Urban Growth and Land Use Simulation Using SLEUTH Model for Adama City, Ethiopia

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Abstract. Urban Growth Model has been adapted to study the urban growth and its impact on the surrounding environment. Here a cellular automaton model known as SLEUTH has been standardize using multi historical digital maps of areas to forecast the future coverage of an urban and land use. The model will use the best fit growth rule parameters by narrowing coefficients throughout calibration mode and passed down to predict future urban growth pattern, generate various probability map and LULC map. As per SLEUTH modelling, the generated future urban growth pattern prediction of Adama city shows that nearly 42.89% urban rise in 2020, 46.85% in 2030, 49.15% in 2040 and 50.49% in 2050. Generally, the expansion of the urban growth pattern is exhibiting new spreading centre which are indication of a city to expand also the result present useful information for future urban planning and improvement.

Keywords: Urban growth · GIS and remote sensing · SLEUTH

1 Introduction

Modelling urban growth is a significant information for analysis and evaluation towards the sustainable improvement of a city. The ecological effects and degree of urban issues have been developing and producing solid imbalance between the city and its environment. The need to address this intricacy in evaluating and checking the urban arranging and the executive's procedures and practices is unequivocally felt in the recent years (Lavalle 2002).

The international contributors are progressively connected with the critical ecological errands for the feasible improvement of their urban areas, the planning difficulties looked by the nearby authorities, and the significance of remote sensing data and GIS techniques in the investigation of urban growth to address these difficulties. Deciding the rate of urban spatial arrangement and urban growth, from remote sensing data, is a pervasive approach in contemporary urban geographic studies. Characterized urban structure, map of growth from remotely sensed data can help planners to visualize the directions of the urban, basic frameworks, functions, and structures (Bhatta et al. 2010). However, despite the fast improvement of remote sensing technologies, there is no end phases of intriguing

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logical inquiries to be posed about urban areas and their growth, however at times these inquiries don't coordinate the operational exertion and uneasiness of a given city. This requires increasingly engaged research and discussion in the territories of urban growth analysis, in perspective on their applications (Bhatta 2012).

The study aims to predict future urbanization, by compiling remote sensing, GIS, and SLEUTH model with cygwin as a tool with the intention that the urban growth and the land transformations.

2 Study Area

Adama (see Fig. 1) is a central city in Oromiya regional state and a major city of Ethiopia. It is about 98 km away from Addis Ababa in the southeast direction. Its approximate location is 8°33′35′ N–8°36′46′ N latitude and 39°11′57′ E–39°21′15′ E longitude in a UTM/WGS84, zone 37 N projected coordinate system. The city has an average altitude of 1,712 m (5,617 ft) above mean sea level (a.m.s.l).

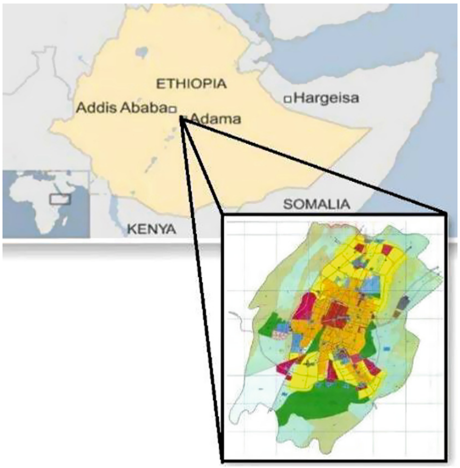


Fig. 1. Study area.

3 The SLEUTH Model

Sleuth is a cellular automata (ca) based model that recreates urban growth and land use changes through time. The model has been applied to various urban areas and in many regions of the world (Chaudhuri et al. 2013; Clarke 2008; Clarke and Gaydos 1998; Clarke et al. 2007; Clarke et al. 1997). The name sleuth originates from GIS input data images that are incorporated into model: slope, land use, exclusion layer (where development can't happen), urban, transportation, and hill shade (Gazulis and Clarke 2006).

SLEUTH is a firmly coupled model including two modules, the Urban Growth Model (UGM) and the DELTATRON Land Cover (LCD) Model. The UGM is a C program running under UNIX that uses the standard GNU C Compiler (GCC) and might be executed in parallel. The LCD model is incorporated inside the code and will be called and driven by the UGM. The LCD is firmly tied with an urban rule, while UGM can run autonomously. Together, these joined models are called to as SLEUTH.

In the structure of the SLEUTH model as appeared in Fig. 2, the urban territory inside this CA model work as a living organism trained by a limited arrangement of transition rules that impact the state changes inside the two modules in a set of nested loops. During model adjustment, the outer control loops executes Monte Carlo iterations on chronicled maps and scans for the parameters that best repeat the changes between input data of the first year (the seed layer) and the last year, holding aggregate factual data. The second or the internal loop executes the growth rules to imitate the growth and advances between the individual input time frames (Clarke and Gaydos 1998; Sietchiping 2004; Gazulis and Clarke 2006; Dietzel and Clarke 2007).

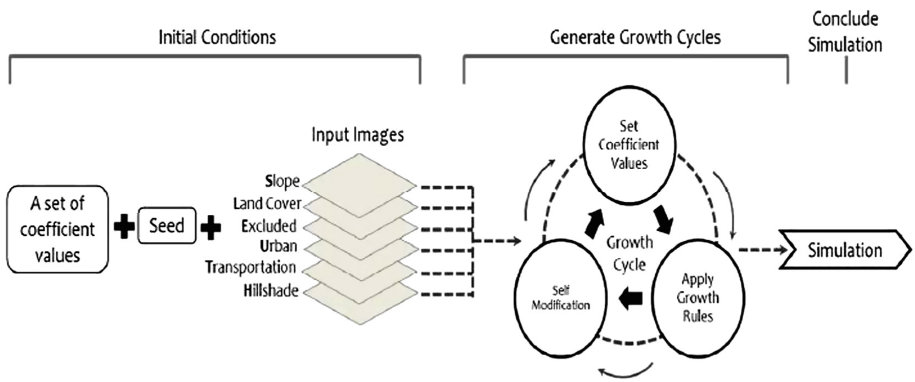


Fig. 2. Structure of the SLEUTH model (Chaudhuri and Clarke 2013).

SLEUTH modelling start by calibrate the historical input data to derive a set of five control parameter coefficients (dispersion coefficient, breed coefficient, spread coefficient, road gravity, and slope resistance) which control the behaviour of the system and encapsulate the past urbanization trends of that region. The impact of these coefficient values determines the degree to which each of the four growth rules influences urban growth in the system (Clarke et al. 1997; Gazulis and Clarke 2006).

The most generally utilized calibration procedure is known as brute force calibration, and during this mode of the modelling, a set of control parameters are refined by three consecutive calibration stages: coarse, fine and final calibrations (Silva and Clarke 2002; Dietzel and Clarke 2007).

The Optimal SLEUTH Metric (OSM) (Dietzel and Clarke 2007) is utilized to determine the best fit (level of closeness between simulated images and control years) and to give the most robust outcomes to SLEUTH calibration (Clarke 2008). The ideal arrangement of parameters dependent on the OSM produces a yield map that most intently looks like the control data (Dietzel and Clarke 2007; Clarke 2008) and is utilized in the subsequent stage of calibration. The mix of parameters with the most noteworthy OSM value in the final calibration stage is then utilized for prediction, after adjustment to reflect their values at the end of the calibration period rather than the start. At long last, the accuracy of the anticipated maps is estimated outside the model utilizing distinctive map correlation techniques and an observed map of the anticipated year (if accessible).

The model simulation is comprised of a progression of growth cycles and four sorts of growth can occur in the model: Spontaneous, Diffusive, Organic, and Road influenced growth of the non-urbanized cells (Clarke and Gaydos 1998). Aside from the initial growth rules there is a second degree of rules, which controls the conduct of the large-scale framework called the 'self-modification' rules. These rules react to the total growth rate, they begin to increment or abatement the growth control parameters in every one of the accompanying growth cycles (Sietchiping 2004). Self-modification is imperative to keep away from straight or exponential growth of the zone in the model (Silva and Clarke 2002). Table 1 shows the relation between every growth rule with growth coefficients that control the growth rules.

Table 1. Type of growth rules and controlling coefficients.

Growth cycle order	Growth rules	Controlling coefficients	Summary descriptions
1	Spontaneous	Dispersion, Slope	Simulates random urbanization of new growth cells
2	New Spreading Center	Breed, slope	Simulates development of new urban growth cells
3	Edge	Spread, slope	Branched growth from existing urban centers
4	Road-Influenced	Road-Gravity, Dispersion, Breed, slope	Simulates development pattern along transportation network
Throughout	Slope Resistance	Slope	Slope effect on urbanization
Throughout	Excluded Layer	User-Defined	Excluded development areas specified by users

3.1 Input Data

For measurable calibration of SLEUTH model, six different input layers are required. From Table 2, input data shows that the topographic data (slope and hill shade) got from Aster digital elevation model; two land use layers of the year 1984 and 2014 utilized for anticipating area use in the deltatron land use model; regions over 25% slope fined as undevelopable in the excluded layer; four urban layers (arranged from Landsat 5 TM (1984 and 1994), Landsat 7 ETM+ (2004 and 2014); and four weighted street system maps utilized from various timeframes (Chaudhuri and Clarke 2013). All information must be in grey scale.gif image files with a steady number of lines and segments.

A supervised classification was performed on the images for land use grouping. The study area has been sorted into five distinctive LULC classes, in particular, urban, agriculture, shrub and bushes, barren area and hilly area. The target of supervised classification is to arrange each image pixel into one of a few pre-characterized land type classes (Harris 1965). For the urban layer, the developed regions was considered as urban and the rest of the region was classified as non-urban and the street layers were made from 1984 to 2014 topographic maps.

Table 2. Detail of input data sets for SLEUTH modelling.

Input data	Input data type	Format & input data years
Slope layer	DEM	Raster (in percent) (1)
Land cover layer	Landsat TM, ETM	Raster, 1984 & 2014 (2)
Exclusion layer	Landsat TM	Rasterized from vector (1)
Urbanization layer	Landsat MSS, TM, ETM	Raster, 1984, 1994, 2004, 2014 (4)
Transportation layer	Shapefiles	Rasterized from vector, 1984, 1994, 2004, 2014 (4)
Hill shade layer	DEM	Raster (1)

4 Methodology

The flow chart of the proposed technique embraced in SLEUTH modelling for simulation of urban growth and land use appeared in Fig. 3. In the first place, readiness of input data is carried out i.e. preparation of slope map, land use map, exclusion map, urban map, transportation map and hill shade map. Since SLEUTH has the ability to consider different factors and limitations responsible for urban growth, urban growth has been determined utilizing best in class SLEUTH model. Further, examination utilizing SLEUTH has three consecutive steps, which are Calibration mode and Prediction mode utilizing various spatial lattices. The input data were adjusted utilizing data up to 2014 and anticipated from 2020 to 2050. After thorough calibration of the SLEUTH model, the best-fit parameter esteems were utilized to run predictions from 2014 to 2050 (Chaudhuri and Clarke 2013).

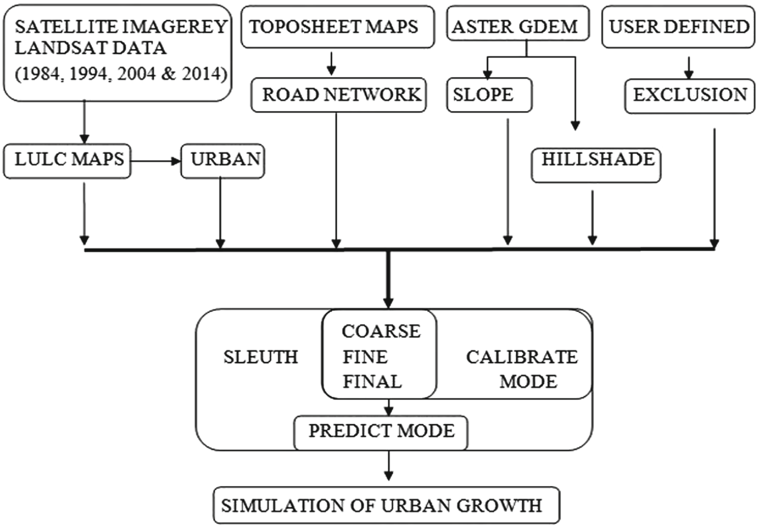


Fig. 3. Flowchart of methodology adapted for SLEUTH.

5 Result Analysis

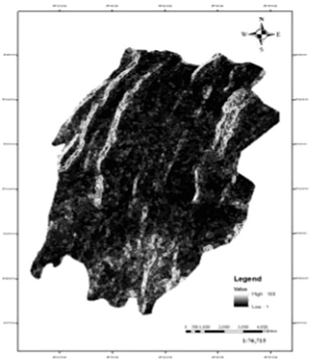
5.1 Input Data Preparation

Two types of datasets have been prepared. One category belongs to GIS obtained dataset using satellite imagery including ASTER DEM and the other one is prepared using topo sheet map. From satellite imagery different types of maps have been prepared one is LULC map, urban map, slope map, exclusion map and hill shade map. Using topo sheet transportation map have been prepared. (See Fig. 4). Shows different input map in a different years.

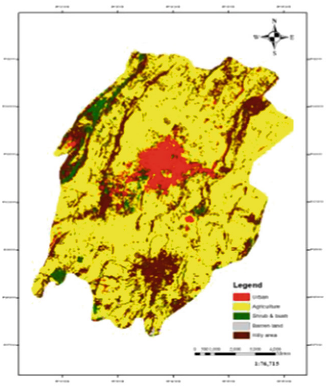
5.2 Model Calibration

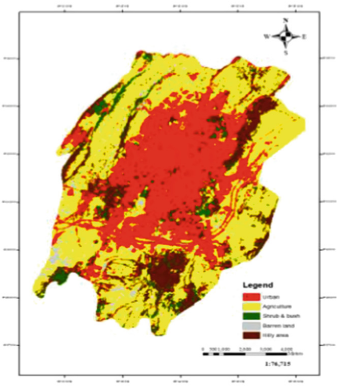
Calibration is the most mind-boggling mode in SLEUTH. Every blend of coefficient set is created by START, STOP and STEP values so as to introduce a run (R). Each run will be executed by MONTE CARLO ITERATIONS number of times. Generally, calibration is practiced in three stages: coarse, fine and final, which is reflected in the best scope of model's coefficients.

In Table 3, the result of model calibration coefficient are appeared. In the coarse stage, the underlying parameter go for all growth coefficient is 0–100 which is the incentive for start and stop respectively. Consequently, in the fine stage, coefficients' diminished to the estimations of 0–20, 50–100, 25–75, 0–25 and 0–100, representing the dispersion, breed, spread, slope resistance and road gravity coefficients, respectively. The following stage, final calibration, utilized the yield of fine alignment growth coefficient as input coefficient and gave the diminished estimations of 0–20, 50–100, 25–65, 0–20 and 0–100 indicated to the model parameters' values respectively. This values prompts final

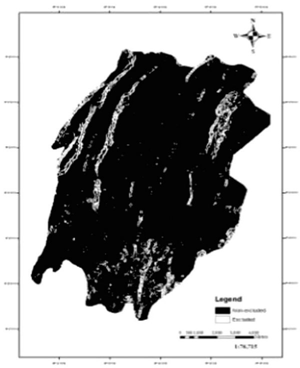


Slope



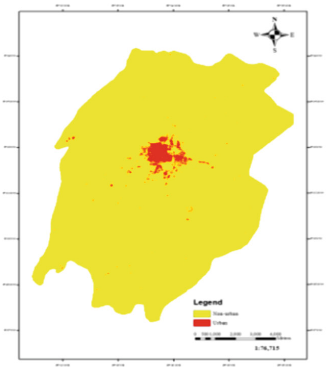


1984 LULC 2014 LULC

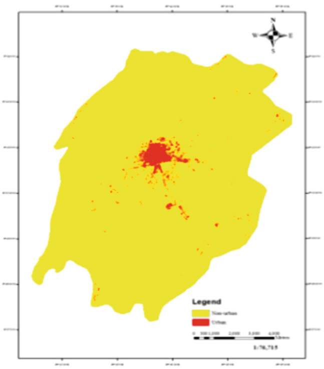


Excluded

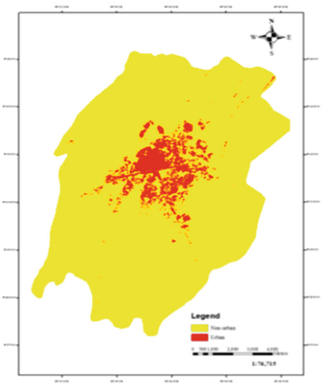
Fig. 4. Input layer (Color figure online).



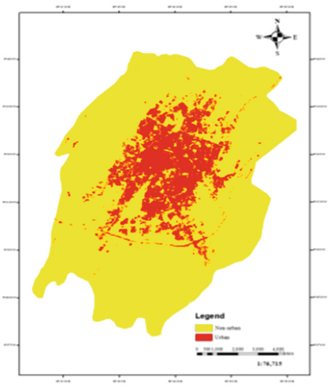
1984 Urban



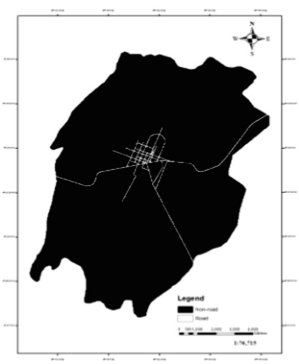
1994 Urban



2004 Urban



2014 Urban



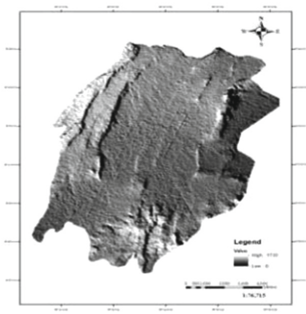
1984 Transportation

1994 Transportation

Fig. 4. (*continued*)

2004 Transportation

2014 Transportation



Hill shade

Fig. 4. (*continued*)

mode coefficient values of predict mode. The predict mode gave the estimation of 1, 67, 55, 2 and 26 respectively for the SLEUTH model forecasting.

5.3 Prediction

Models are frequently made a decision by their prescient power (Silva and Clarke 2002). As appeared in Table 3, coefficient of expectation has a high estimation of 67. The high breed parameter indicated that Adama city significant growth is new spreading from centers. The spread coefficient has a moderately high estimation of 55, that edge growth is another significant growth type. In this city, the estimation of slope coefficient of 2 shows that the topography has low dynamic for urban growth. Consistent low diffusion coefficient estimation of 1 shows that no irregular urbanization of land, that occurred close to the current urban regions and new urban focuses. The relatively even road gravity coefficient estimation of 26 shows that the street systems has influence the urban growth.

The predicted urban growth map of simulated years' and the probabilities of urbanization for years' of 2020, 2030, 2040 and 2050 has shown in different colors in Figs. 5 and 6. Red shaded are areas that has 81–100% certainty of growth. Most conservatively,

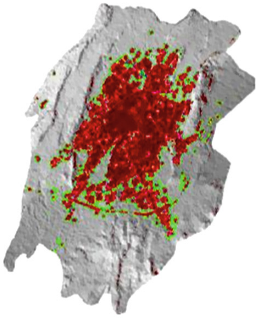
Table 3. Summary of growth coefficient values during each process.

Mode	Coarse		Fine		Final		Prediction mode
Pixel dimension	(1732 * 2204)		(866 * 1102)		(433 * 551)		(433 * 551)
Growth parameter	MC iteration = 4		MC iteration = 7		MC iteration = 9		MC iteration = 100
	Lee sallee statistic = 0.23		Lee sallee statistic = 0.23		Lee sallee statistic = 0.29		Lee sallee statistic = 0.3
	Range	Step	Range	Step	Range	Step	Best fit value
Dispersion	0–100	25	0–20	5	0–20	4	1
Breed	0–100	25	50–100	10	50–100	10	67
Spread	0–100	25	25–75	10	25–65	8	55
Slope	0–100	25	0–20	5	0–20	4	2
Road gravity	0–100	25	0–100	25	0–100	25	26

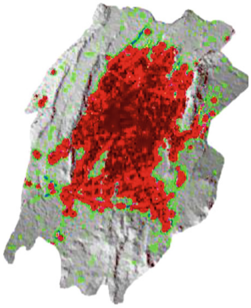
this area most likely growth zones which include infilling of existing settlement, and outward expansion. Pink, yellow and blue shaded are areas with a range of 61–80%, 41–60%, and 21–40% certainty respectively. This class of prediction has an even chance of growth probabilities. Finally, a projection category of 1–20% certainty is shown in light green. In this zone, the combination of the extent of the city and new urban centers are included. When a new spreading center forms in repeated model run, it could be identified as a 'city waiting to happen', a site so potentially ripe for growth that it is merely a matter of time before urbanization arrives (Clarke and Gaydos 1998).

Land use change studies usually compare the landscape at two points in time and model the transition quantities and proportions of change both across the landscape and among land use and cover classes (Lambin and Geist 2008). Due to involvement of remote sensing, GIS and SLEUTH modeling it is also possible to simulate LULC map as shown in Fig. 7 and also possible to calculate the area and percentage of each LULC distribution as shown in Table 5. Table 4 shows the percentage of annual transition probabilities for simulated years and probability of urban change from different land use classes are;

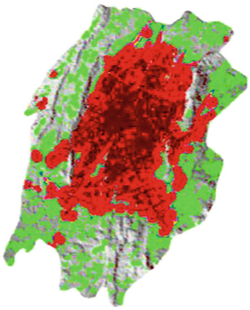
1. About 23.75% area of agriculture cover has probability of conversion into urban;
2. About 12.45% area of Shrub and bushes cover has probability of conversion into urban;
3. About 6.08% area of Barren area cover has probability of conversion into urban;
4. About 18.59% area of hilly area cover has probability of conversion into urban.



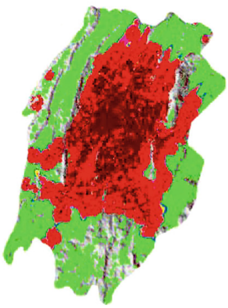
(a) 2020



(b) 2030



(c) 2040



(d) 2050

Fig. 5. SLEUTH model prediction for Adama city in different years (Color figure online).

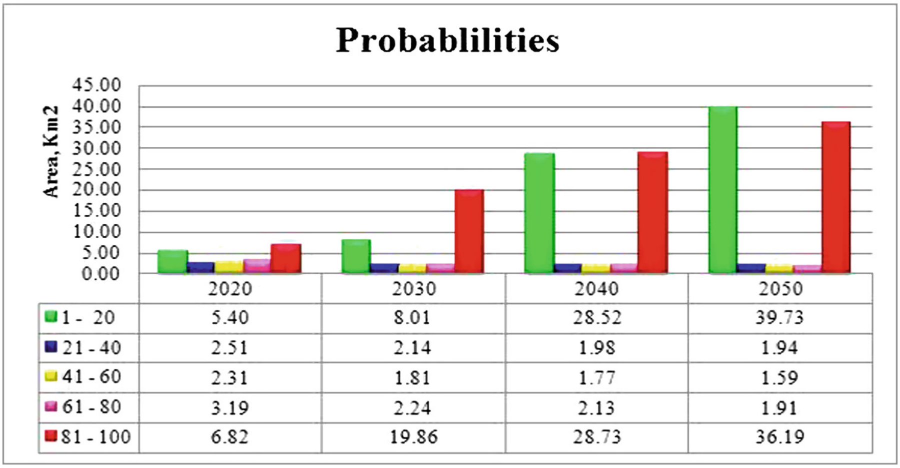


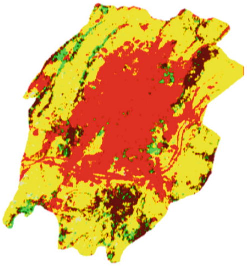
Fig. 6. Probability of number of pixels for different years (Color figure online).

Table 4. Logging annual transition probabilities in percent.

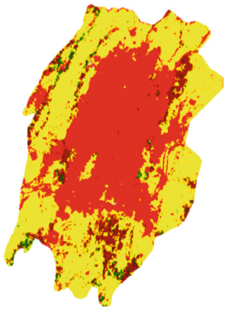
Class name	Urban	Agriculture	Shrub and bushes	Barren area	Hilly area
Urban	82.13	5.17	5.55	0.21	6.93
Agriculture	23.75	58.50	3.73	4.78	9.25
Shrub and bushes	12.45	23.52	38.35	1.05	24.64
Barren area	6.08	62.05	8.11	14.86	8.90
Hilly area	18.59	38.78	8.86	3.53	30.24

Table 5. Area of different LULC categories

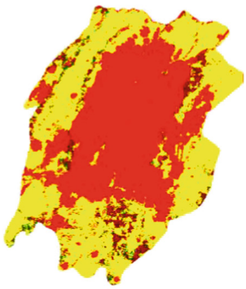
Class name	Area, km^2							
	2020	%	2030	%	2040	%	2050	%
Urban	57.67	42.89	63.00	46.85	66.09	49.15	67.9	50.49
Agriculture	47.41	35.26	41.68	31.0	38.48	28.62	36.67	27.27
Shrub and bushes	9.18	6.83	10.25	7.62	10.68	7.94	10.88	8.09
Barren area	4.17	3.10	3.67	2.73	3.34	2.48	3.15	2.34
Hilly area	16.03	11.92	15.86	11.8	15.87	11.80	15.87	11.80
Total	134.46		134.46		134.46		134.46	



(a) 2020



(b) 2030



(c) 2040

(d) 2050

Fig. 7. Simulated LULC in Adama city of different years (Color figure online).

6 Conclusion

This study intended to consolidate simulation of urban growth and LULC of Adama city utilizing SLEUTH model. SLEUTH model simulated Adama city urban growth of the year 2020, 2030, 2040 and 2050. Simulation of urban expansion, land use land cover change detection, zoning policies change, town planning and land use planning, growth-control strategies, waste disposal management, road network modelling, utility line supply i.e. electricity, water supply, sewerage disposal and so on.

1. The analysis of thirty years' of Landsat satellite imagery illustrate that urban area has been drastically increased through- out the years. From SLEUTH model analysis, the calibrate mode is quite complex and require careful adjustment. A possible combination of coefficients is seriously explored through each combination step that lead to best fit of the model coefficients. Prediction mode of SLEUTH model shows that about 81–100% probability of other class being converted into urban area. About 6.82 km^2 area has been converted into urban in 2020, about 19.86 km^2 area has been converted in urban in 2030, about 28.73 km^2 area has been converted in urban in 2040 and about 36.19 km^2 area has been converted in urban in 2040.
2. It is further predicted that in the future 36 years' from 2014, there will be nearly 42.89% urban rise in 2020, 46.85% in 2030, 49.15% in 2040 and 50.49% in 2050. The annual transition probability of LULC shows that the major likelihood of urban area growth will be 23.75% from agriculture land, 12.45% shrub and bushes, 6.08% from barren land and 18.59% from hill shade.
3. Generally, the repeated model run for future urbanization patterns are exhibiting new spreading center i.e. outward expansion and infilling of existing settlement, are indication of a city to expand in spontaneous growth manner.

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