout each growth cycle or year. In combination with the excluded layer probabilities, the five growth coefficients delimit the likelihood of

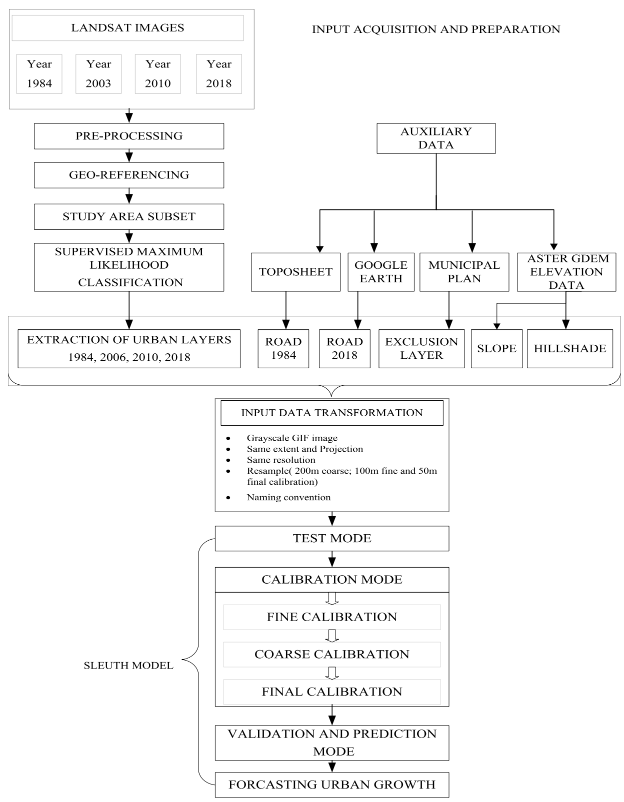

FIGURE 3. Methodology flow chart.

any given location becoming urbanized. Table 3 shows the correlation between growth types and growth coefficients. The user-defined excluded layer stipulates areas that are entirely or partially unavailable for urban growth.

In this study, a Cygwin Dynamic Link Library (DLL) run on windows operating software was used to compile the urban growth model. Figure 3 demonstrates the procedures for the implementation of the SLEUTH model in Praia City.

C. MODEL CALIBRATION

The calibration mode is the most crucial and complex step in SLEUTH modeling. It consists of three phases namely; coarse, fine and final calibration. The main objective of calibration is to obtain a set of values for the growth parameters that can successfully model the growth during the historic time period [58] which in our study is from 1984 to 2018. Between the phases of the calibration, we extracted the values that best matched the five coefficients controlling the behavior of the system. These five factors are diffusion (overall scatter of the growth), breed (likelihood of new settlements being generated), spread (growth outward and inward from existing spreading centers), slope resistance (flat ground is preferred) and road gravity (attraction of urbanization to roads and diffusion of urbanization along roads).

In order to carry out the calibration phase, there are two accessible methods, namely the brute force and genetic algorithm. Brute force uses a predetermined order of stepping through the coefficient space while genetic algorithm searches through the coefficient space in an adaptive manner [10]. For the purpose of this study, the brute force calibration method was used to derive parameter values and avoid the extensive computational requirements of calibrating the model. This method includes calibrating the model to the data in phases, successively narrowing the range of coefficient values and increasing the data resolution. This is normally achieved in three crucial steps: coarse, fine and final [54].

After each calibration run, 13 least squares regression metrics are produced by the model, such as compare (modeled final population), population (number of urban pixels), cluster (urban cluster edge pixels), edges (urban perimeter), Lee Sallee metric (a shape index), average slope, X mean (average X values), Y mean (average Y values), etc. [48]. Each metric represents the goodness of fit between the simulated growth and the actual growth for the control years. The selection of the range of coefficient to the subsequent phase of calibration is based on these 13 metrics (Table 4 provides a general overview of the SLEUTH indexes used in the calibration). There are several approaches that can be used to narrow the coefficient space such as weighting some metrics heavier than others, sorting on metrics equally and sorting only one metric [55].

For the purpose of this study, the optimum SLEUTH metric (OSM) was used to sort out the model parameters and narrow down the best coefficient in each phase of the calibration [59]. We downloaded the Optimum SLEUTH Metric code provided in the project Gigalopolis website [60]. After each calibration segment, we obtained the 'top 50' best-fit values by running the control_stats.log file using the OSM code. In the coarse calibration phase, we considered the widest range of parameter values from 0-100, where 0 is the start value, 25 the step value and 100 the stop value. We used 4 as the Monte Carlo iteration value and 200m as the lowest spatial resolution. In order to improve the modeling results, the parameter range and the size of increments were further narrowed down. Hence, in the fine calibration, the Monte Carlo iteration and image resolution used was 8 and 100m. For the final calibration, the Monte Carlo iteration was 10 and we used the full image resolution of 50m.

TABLE 4. Indices for assessment of the calibration outcomes on the SLEUTH modeling [48].

Index	Description
Compare	Correlation between the modeled final urban extent to a real final urban extent.
r^2 Population	Least square regression score of modeled sprawl as against actual sprawl for control years.
Edge r^2	The least-square regression score of modeled urban edge count equaled with actual urban edge count for control years.
R^2cluster	Least square regression score of modeled urban clustering equated with acknowledged urban clustering for control years.
Lee salee	A shape index, a proportion of spatial fit among the modeled development and the known urban extent for control years.
Average slope r^2	Least square regression of average slope of recognized urban cells for control years.
% Urban	The percent of presented pixels urbanized throughout simulation matched to the actual urbanized pixels for each control years.
X- r^2	Center of gravity [x]: Least square regression of average x values for modeled urbanized cells equaled with average x values of identified urban cells for control years.
Y-r^2	Center of gravity [y]: Least square regression of average y values for modeled urbanized cells associated with average y values of recognized urban cells for control years.
Radius	The average radius of the circle that surrounds the replicated urban pixels linked to the actual urban pixels for each control year.

The coefficient values that best simulate historical growth for a region is produced through the calibration phase. However, as a consequence of SLEUTH's self-modification abilities, coefficient values at the START_DATE of a run may be modified by the STOP_DATE. For prediction initialization, the STOP_DATE values from the best-calibrated coefficients are desired. Using the best coefficient resultant from calibration and running SLEUTH for the historical time period will produce a single set of STOP_DATE coefficients to initialize forecasting. However, based on the random variability of the model, the results of the averaged coefficients of many Monte Carlo iterations will produce a more robust forecasting coefficient set [54]. Due to this, we used the best parameter values from the final calibration with a one-step value and 100 Monte Carlo iterations to derive the best fit values for the predictions.

TABLE 5. Calibration results.

Calibration Phase	Compare	Pop	Edges	Clusters	Size	Lee salee	Slope	% Urban	X mean	Y mean	Rad
Coarse	0.88969	0.97814	0.97963	0.19268	0.85377	0.56829	0.55723	0.99952	0.80814	0.86096	0.98075
Fine	0.94788	0.99533	0.90832	0.24581	0.67102	0.57852	0.73121	0.99927	0.08691	0.88782	0.99559
Final	0.86052	0.99859	0.58542	0.58461	0.84998	0.58138	0.91710	0.99807	0.44118	0.93312	0.99831

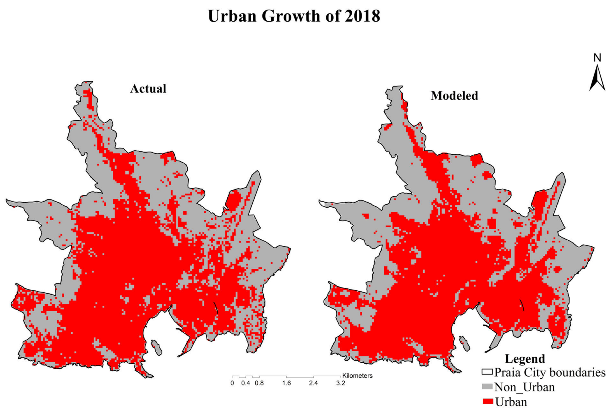

FIGURE 4. Correlation between the actual and modeled growth of Praia city.

D. MODEL VALIDATION AND PREDICTION

The efficiency of the SLEUTH model can be validated by equating the number of the simulated pixels to the number of urban pixels presented in the urban extent layers from the Landsat images using the maximum likelihood classification method. The prediction of best-fit values was also derived from an avg.log file produced in the course of the final calibration and subsequently used as the coefficient to run the forecast. One hundred Monte Carlo iterations were performed and we used one as the step value. The model was initialized with 1984 urban extent and growth was predicted up to the year 2018. After the visual interpretation and comparison between the modeled urban growth and the actual urban growth (supervised maximum likelihood), we came to the conclusion that the SLEUTH model successfully generated the overall urban growth of Praia city by 2018 (Figure 4).

The confusion matrix is calculated for the observed versus forecast urban areas in 2018. We observed a high overall classification accuracy of 92% and a high kappa coefficient, 0.84 between observed urban area and predicted urban area.

Models are often judged by their predictive power [48]. Prediction is the last stage of SLEUTH modeling and it depends on repeating growth tendencies from the past. Therefore, after successful calibration, the best-fit coefficients were used to predict the urban growth of Praia city to the year 2050. Here, a full-resolution data, 100 Monte Carlo iterations with one step value were used. The main result from the prediction

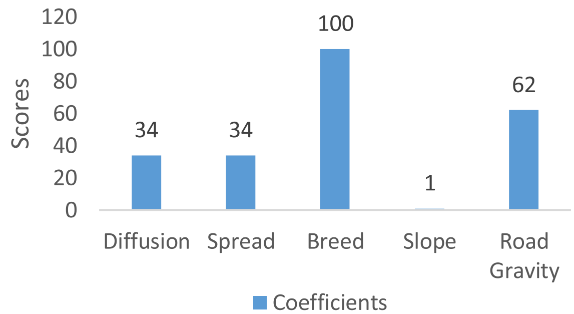

FIGURE 5. Prediction best-fit values.

is a probabilistic map of Praia city from the year 2018 to 2050 showing the possibility of the grid cells being urbanized in the future.

IV. RESULTS AND DISCUSSION

A. CALIBRATION

Most statistics for the best-fit parameters of the outcome of the simulation of Praia city shows high values of fit. This demonstrates that the SLEUTH model can reproduce previous growth (Table 5). This also implies that future growth forecasts can also be embraced with great confidence.

The calibrated results (table 5) show that the final calibration at the calibration phase was more suitable for our study area. Our study also illustrated that the metrics with high summary correlation were "population" (pop) and urbanization (% urban), both having a value of 0.99, which is similar to results from Rafiee *et al.* [61], Feng *et al.* [62], Akin *et al.* [63] and Sandamali *et al.* [64]. This means that the SLEUTH model predictions based on the initial seed year of the present urban pattern using those refined values are very similar to what happened in reality.

The compare and Lee-Sallee indicators (table 4) of our SLEUTH model were greater than 0.86 and 0.58, which suggest acceptable accuracy of the calibration when compared to other comparable studies of Dezhkam et al. [65] and Bihamta *et al.* [66]. The Average slope r^2 and Y-r^2 (see table 4 for description) increased from coarse calibration (Average slope r^2 is 0.55; Y-r^2 is 0.86) to final calibration (Average slope r^2 is 0.91; Y-r^2 is 0.93). Moreover, most of the metrics in our study area increased with an increase in spatial resolution,

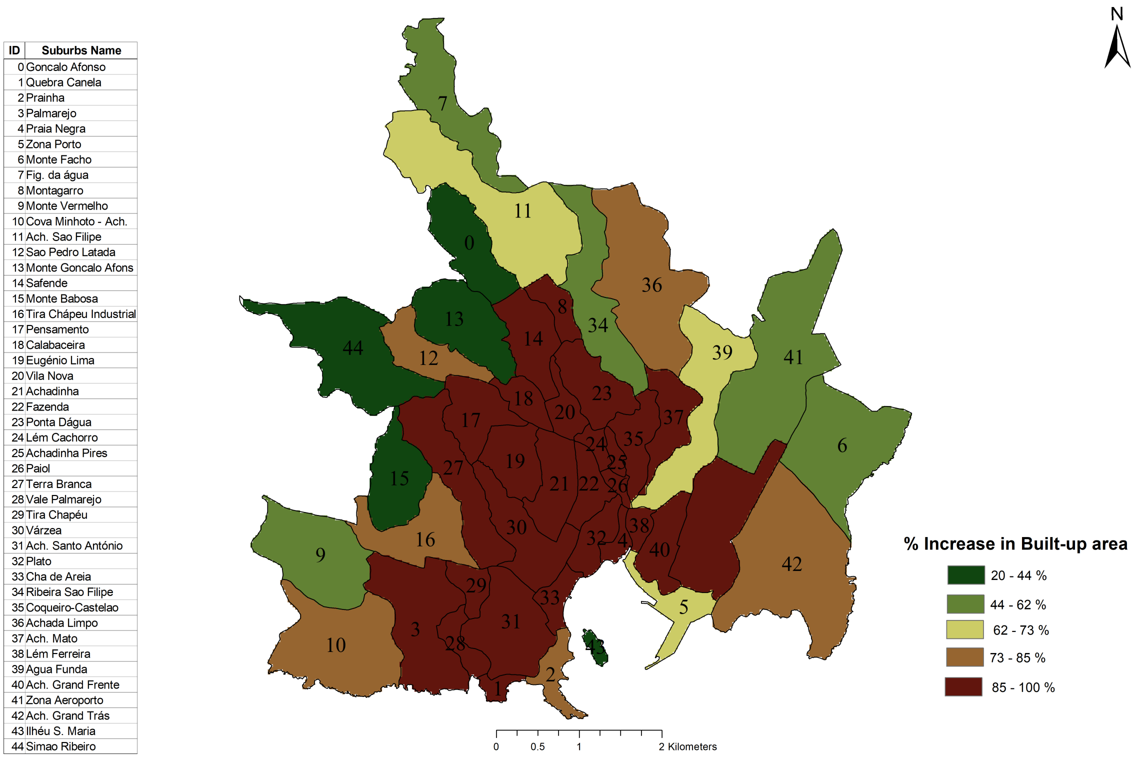

FIGURE 6. Probability of increase in build-up of Praia city from 2018-2050.

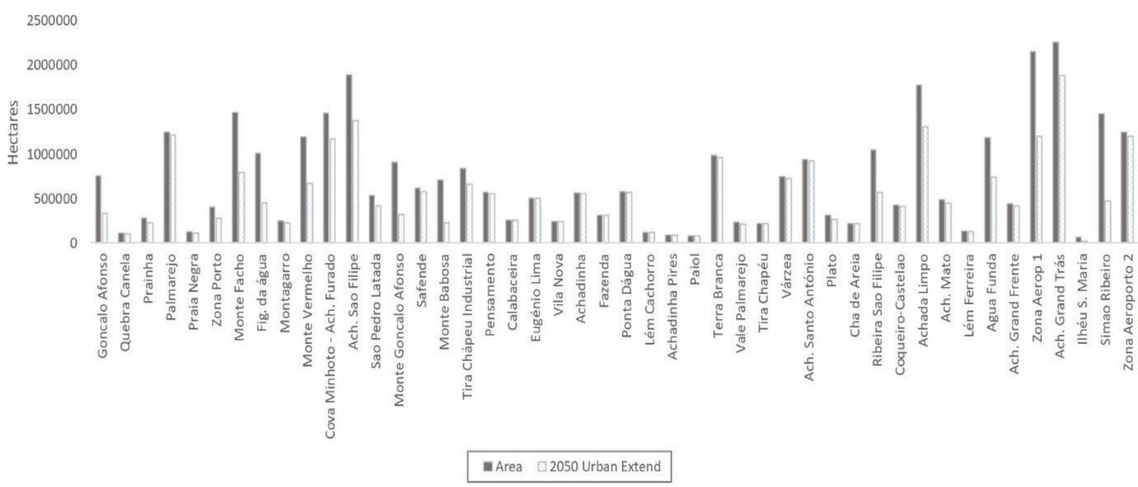

FIGURE 7. The relationship between the urban expansions in the suburbs of Praia city by the year 2050 with their corresponding areas.

indicating that the SLEUTH model was able to deal with the existence of high undulations in the study area.

B. PREDICTION

The best fit values for the prediction were derived from the avg.log.file that was created during the final calibration and these values are presented in Figure 5. This demonstrated a high score in the breed, which mirrors a great possibility of the creation of new urban centers in Praia City. These results are similar to the findings of other studies (Dezhkam *et al.* [65] and Rafiee *et al.* [61].

The low score in the spread parameter also reflects a low possibility of outward urbanization from the current urban centers. The low diffusion parameter indicates that Praia City has a compressed form of growth with its focal urbanization happening close to the present urban areas and urban cores. This can be attributed to the possibility that the establishment of new urban centers near the main city center through

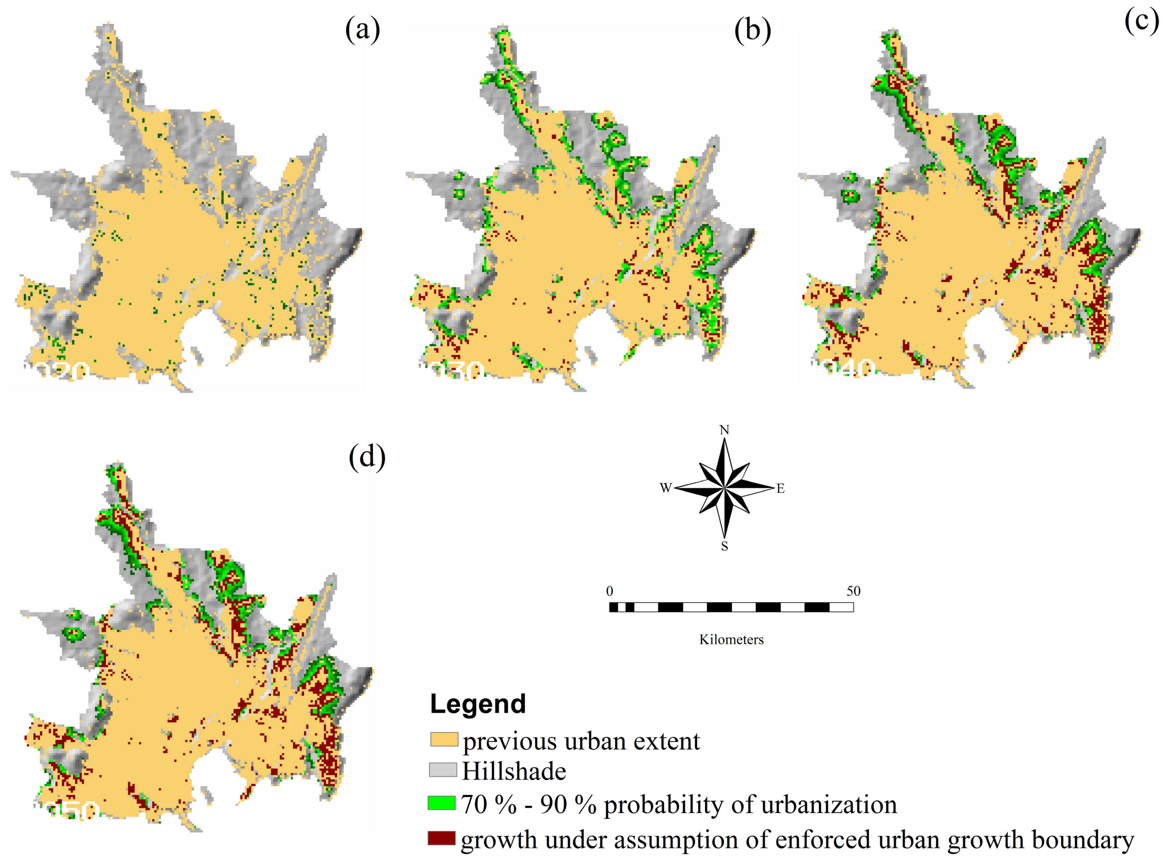

FIGURE 8. **Prediction of Praia city's urban expansion (a) 2020 (b) 2030 (c) 2040 and (d) 2050.**

spontaneous growth is very low. The high road gravity score shows that road networks have affected urban growth significantly. Finally, the lowest score for slope means that the topography was not a restrictive factor for urban sprawl. These results are the same when compared to the findings of other studies such as Dezhkam *et al.* [65], Rafiee *et al.* [61] and Sandamali *et al.* [64].

According to the SLEUTH forecast results, we can say that urban expansion in Praia city is a mixture of breed coefficient and road gravity. Therefore, the urban sprawl by 2050 will be more influenced by breed with a high coefficient value of 100 and then the road gravity with a coefficient value of 62. The maximum coefficient value in the breed as we stated previously means that the future growth type in Praia city will be "new spreading center" of which the main character will be the establishment of new urban centers. The high road gravity coefficient indicates the abundance of urban growth along the roadside and as a result, many new buildings will be developed along the roadside. According to Silva [67] who worked on the urban expansion of Praia city, different factors influenced urban expansion in different forms and at different times. For example, only two variables, population and road density explained 90% of variation in urban expansion in the year 1993, population, distance from industrial zones, and road density explained 81% of urban expansion in 2003, and in the year 2010, distance to arterial roads, road density, and extent of infrastructure explained 63% of urban expansion. This study supports the SLEUTH result concerned with the road gravity influence in Praia city urban growth.

As can be seen from Figure 6, the suburbs with more probability of increasing in build-up area by 2050 are Pensamento, Plateau, Varzea, Safende, Achadinha, Fazenda, Eugenio Lima, Ponta Dagua, Tira chapeu, etc. Most of these suburbs are older suburbs that have seen a boom of formal and spontaneous construction in recent years. The Sleuth prediction showed that between 85 to 100 percent of these areas will be urbanized by the year 2050, and there will be an emergent need for new urban settlements in suburbs such as Achada Limpo, Tira Chapeu industrial and Cova Minhoto, where the urban expansion was not very accentuated in 2018. It is therefore very important for the entities responsible for planning the city to pay attention to these areas to prevent unauthorized constructions and avoid the negative consequences it will bring. When this is done properly, the future expansions will be in consonance with the Praia city PDM [68].

Figure 7 illustrates the relationship between the urban expansions in the suburbs of Praia City by the year 2050 with

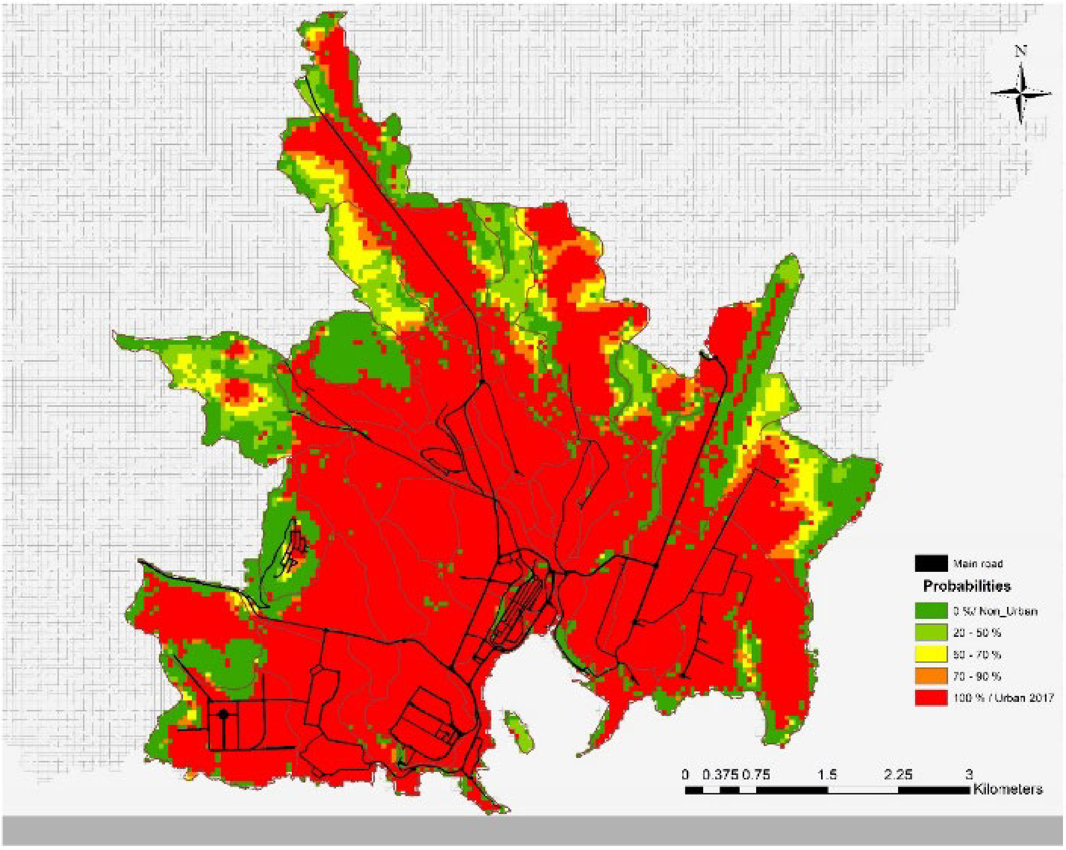

FIGURE 9. The probability Map of Praia city urban growth of 2050.

its corresponding areas. Considering the results of this figure, we concluded that there is no direct relationship between the area size of the zones and urban growth. This is because the older zones tend to be more urbanized than the newer ones. For instance, there are suburbs like Plateau, Quebra Canela, Prainha, Pensamento, Fazenda, Safende, Paiol, and Achadinha Pires, which are small in size but will be 100% urbanized by 2050. On another hand, there are suburbs with large areas and available land for urban expansion like, Goncalo Afonso, Monte Facho, Ribeira de S. Felipe, Simao Ribeiro, Zona do Aeroporto, and Achada Limpo, that will not have much pressure compared to the ones mentioned earlier. This could be for the fact that these areas are relatively distant from the principal center of Praia city. Despite these zones not being 100% urbanized, the prediction shows a great increase in the build-up in those zones compared to 2018.

Historical growth shows that there are no limitations to urban growth. Urban renewal can, consequently, be an imperative driver of structural transformation in the coming years. Praia city will expand from 62% in 2020 to 88% by 2050. This growth as per our research will not be at the same rate at all times. It is, therefore, logical to address the issues that, over the next three decades, the available free lands of the city will be under a dense pressure. As can be seen from Figure 8, there was a high percentage increase in urban growth from the year 2020 until 2040, and then from 2040 to 2050, the urban growth rate slowed down. The slowing down of the urban growth rate from 2040 to 2050 could be attributed to the limitation of available land in Praia city at that time, which could possibly lead to the expansion of Praia city beyond its borders into other parts of Praia municipality.

The slope has a low coefficient that translates into a small effect on the possibility of the study area becoming urban in the future. This has translated into overcrowding in the city, leading to irregular settlements caused by limited access to land in Praia city. This situation is causing people to build on steep slopes and waterbeds, which are dangerous for settlement.

Our study shows that the situation of constructing on steep slopes and waterbeds may continue into the future and we recommend that decision-makers responsible for the urban planning of Praia city pay special attention to these areas.

The extension of the urban sprawl of Praia city that has not been inhibited hitherto until 2018 has a 20–50% chance of being urbanized by the year 2050. An example of such an unoccupied area is ilheu Santa Maria. This fact is confirmed with the integrated tourist project of ilheu S. Maria and Gamboa, which will occupy an area of 17.08 hectares, 3.52 hectares on Gamboa beach, 3.17 hectares on the sea and 10.39 hectares on the ilheu Santa Maria.

Figure.9 illustrates the probabilities of future urban growth and extent of Praia city according to the model simulation.

The presented results in this study, when compared with other previous works, indicate that the SLEUTH model is appropriate for urban evolution studies. For example, Garcia *et al.* [69] compared some of the most widespread urban CA models, namely MOLAND, Engelen, Wu, SLEUTH and White to assess how these models conform to the simulation of urban land-use change patterns in a study area with different characteristics from those in which these models are commonly applied. Among the models considered, the results showed that the Wu and SLEUTH models when comparing real and simulated growth produced a much lower new growth and a much higher infill growth. In Berberoglu *et al.* [4], the focus was to quantify the amount of urbanization in the fast-growing Mediterranean city of Adana and determine the most appropriate model for the region. The CA modeling approaches applied include Markov Chain, SLEUTH, Dinamica with Logistic Regression (LR), Regression Tree (RT) and Artificial Neural Networks (ANN). The results revealed that for the gain and loss of built values, SLEUTH and Markov models were the most consistent with the real data in terms of allocation maps. The respective Kappa results were 0.7463, 0.7214 and 0.7108 with SLEUTH the most accurate followed by Markov Chain and RT, respectively.

V. CONCLUSION

In 1990, 56% of Cabo Verde's population lived in urban areas. In two decades, this had increased to more than 60%, making it one of the most urbanized countries in Africa [53]. Our study area, Praia city, which is the administrative seat of the government of Cabo Verde and the country's commercial center, shelters more than 25% of the nation's population. It is also, where many local and international firms and organizations are situated. The construction of the country's international airport and improvement of the seaport in Praia have added additional economic dynamism to the city.

The result of the application of the SLEUTH to model the urban growth of Praia city shows that the city will continue to grow in the future. The results from this study further demonstrate how the SLEUTH model, a form of cellular automata, can successfully model and forecast the urban growth of Praia city using historical data. This research also brought to light the fact that SLEUTH can be useful in estimating the potential appearance of new urban centers in the future.

We, therefore, conclude on the basis of the results from the urban growth modeling in Praia city using the GIS tools Remote sensing Data and SLEUTH model as an alternative approach in assisting the managers and decision-makers of the city when making informed decisions. This information can be useful in order to take preventive measures and control the negative effects of the predicted changes. It can also be used to make provisions for future infrastructures to avoid unwanted changes in the city.

To this end, despite a large number of artificial intelligence (e.g. cellular automata, artificial neural network, decision trees, etc.) applications in urban planning, approaches for integrating spatial and aspatial dynamics are scarce in the literature. One reason is the lack of high-level architecture that integrates different artificial intelligence techniques. Such an integrated approach will enable the methods to complement each other's weaknesses and strengths thereby improving the urban modeling results. Furthermore, AI-based urban modeling is interdisciplinary, relating to many subjects such as computer science, urban studies, system theory, architecture, engineering, geography, and economics; any limitations imposed by subjects will restrict the development process of the modeling [23]. Therefore, it is suggested that in future research works, integration of different artificial intelligence-based methods to create a hybrid urban growth modeling technique can be considered.

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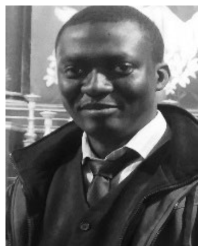

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