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Analysis of Selected Factors Supporting Urban Sprawl Patterns Using Analytical Hierarchy Process Model: A Case Study of Areas Surrounding Eldoret Town, Kenya

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Abstract

Eldoret town is currently experiencing rapid urban growth in all directions exerting great pressure on biophysical and socio-economic environments. This is evidenced by fertile agricultural land being converted into patches of built-up areas which could lead to a decline in food production in a region that has been for a long time known as the grain basket of Kenya. This study analyzed selected factors supporting urban growth around Eldoret town using Analytical Hierarchy Process (AHP) model. A total of eight independent variables: five connectivity factors namely distances to nearest roads, powerline, water line, employment centers and restricted areas; two physical factors namely; slope and elevation and one socio-economic factor namely; population density were applied in this model in order to rank them since all factors don't contribute equally to sprawling patterns. Results showed that distances to roads, powerline and water line had the highest AHP weights of 27.93%, 17.37% and 17.08% respectively and were the most significant supporting factors driving urban sprawl around Eldoret town. Physical factors of slope and elevation were the least driving factors with each having an AHP weight of 4.94%. It is recommended that Uasin Gishu County government should give priorities to roads, power and waterlines in areas planned for urban development to control sprawl patterns.

Keywords: *Analytical Hierarchy Process (Ahp), Urban Sprawl Supporting Factors*

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Introduction

One of the most rapidly growing urban phenomena in the 21st Century is emergence of sprawling settlements. Such settlements provide essential services as well as strain on these centers among others water runoff, pollution and flooding, traffic snarl-ups, solid waste management challenges proliferation of slums and informal settlement. Bhatta et al. 2010 and Siddiqui et al. 2018 in their studies of causes and consequences of urban growth and sprawl in Berlin, Germany and urban growth dynamics of an Indian metropolitan respectively reported that population is the main factor influencing urban growth in peri-urban areas. In another study, Osman et al. 2016 in the study of urban sprawl in Giza Governorate of the Greater Cairo region observed that proximity to urban centers was the main factor leading to sprawl. Elsewhere, Appiah et al. (2014) reported that increased demands for new housing in the city and good accessibility as the most significant factors. In yet another study, Mahamud et al. 2016 in their study of identifying factors influencing urban spatial growth for the George Town Conurbation, Malasyia identified three significant factors namly; distance to public amenities, affordable housing and distance to work place as important factors.

Eldoret Town is the fifth most populated urban Centre in Kenya after Nairobi, Mombasa, Nakuru and Ruiru with a total population increasing in the recent past to 475,716 (2019, KNBS), from 289,380 (2009, KNBS) and 193,830 (1999, KNBS) and is projected to grow to 782, 036 by the year 2029, an increase of 306,320 people despite the town being the grain basket of the country.

Therefore, since models are one of the tools used by researchers to investigate the behavior of urban sprawl, this study used Analytical Hierarchy Process (AHP) to analyze selected supporting factors driving urban sprawl around Eldoret town.

Materials and Methods

Study Area

The study area is located in Uasin Gishu County, Kenya, and covers 58 sub-locations. It is bounded by Latitudes 00°52' 00''N and 00°18'00''N and Longitudes 34°51'00''E and 35°31'00''E covering approximately 1972.77 km^2 (Figure 1).

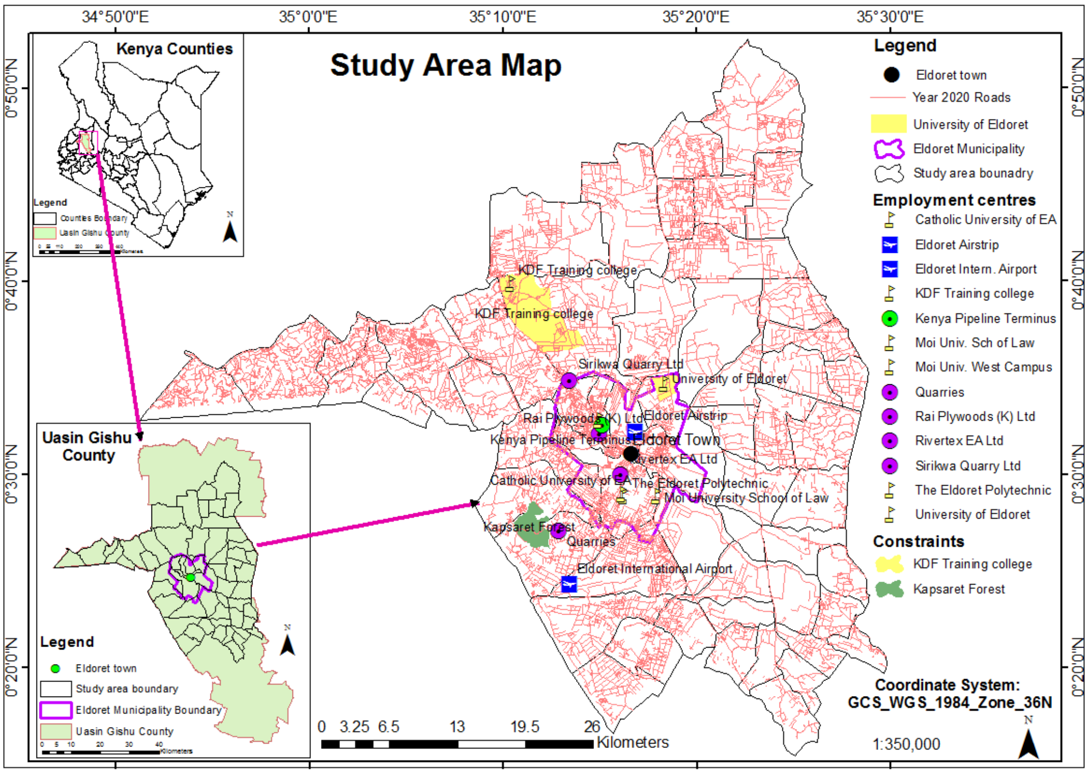

Figure 1: Location of the study area

The average rainfall ranges between 625mm to 1,560mm with two distinct peaks occurring between March, May and September. Dry spells occur between November and February. The temperatures range from 7°C and 29° C. Generally, these conditions are favorable for livestock keeping, crop and fish farming. The dominant soil types are Orthic Ferralsol (Fo) and Humic Nitosols (Hn).

The Southern part is drained by Kerita, Naru and Nureri tributary rivers coming from Tingwa Forest in Keiyo Escarpment confluence forming River Kipkaren which later confluence with River Sosiani at Kiboloss market and eventually joins River Nzoia after Lugari market. The South-Western part of the area is drained by Endoroto, Kipsinandi and Ellegirini tributary rivers coming from Kaptagat Forest in Elgeyo Escarpment confluences at two river dam. The North-Western part is drained by River Chepkoilel which flows into Marura swamp which extends up to Kaprobu Bridge. After the bridge, the name changes to River Sergoit which flows through Soy Bridge to Turbo Bridge where it confluences with River Sosiani.

Data and Data Processing

Literature on urban growth showed various factors that affect urban growth processes including physical factors namely slope and elevation, social factors namely population density and social services, political factors including zoning policies as well as distance from roads, powerline, waterlines, employment centers, and distance from factors that constraints development. Eight factors thought to strongly influence sprawl patterns in the study area were identified. The data obtained were from both primary and secondary sources as shown on Table 2.

Table 2: Characteristics of Datasets Used

S/No.	*Data used*	*Data type*	*Years*	*Source*
1.	Roads network maps (X_1)	Primary	2000, 2016 and 2020	Digitized from their respective high resolution google earth images
2.	Employment centers map (X_2)	Primary	2000, 2016 and 2020	were collected from geographic locations using Mobile Mapper 50 hand held GPS
3.	Water network maps (X_3)	Primary	2000, 2016 and 2020	Eldoret Water and Sanitation (ELDOWAS), GIS Department
4.	Powerline network map (X_4)	Primary	2000, 2016 and 2020	Kenya Power and Lighting Company, Facility Database (FDB), Eldoret office
5.	Restricted areas map (X_5)	Primary	2020	were collected from geographic locations using Mobile Mapper 50 hand held GPS
6.	Decadal Census data (X_6)	Secondary	1999, 2009 and 2019	Kenya National Bureau of Statistics (KNBS)
7.	Elevation map (X_7)	Primary	2020	Obtained from 30m Digital Elevation Model (DEM) from Shuttle Radar Topography Mission (SRTM) USGS website (USGS, https://earthexplorer.usgs.gov/).
8.	Slope map (X_8)	Primary	2020	Obtained from 30m Digital Elevation Model (DEM) from Shuttle Radar Topography Mission (SRTM) USGS website (USGS, https://earthexplorer.usgs.gov/).

Data Analysis

Data analysis was carried out in three steps namely; 1) computation of factors weights, 2) creating a pairwise comparison matrix and 3) calculating consistency ratio (CR).

Computation of Factors Weights

The above supporting and constraints factors maps were used in Multi Criteria Decision model and assigned weights using Analytical Hierarchy Process (AHP) model approach. The first step in AHP was to create the hierarchical structure in which the goal was to rank the eight supporting factors to determine their order of importance in contributing to urban sprawl patterns. The independent variables (X_1-X_8) are the supporting factors leading to growth patterns and are kept in second level. Figure 2 shows AHP structure for weighting of independent variables.

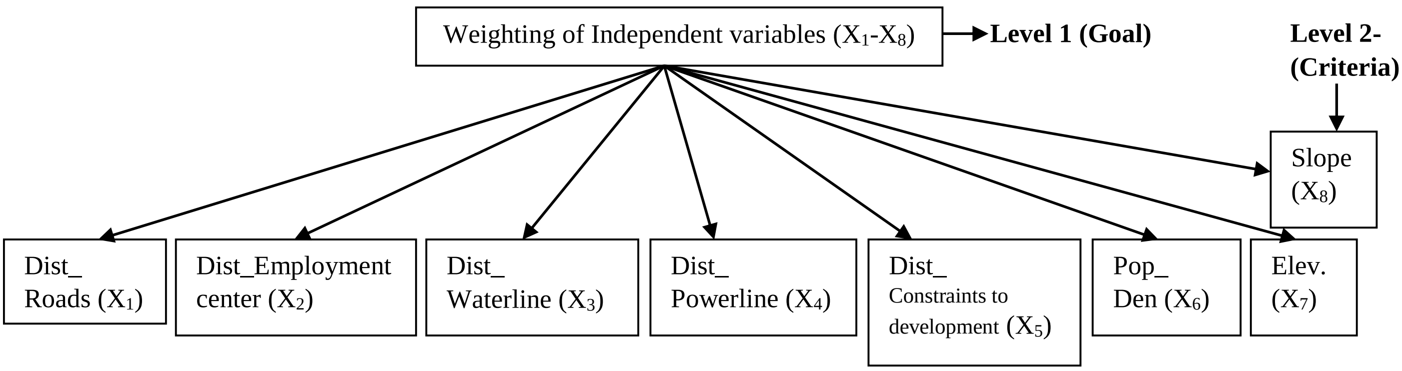

Figure 2: Analytical Hierarchy Process (AHP) Structure

Creating a Pairwise Comparison Matrix

In the second step, a pairwise comparison matrix was created which gives the relative importance of independent variables such as distance to main road networks with respect to the goal. This pairwise comparison matrix was created with the help of scale of relative importance from Saaty's 9 point pairwise comparison table as shown on Table 2 and its length is equivalent to the number of independent variables/criteria used in the decision making process. For this study, it was an 8 by 8 matrix as seen on Table 3.

Table 2: **Saaty's 9 Point Pairwise Comparison Table**

Intensity of importance	**Definition**	**Explanation**
1	Equal importance	Equal importance or indifference

3	Weak importance of one over another	Experience and judgement slightly favor one activity over another
5	Essential or strong importance	Experience and judgement strongly favor one activity over another
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance is demonstrated in practice
9	Absolute importance	The evidence favoring one activity over another is of highest possible order of affirmation
2,4,6	Intermediate values between adjacent scale values	-
1/3, 1/5, 1/7, 1/9	Values for inverse comparison	-

Source: Saaty (1980)

The value in the pairwise matrix was based on the expert's/decision maker's judgment on urban sprawl supporting factors. The diagonal elements were assigned a value of one (1) because each factor is of equal importance to itself, for example, distance to road (X_1) will be of equal importance to distance to road (X_1). The pairwise comparison matrix begins from second row of the first column. If distance to road is considered to be of 'weak to strong importance' than distance to employment centers, a value of four (4) is entered in row two of column one and its fraction (1/4) is entered in row two of column one. Therefore, if employment center is equivalent to n value, then distance to road will be 4n value. The row element (4n) was divided by column element (n) i.e. 4n/n=4. Then dividing the column element by row element i.e. n/4n=1/4. The pairwise comparison process is continued until all possible criteria pairs are evaluated. The lower triangular half is the reciprocal of the upper triangular hence only one is filled to get the values for the other. The values in pairwise comparison table is then entered into AHP model in order to normalize them resulting into a normalized pairwise comparison matrix produced by dividing all column elements by the sum of the column. The criteria weights were calculated by averaging all elements in a row using IDRISI Weights command from the principal eigenvector (Eastman et al. 1993).

Calculating Consistency Ratio (CR)

In order to check whether the calculated criteria weights are correct, consistency was calculated by multiplying the column values in the pairwise comparison matrix which is not normalized with the criteria values. The row values were summed to get the weighted sum values. Each row weighted sum value was divided by each row criteria value and calculating the average summation the results to get the lambda. The consistency index (CI) was then calculated using the formula lambda minus n divided by n-1 where n=8 number of supporting factors. Finally, consistency ratio (CR) was calculated by dividing the CI with random index (RI) which is the consistency of index of randomly generated pairwise matrix.

Results and Discussions

1. Results

Pairwise Comparison Matrix

This section shows the results of how the eight factors are of equal importance (value 1), equal to weak importance (value 2), weak importance (value 3), weak to strong importance (value 4), strong importance (value 5) and very strong importance (value 7) with their reciprocal importance to each other as in Table 3.1.

Table 3: Pairwise Comparison Matrix

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
X_1	**1**	4n/n=4	3	2	2	1	7	7
X_2	n/4n=¼	**1**	½	1	3	1	3	3
X_3	1/3	2	**1**	1	3	1	3	3
X_4	½	1	2	**1**	4	5	2	2
X_5	½	1/3	¼	1/3	**1**	1	1	1
X_6	1	1	1/5	¼	1	**1**	3	3
X_7	1/7	1/3	½	½	1	1/3	**1**	1
X_8	1/7	1/3	½	½	1	1/3	1	**1**

Consistency Ration (CR)

The calculated consistency ratio value was 0.10 as shown in Figure 3. The standards for consistency ratio is that it should be less than (<0.10) and since the calculated CR was 0.10, hence the suitability of the defined weighting scheme was confirmed and assumed that the matrix was reasonably consistent. If the calculated CR is higher than the standard CR, the matrix is re-evaluated. The criteria weights calculated above were used to make a decision/

rank the independent variables in the order that each contributes to urban sprawl growth patterns. The method is iterative since it allows those assigning weights a chance to revise their previous pairwise comparison table on the basis of criteria. Factors with higher weights are statistically more important.

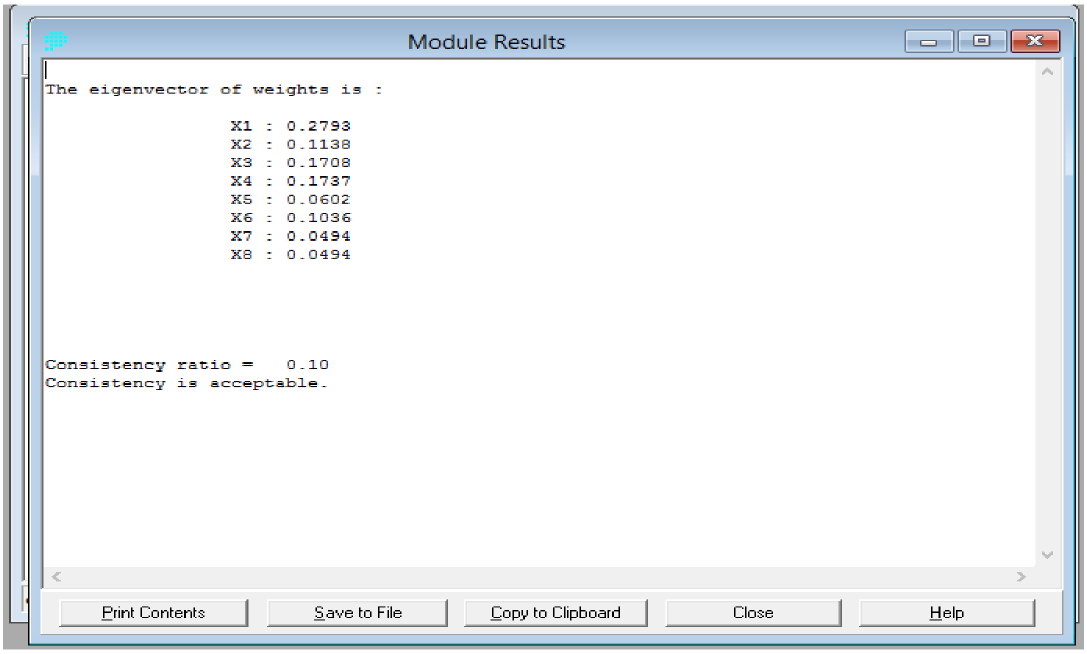

Figure 3: Eigenvectors of Weights

Ranking of urban sprawl supporting factors

The findings of AHP, indicated that distance to roads (X1) 27.93% contributes more to urban sprawl growth patterns in the study area as shown on Table 4.

Table 4: Ranked AHP Weights of Supporting Factors

S/No.	Supporting Factors	AHP Weight for each Factor
1.	Distance to roads (X_1)	27.93%
2.	Distance to powerline (X_4)	17.37%
3.	Distance to waterline (X_3)	17.08%
4.	Distance to employment center (X_2)	11.38%
5.	Population density (X_6)	10.36%
6.	Distance to restricted areas (X_5)	6.02%
7.	Elevation (X_7)	4.94%

8.	Slope (X_8)	4.94%

Discussion

There were higher AHP weights for distance to roads. This result concurs with reports of Mohammad et al. (2013) in his study of urban growth simulation through cellular automata, AHP and GIS in Isfahan. Thus, when sprawl is taking place in the study area, roads are created for accessibility purposes.

There were lesser weights for population density than expected. Interestingly, results of similar studies conducted by Muhammad et al. (2019) on factors during urban expansion in the peri-urban areas using logistic regression in greater Cairo region demonstrated that population density had a weight of 0.933 hence contradictory since it had a greater effect on urban expansion (2017) in a study of improving the capability of an integrated CA-Markov model to simulate spatio-temporal urban growth trends using an Analytical Hierarchy Process and Frequency Ratio in Malasyia observed that population density had a lesser AHP weight of 0.42 compared to slope with 0.83. The reason for lesser AHP weight for population density in the study area can be linked to the fact that Eldoret town is still urbanizing hence there is still more space for settlement.

Conclusions and Recommendations

Results of this study demonstrated that urban sprawl patterns in the study area is affected by distance to roads (X_1) 27.93% contributing more to urban sprawl patterns followed by distance to powerline (X_4) 17.37%, then distance to waterline (X_3) 17.08%, distance to employment centres (X_2) 11.38% is fourth, population density (X_6) 10.36% is fifth, and the weakest being distance to constraints to development (X_5) 6.02% being sixth with elevation (X_7) and slope (X_8) being the weakest similar weights of 4.94%.

In order to control sprawl, it is recommended that Uasin Gishu county government should not give priority to transportation network in areas not projected for development to control sprawl and instead provide such utilities in areas destined for development in order to protect agricultural land since urban sprawl are found in areas connected by roads networks.

Conflict of interest: the authors declares no conflict of interest

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