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Investigating the socioeconomic factors shaping urban sprawl: evidence from the Batticaloa municipal council, Sri Lanka

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ABSTRACT

Urban sprawl is a socioeconomic phenomenon, which affects sustainable urban growth. Several socioeconomic factors cause urban sprawl growth in different world cities, which were identified from the previous literature. However, a comprehensive study focusing on many socioeconomic factors is still a gap. This study aims to determine the influencing socioeconomic factors of urban sprawl in the Batticaloa municipality, Sri Lanka. The data were collected through a questionnaire survey from 400 respondents in Batticaloa. Exploratory factor analysis, reliability test and multiple linear regression stepwise methods were employed to identify the significant socioeconomic factors of urban sprawl. The results indicate that policy regulations, land value, regional accessibility, and demographic dynamics influence urban sprawl in the Batticaloa municipality. Besides, housing preference, income inequality, education, employment and living standards were insignificant to urban sprawl. These significant factors may increase the urban sprawl growth in the municipality since Batticaloa is expected to become a metropolitan city by 2030, which affects the city's sustainable development. Decision-makers and planners can use these findings to enhance development measures to reduce future sprawling. Finally, this study was conducted in Batticaloa, a medium-sized city; therefore, this finding can help similar cities in Sri Lanka and the world with strategic planning.

Keywords: urban sprawl, socioeconomic factors, survey, EFA, multiple regression, stepwise regression

1. INTRODUCTION

Rapid urbanisation has altered land cover patterns irreversibly and has prompted urban sprawl or the expansion of cities outside their core typologies (Chettry & Surawar, 2021; Sahana, Hong, & Sajjad, 2018). A pattern of sprawl can be called a static phenomenon, whereas a sprawling process can be known as a dynamic phenomenon. Besides, scholars have varying views on whether sprawl is a dynamic or a static phenomenon; nonetheless, many researchers believe it is both. Sprawl helps us better comprehend spatial scattering as a pattern, yet it is often part of the dynamic in urban land use (Ismael, 2021). The pressure of urbanisation causes discontinuous development, which results in a low-density and dispersed expansion due to the fewer buildings on the urban edge, leading to urban sprawl (Antalyn & Weerasinghe, 2020). The urban fringe, edge expansion, leapfrog growth, scattered growth, low-density development, and ribbon development have been characterised as urban sprawl typologies (Chettry & Surawar, 2021; Sahana et al., 2018; Seevarethnam, Rusli, Ling, & Said, 2021).

According to Zhao (2013), sprawling growth in the peri-urban areas is characterised by informal development, low-density luxury villas, gated communities, and an uneven distribution of transportation infrastructures and public services. This has resulted in growing residential segregation between those with high incomes and low incomes, as well as between local inhabitants and migrants. Residents in sprawl areas have less access to work, services and recreation because of land-use segregation and the absence of mixed-use. Hence, a greater reliance on private automobiles will result from this problem (Amarawickrama, Singhapathirana, & Rajapaksha, 2015).

The spatial patterning of urban growth and development in connection to specific driving factors constitutes urban sprawl on a wide scale (Grigorescu, Kucsicsa, Mitrică, Mocanu, & Dumitraşcu, 2021; Shahraki et al., 2011). Urban sprawl is a social and economic phenomenon caused by different driving factors in the municipalities (Mehriar, Masoumi, & Mohino, 2020). Urban sprawl is largely a result of socioeconomic driving factors rather than physical driving factors. The socioeconomic driving factors that contribute to urban sprawl vary from city to city. Hence, it is difficult to say which driving factor is most important in the city. As an urban built environment linked explicitly to the need for sustainable development goals, urban sprawl needs to be viewed in varied socioeconomic settings in order to move towards sustainability (Mehriar et al., 2020). According to Gavrilidis, Niță, Onose, Badiu, and Năstase (2019), cities, regions, and countries have different causes for sprawling growth, including topography, demographics, property values, technological advancements, transit options, globalisation and societal influences. Per capita land utilisation, increasing population, large-scale migration, and economic growth are common causes of increasing built-up area. Urban land growth is influenced by many factors, including economics, policy, governance, legislation, social processes, and demographics, as discussed in the majority of urban planning and geography literature (Grigorescu et al., 2021). The low-income population is forced to buy the inexpensive property and build affordable homes with high tax subsidies, minimal building regulations, and less communal costs at the urban edge because of economic problems (Antalyn & Weerasinghe, 2020).

Due to a common perception of sprawling characteristics and factors inherited from developed countries, there is still a knowledge gap in socioeconomic studies of urban sprawl in developing countries. Urban sprawl is a global phenomenon, but socioeconomic circumstances in emerging and developed nations influence the extent to which it occurs (Mehriar et al., 2020).

Researchers in developed and developing countries mainly considered population changes while conducting urban sprawl research. Simultaneously, poverty, income changes, and land value are featured in emerging countries, including Iran (Mehriar et al., 2020), China (Y. Liu, Fan, Yue, & Song, 2018) and Turkey (Karakayaci, 2016) compared to developed nations. In contrast, in developed countries, housing preferences (Polyzos, Minetos, & Niavis, 2013), employment (Weilenmann, Seidl, & Schulz, 2017) and living standards are played a significant role. Even though no one had previously researched socioeconomic factors of urban sprawl thoroughly, the same driving factors have been responsible for it in both developed and developing countries. Land value, population dynamics, housing preferences and income changes have been common socioeconomic factors. In addition, only secondary and census data were utilised to determine the socioeconomic characteristics in developing countries in the Middle East (Kourosh Niya et al., 2020), East Asia (G. Li & Li, 2019) and South Asia (Thakur, Kumar, & Gosavi, 2020). Nevertheless, studies on socioeconomic factors of urban sprawl in Sri Lankan cities has not been found in the literature. Therefore, as an emerging city, Batticaloa municipality in Sri Lanka should have to comprehend the socioeconomic factors of urban sprawl.

Table 1. A summary of socioeconomic factors of urban sprawl.

Authors	Country	Housing preference	Income inequality	Demographic dynamics	Land value	Education	Employment	Regional Accessibility	Living Standards	Policy Regulations
Europe										
Grigorescu et al. (2019)	Romania			X			X			
Weilenmann et al. (2017)	Switzerland		X	X	X		X	X		
Christiansen and Loftsgarden (2011)	Norway	X		X	X				X	X
De Vos and Witlox (2013)	Belgium		X	X		X	X			
Polyzos et al. (2013)	Greece	X		X						X
Hortas-Rico and Solé-Ollé (2010)	Spain	X	X	X		X	X			
North America										
Lee, Ambrey, and Pojani (2018)	USA		X							

Kim, Newman, and Güneralp (2020)	USA			X	X		X			X
Middle East										
Karakayaci (2016)	Turkey	X		X	X					
Mehriar et al. (2020)	Iran	X	X	X			X			
Southeast Asia										
Rosni and Noor (2016)	Malaysia		X	X	X	X	X	X		
East Asia										
G. Li and Li (2019)	China			X						
Z. Liu, Liu, Qi, and Jin (2018)	China			X	X					
X. Li, Zhou, and Ouyang (2013)	China								X	
South Asia										
Bhatta (2010)	India		X	X						

According to the literature gap, nine (9) socioeconomic factors for urban sprawl were identified in developed and developing countries in the world (see Table 1). This literature was classified based on major world regions, such as North America (Lee et al., 2018), Europe (Weilenmann et al., 2017), Middle East (Mehriar et al., 2020), East Asia (G. Li & Li, 2019), Southeast Asia (Rosni & Noor, 2016) and South Asia (Bhatta, 2010). The review indicates that specific socioeconomic factors of urban sprawl have only been studied in the previous literature. In both developed and developing countries, socioeconomic research on urban sprawl is rare, and the available studies did not comprehensively capture many socioeconomic driving factors in a particular metropolitan area (Grigorescu et al., 2019; Lee et al., 2018; G. Li & Li, 2019). Thus, nine factors, each from different literature apt for this study, were considered comprehensively to understand the level of influence of these factors in the Batticaloa municipality. These findings of socioeconomic factors in Batticaloa, a medium-sized city, can use to comprehend the influence of these factors in cities with similar characteristics to Batticaloa. Therefore, this study aims to determine the influencing socioeconomic factors of urban sprawl in the Batticaloa municipality, Sri Lanka.

2. METHOD AND MATERIALS

2. 1. Population and Sampling

Population and sampling are important to achieve a level of confidence and precision in the results. According to Israel (Israel, 1992), for a total population of about 100,000, the sample

size can be 398 people. The total population of almost 94,131 was in the Batticaloa municipality, where the population of 400 was considered to confirm the generalizability of the results. Furthermore, the results can have a confidence level of 95% and a margin of error of $\pm 5\%$ in the analyses. The sample was determined as follows (see equation 1):

$$n = N / 1 + N (e)^2 \quad (1)$$

where n indicates a total number of samples, N is the total population in Batticaloa municipality, e is the margin of error 0.05 which has the confidence interval of 95%.

The number of sample achieved as follows (Cobbinah & Aboagye, 2017):

$$\begin{aligned} n &= 94,131 / 1 + 94,131 (0.05)^2 \\ n &= 94,131 / 1 + 94,131 (0.0025) \\ n &= 94,131 / 1 + 235.3 \\ n &= 94,131 / 236.3 \\ n &= 398 \end{aligned}$$

Stratified random sampling was used to gather data from respondents in the Batticaloa municipality. The respondents were men and women, who were between 18 and 55 years old, designated to complete the questionnaire. The survey included dichotomous (yes, no), multiple-choice, and Likert-scale questions (1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree) about urban sprawl and socioeconomic factors such as demographic dynamics, housing preferences, policy regulations, income inequality, employment, land value, education, regional accessibility, and living standards. The questionnaire was translated into the Tamil language and conducted through a face-to-face survey with the respondents. The collected data was examined with SPSS 27.0 to interpret the results.

2. 2. Data Analysis

First, a normality test with an explore function, and kurtosis and skewness analysis with a descriptive function were performed to confirm the normality of the data. The data were normally distributed according to these analyses. Hence, the data were used for further investigations.

2. 2. 1. Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) is a method frequently used in social science (Osborne, 2015). The factor analysis function in SPSS is a multivariate statistical method used to discover new variables categorised as factors and dimensions (Ayazli, 2019). This analysis provides a summary of the data in order to gain a better understanding of the variable patterns and relationships. The purpose of this analysis is to either discover the number of factors or classify commonly observed variables. For this analysis, a sample size of at least 300 respondents is recommended (Yong & Pearce, 2013).

The equation 2 can be used to describe factor loading:

$$X_j = a_{j1}F_1 + a_{j2}F_2 + \dots \dots a_{jm}F_m + e_j \quad (2)$$

where $j = 1, 2, 3, \dots, p$. The factor loadings are $a_{j1}, a_{j2}, a_{j3}, \dots, a_{jm}$ indicating that a_{j1} represents the factor loading of j^{th} variable on the 1st factor. The particular or unique factor is indicated by e_j (Yong & Pearce, 2013).

In order to evaluate the degree of correlation between the items used in the factor analysis, Bartlett's Test of Sphericity was carried out (Mohd Yusof, Ramlee, Syed, Seri Bunian, & Siti Salina, 2014). Bartlett's Sphericity Test provided confirmation of the relationships ($p < .05$). The Kaiser-Meyer-Olkin Measure (KMO) was used to conduct the sampling adequacy test that was carried out by EFA. KMO values below 0.50 are considered unacceptable; values in the 0.50s are considered miserable; values in the 0.60s are considered mediocre; values in the 0.70s are considered middle; values in the 0.80s are considered meritorious; values in the 0.90s are considered marvellous (Ayazli, 2019; Watkins, 2018). Variances equal to the square of the variable factor loading are used in factor analysis. The variation of items that are observed within a common factor is referred to as the communality. Items that had communalities of less than 0.2 were excluded from the factor analysis to better understand the variance in the data by identifying common factors (Yong & Pearce, 2013).

Principal Axis Factoring (PAF) is a technique used to extract the maximum number of variables. PAF helps reduce the number of variables into factors. Rotation is used in the extraction process regardless of the method chosen. The principal axis factor is responsible for the production of factors. Since the factor loads are generally comparable, rotating should be done regardless of the extraction method (Ayazli, 2019; Osborne, 2015; Watkins, 2018; Yong & Pearce, 2013). For the purpose of counting factors, Kaiser eigenvalues and scree plots were utilised. The factor is determined based on the Kaiser criterion. When performing analysis, it is essential to maintain all eigenvalue factors at a value greater than 1.

Rotation was carried out by the Varimax method with Kaiser normalisation. The varimax rotation produced orthogonal factors. Rotating factors improve data quality by reducing the ambiguity caused by non-rotating factors. This rotation method classifies items according to similar measurements to eliminate irrelevant items (Mohd Yusof et al., 2014). Structures with rotated factors are straightforward to comprehend due to their simplicity. High-loading variables can be reduced using Varimax, which results in smaller loadings (Lloret, Ferreres, Hernández, & Tomás, 2017; Watkins, 2018; Yong & Pearce, 2013). The study looked at nine socioeconomic factors that contribute to urban sprawl.

2. 2. 2. Reliability Analysis

In the social sciences, Cronbach's alpha is used as a reliability measurement (Bonett & Wright, 2015). It provides internal consistency on a scale of 0 to 1. The degree to which different questionnaire items measure the same construct or concept is referred to as their "internal consistency." The items on the questionnaire are validated before the primary analysis is performed. Alpha is between 0.70 and 0.95 (Tavakol & Dennick, 2011).

Cronbach's Alpha was utilised through the reliability function of SPSS to investigate the questionnaire items' level of internal consistency. This analysis was conducted for ten different groups using the Likert scale items. The survey measured urban sprawl (B4–B13), land value (D1–D7), education (E1–E4), policy regulations (F1–F4), housing preferences (G1–G4), regional accessibility (H1–H4), employment (I1–I5), demographic dynamics (J1–J4), living standards (K1–K3), and income inequality (L1–L3). For the purpose of determining the reliability of dichotomous questions, the Kuder-Richardson 20 (KR-20) was utilised for B1, B2, and C1.

2. 2. 3. Multiple Linear Regression Analysis

Multiple linear regressions allow for examining the connection between a dependent variable and many independent variables. In this study, nine independent variables were used; thus, this model was chosen to comprehend their correlation. Urban sprawl (Y) is the dependent variable; at the same time, regional accessibility (X_1), policy regulations (X_2), land value (X_3), education (X_4), income inequality (X_5), living standards (X_6), housing preferences (X_7), demographic dynamics (X_8), and employment (X_9) are the independent variables in this case. Several independent variables and their corresponding coefficients and a constant are used to model the dependent variable. Equation 3 illustrates the multiple linear regression model (Ghani & Ahmad, 2010; L. Li, Rong, & Zhang, 2015).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon \quad (3)$$

where Y is the dependent variable, X_1 to X_p are different independent variables, β_0 is the Y value when all independent variables are equal to 0, and β_1 to β_p are constants known as the expected regression coefficients. A regression coefficient represents the change in Y for each unit change in the independent variable, and ε is the error term (L. Li et al., 2015). All X values are used to calculate R^2 , the percentage of variance in the Y value (dependent variable) explained by all X values (independent variables). When the number of variables in an equation has been adjusted, the result is referred to as adjusted R^2 (Ghani & Ahmad, 2010).

A stepwise analysis in SPSS was carried out on the mean values for the Likert scale items. Multiple linear regression includes three methods, including forward selection, backward elimination, and stepwise regression, all of which have been classified as stepwise techniques. Backward elimination and forward selection are combined in stepwise regression to determine the socioeconomic factors that influence urban sprawl. Add or remove control variables as needed for each step in stepwise regression. At a significant level of the p-value (<0.5), this model terminates the procedure (Ghani & Ahmad, 2010).

3. RESULTS

Socioeconomic factors mainly drive urban sprawl growth as the key phenomena. Therefore, the study used nine (9) socioeconomic factors cited in the literature to recognise the influencing socioeconomic factors in the Batticaloa municipality.

3. 1. Determining the Socioeconomic Factors of Urban Sprawl

The socioeconomic factors were retrieved using the Principal Axis Factoring method in SPSS. The appropriateness of socioeconomic factors for extraction was assessed using the Kaiser-Meyer-Olkin (KMO) and Bartlett tests of Sphericity. Bartlett's Test of Sphericity indicated a significant value ($p < 0.001$) for the KMO value of 0.902 (see Table 2). Minimum requirements for factor analysis include the KMO value of 0.80 and the Bartlett test for Sphericity of $p < 0.01$ (Watkins, 2018). It means that the data do not have any major issues with multicollinearity, and the items can be used to continue factor analysis.

Factor analysis tries to explain variance by common factors; thus, items with low communalities (<0.20) have to be eliminated (Yong & Pearce, 2013). A total of 38 Likert scale

items were found to have communalities higher than 0.50, which showed a high value for each item. The Kaiser's eigenvalue and Scree plot were used to determine how many factors each item had. Despite the fact that these two approaches are compatible with one another, they each obtain a disproportionate number of objectives (Çokluk & Koçak, 2016).

Table 2. KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.902
Bartlett's Test of Sphericity	Approx. Chi-Square	10743.533
	df	703
	Sig.	0.000

The Eigenvalue was adjusted to ≥ 1.00 to minimise the total number of variables. The total items could be broken down into nine factors, each with an Eigenvalue value of ≥ 1.00 . The scree plot also showed nine eigenvalue factors (Figure 1). The total explained variance is limited to nine factors with 72.307%. The factor had an eigenvalue of 13,287, the highest and first value, and it explained 34,966% of the variance. The ninth and lower value was 1.147, which accounted for 3.019% of the total variance. The contributions of the rest factors were insignificant to the total variance of the eigenvalue ≥ 1.00 (see Table 3).

Table 3. Total Variance Explained.

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.287	34.966	34.966	13.287	34.966	34.966	4.177	10.992	10.992
2	2.738	7.205	42.171	2.738	7.205	42.171	4.135	10.881	21.873
3	2.486	6.542	48.712	2.486	6.542	48.712	3.221	8.475	30.348
4	2.097	5.519	54.231	2.097	5.519	54.231	3.146	8.278	38.627
5	1.597	4.202	58.433	1.597	4.202	58.433	3.044	8.009	46.636
6	1.488	3.914	62.348	1.488	3.914	62.348	2.973	7.823	54.459
7	1.397	3.676	66.023	1.397	3.676	66.023	2.482	6.532	60.991
8	1.240	3.264	69.287	1.240	3.264	69.287	2.177	5.728	66.719
9	1.147	3.019	72.307	1.147	3.019	72.307	2.123	5.588	72.307
10	0.957	2.519	74.825						

11	0.910	2.396	77.221						
12	0.741	1.951	79.172						
13	0.725	1.907	81.079						
14	0.637	1.676	82.755						
15	0.539	1.420	84.174						
16	0.514	1.352	85.526						
17	0.432	1.137	86.663						
18	0.423	1.113	87.776						
19	0.386	1.016	88.792						
20	0.356	0.936	89.728						
21	0.339	0.892	90.620						
22	0.324	0.852	91.472						
23	0.300	0.790	92.262						
24	0.283	0.745	93.007						
25	0.264	0.696	93.703						
26	0.260	0.685	94.388						
27	0.255	0.671	95.059						
28	0.243	0.638	95.698						
29	0.224	0.589	96.287						
30	0.212	0.557	96.844						
31	0.196	0.515	97.359						
32	0.172	0.453	97.812						
33	0.165	0.433	98.245						
34	0.151	0.397	98.642						
35	0.145	0.382	99.023						
36	0.142	0.373	99.397						
37	0.119	0.314	99.711						
38	0.110	0.289	100.000						

Extraction Method: Principal Axis Factoring.

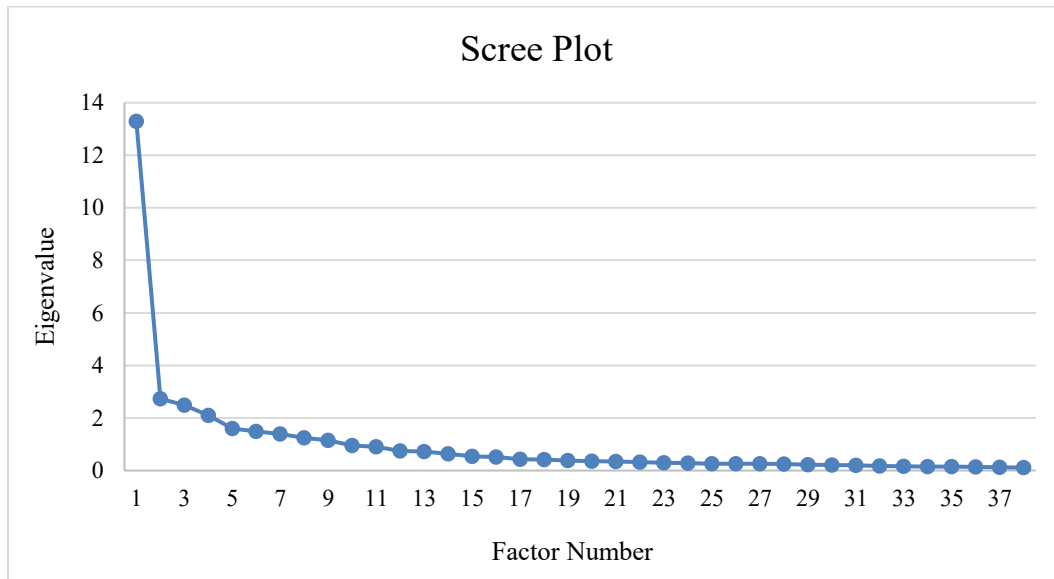


Figure 1. Scree plot for factor loading

In addition, Varimax with Kaiser Normalization for Rotation technique was utilised to acquire the items that comprised the total number of socioeconomic factors contributing to urban sprawl. A total of nine factors were extracted from a total of 38 items. Every factor was composed of some items (see Table 4). Factor 1 is land value, which varies from 0.521 to 0.799, and factor 2 is education, which ranges from 0.781 to 0.843. Policy regulation is the third factor, which fluctuates between 0.769 and 0.829, and factor 4 is housing preferences, which range between 0.698 and 0.804. Factor 5 is regional accessibility, which varies from 0.722 to 0.785, while factor 6 is employment, which ranges from 0.525 to 0.804. Factor 7 is demographic dynamics, which fluctuate from 0.636 to 0.744, factor 8 is living standards, which range from 0.708 to 0.762, and factor 9 is income inequality, which varies from 0.530 to 0.842. As a result of the EFA finding, the values obtained from the study were consistent.

Table 4. Rotated Factor Matrix.

Rotated Factor Matrix ^a									
	Factor								
	Land value	Education	Policy regulations	Housing preferences	Regional accessibility	Employment	Demographic dynamics	Living standards	Income inequality
D1)	0.521								
D2)	0.595								

D3)	0.695								
D4)	0.785								
D5)	0.799								
D6)	0.694								
D7)	0.746								
E1)		0.838							
E2)		0.814							
E3)		0.843							
E4)		0.781							
F1)			0.829						
F2)			0.809						
F3)			0.769						
F4)			0.773						
G1)				0.775					
G2)				0.804					
G3)				0.753					
G4)				0.698					
H1)					0.763				
H2)					0.785				
H3)					0.743				
H4)					0.722				
I1)						0.775			
I2)						0.804			
I3)						0.672			
I4)						0.527			
I5)						0.525			
J1)							0.636		

J2)							0.744		
J3)							0.712		
J4)							0.739		
K1)								0.735	
K2)								0.762	
K3)								0.708	
L1)									0.806
L2)									0.842
L3)									0.530
Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization. a. Rotation converged in 7 iterations.									

Items having a factor loading of less than 0.50 were omitted from the assay to maintain their validity (Mohd Yusof et al., 2014). The factor loading has shown values ≥ 0.35 , and all items have a high communality value > 0.20 (Estabrooks, Squires, Cummings, Birdsell, & Norton, 2009; Watkins, 2018), which demonstrated that the results have discriminant and convergent.

Table 5. Reliability Statistics.

	Variable	Cronbach's Alpha	No of Items
1	Urban Sprawl	.865	12
2	Land Value	.879	7
3	Education	.934	4
4	Policy Regulations	.895	4
5	Housing Preferences	.843	4
6	Regional Accessibility	.879	4
7	Employment	.860	5
8	Demographic Dynamics	.823	4

9	Living Standards	.826	3
10	Income Inequality	.831	3

To find the consistency, a total of ten (10) components (50 Likert scale items) had a Cronbach's Alpha reliability test (see Table 5), while three (3) dichotomous items had a Kuder-Richardson 20 (KR-20) reliability test. Urban sprawl ($\alpha = .865$), land value ($\alpha = .879$), education ($\alpha = .934$), policy regulations ($\alpha = .895$), housing preferences ($\alpha = .843$), regional accessibility ($\alpha = .879$), employment ($\alpha = .860$), demographic dynamics ($\alpha = .823$), living standards ($\alpha = .826$), and income inequality ($\alpha = .831$) has shown high reliability of the Cronbach's Alpha test (see Table 4). All of the components were ≥ 0.70 , which is an indication of greater reliability and internal correlation (Tavakol & Dennick, 2011). Additionally, the KR-20's .535 dependability, which is $> .50$, was deemed reliable in the study (Estabrooks et al., 2009). It signifies that the strength of the association between the variables studied was sufficient to investigate their effects on urban sprawl in Batticaloa.

3. 2. Influencing Socioeconomic Factors of Urban Sprawl

Stepwise multiple linear regression in SPSS was used to identify socioeconomic factors contributing to urban sprawl. A dependent variable and nine (9) independent variables were analysed to build the model. The dependent variable is urban sprawl (Y), while regional accessibility (X1), policy regulations (X2), land value (X3), education (X4), income inequality (X5), living standards (X6), housing preferences (X7), demographic dynamics (X8), and employment (X9) were the independent variables.

Table 6. Regression Model Summary.

Model Summary				
Model	R	R-Square	Adjusted R-Square	Std. Error of the Estimate
1	.413 ^a	.171	.169	.401130589869363
2	.487 ^b	.237	.233	.385305854425026
3	.503 ^c	.253	.248	.381621452001115
4	.513 ^d	.263	.256	.379537421775515
a. Predictors: (Constant), Policy regulations				
b. Predictors: (Constant), Policy regulations, Land value				
c. Predictors: (Constant), Policy regulations, Land value, Regional accessibility				
d. Predictors: (Constant), Policy regulations, Land value, Regional accessibility, Demographic dynamics				

Table 6 summarises the findings of the regression model, which shows that four socioeconomic factors solely drove urban sprawl in Batticaloa municipality. Using model 1, the R-squared value is .171 ($R = .413$), which indicates a 16.9% change in the dependent variable, such as urban sprawl. Policy regulations caused these changes, which explains that it plays a significant role in the sprawl of cities. Model 2 revealed that the R-square is 0.237 ($R = .487$), with a 23.3% change in the dependent variable for urban sprawl. The changes in this model were produced by the combination of two independent variables, such as policy regulations and land value. There are 24.8% of changes in the dependent variable due to changes in the combination of three independent variables, such as policy regulations, land value, and regional accessibility, according to the R-squared value of 0.253 ($R = 0.503$) for model 3. The R-square value in Model 4 is 0.263, which means that urban sprawl has changed by 25.6%. Policy regulations, land value, regional accessibility, and demographic dynamics all worked together to bring about these changes. When compared to the results, Model 4 had a higher R-squared and adjusted R-square value than models 1, 2, and 3 (the values for model 1 = .169; model 2 = .233; model 3 = .248; model 4 = .256).

Table 7. Analysis of variance (ANOVA)

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.190	1	13.190	81.973	.000 ^b
	Residual	64.040	398	.161		
	Total	77.230	399			
2	Regression	18.292	2	9.146	61.604	.000 ^c
	Residual	58.939	397	.148		
	Total	77.230	399			
3	Regression	19.559	3	6.520	44.767	.000 ^d
	Residual	57.671	396	.146		
	Total	77.230	399			
4	Regression	20.331	4	5.083	35.285	.000 ^e
	Residual	56.899	395	.144		
	Total	77.230	399			
a. Dependent Variable: Urban sprawl						
b. Predictors: (Constant), Policy regulations						

c. Predictors: (Constant), Policy regulations, Land value
d. Predictors: (Constant), Policy regulations, Land value, Regional accessibility
e. Predictors: (Constant), Policy regulations, Land value, Regional accessibility, Demographic dynamics

The multiple linear regression output included an analysis of variance (ANOVA) (see Table 7). The data variance was broken down into several components using this procedure. The p-value for R-square statistics, which is indicated by the ANOVA test, is the most significant. The model statistically significant would have a P-value of less than 0.05, as was described earlier. According to the model, four (4) sets of components ($p = 0.000$) were statistically significant, less than the p-value of 0.05. As a result, policy regulations, land value, regional accessibility, and demographic dynamics were all included in the model.

Table 8. Coefficients.

Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.403	.110		21.929	.000	2.188	2.619
	Policy regulations	.268	.030	.413	9.054	.000	.210	.327
2	(Constant)	1.807	.146		12.347	.000	1.519	2.095
	Policy regulations	.194	.031	.299	6.241	.000	.133	.256
	Land value	.225	.038	.281	5.862	.000	.150	.300
3	(Constant)	1.702	.149		11.400	.000	1.408	1.995
	Policy regulations	.161	.033	.247	4.876	.000	.096	.225
	Land value	.184	.040	.230	4.543	.000	.104	.264
	Regional accessibility	.102	.035	.155	2.950	.003	.034	.170
4	(Constant)	1.605	.154		10.411	.000	1.302	1.909
	Policy regulations	.144	.034	.221	4.277	.000	.078	.209
	Land value	.166	.041	.208	4.059	.000	.086	.247
	Regional accessibility	.084	.035	.128	2.391	.017	.015	.154

	Demographic dynamics	.079	.034	.117	2.315	.021	.012	.146
a. Dependent Variable: Urban sprawl								

Also included in Table 8 are the coefficients of the model, which were utilised to create four different forms of multiple linear regression. The following is a list of the four models:

- Model 1: $Y = 2.403 + .268X_2$
 Model 2: $Y = 1.807 + .194X_2 + .225X_3$
 Model 3: $Y = 1.702 + .161X_2 + .184X_3 + .102X_4$
 Model 4: $Y = 1.605 + .144X_2 + .166X_3 + .084X_4 + .079X_5$

The model shows that the independent variables were selected in four steps. Model 1 showed a statistically significant value of standardized coefficients for policy regulations ($\beta = .413$, $p < 0.05$). It indicates that urban sprawl may be attributed solely to policy regulations. While the standardized coefficients for policy regulations ($\beta = .299$, $p < 0.05$) and land value ($\beta = .281$, $p < 0.05$) were not significant in model 1, they were in model 2, policy regulations and land value can explain urban sprawl. Aside from that, model 3 corroborated the significance of the standardized coefficients for the factors, such as policy regulation ($\beta = .247$, $p < 0.05$), land value ($\beta = .230$, $p < 0.05$) and regional accessibility ($\beta = .155$, $p < 0.05$). It means that the determinants of urban sprawl include policy regulations, land value, and regional accessibility. In model 4, the standardized coefficients were significant for the factors such as policy regulations ($\beta = .221$, $p < 0.05$), land value ($\beta = .208$, $p < 0.05$), regional accessibility ($\beta = .128$, $p < 0.05$), and demographic dynamics ($\beta = .117$, $p < 0.05$). Hence, four main variables contribute to urban sprawl, such as policy regulations, land value, regional accessibility, and demographic dynamics. As a result of this investigation, it has been determined that model 4 fits better than models 1, 2, and 3. Therefore, the findings indicated that the urban sprawl in Batticaloa municipality had been impacted only by four distinct socioeconomic factors.

4. FINDINGS AND DISCUSSION

Urban sprawl is a socioeconomic phenomenon caused by different drivers. Socioeconomic variables contribute far more to urban sprawl than physical factors. Thus, policy regulations, land value, regional accessibility, and demographic dynamics were the only socioeconomic factors that drove urban sprawl in the Batticaloa municipality. Built-up development has an impact on urban sprawl because of policy guidelines. There are a few policy laws that can be bent to flexible for some persons who create sprawl in the municipality in leapfrog or scattered development. Another issue raised by the municipality's rapid growth is the issue of illegal land occupation. The lack of a municipal land management system makes it difficult to detect illegal land use. Problems with property ownership and low-income landowners are prevalent in the Puliyanthivu South, Nochchimunai, Kokkuvil, Sinna Oorani, Amirthakali, Kallady uppodai, and Mamangam areas.

As a result of these issues, subdivisions and vacant lands have formed in the municipality. More subdivisions of land have created low-density urban sprawl in Saththurukondan and

Uppukarachai. Weak municipal land use planning paved the way for rapid population increase and shifting away from environmentally friendly land use practices. Thus, the Batticaloa development plan project should be implemented quickly to control sprawling growth. Yue, Liu, and Fan (2013) found that the failure to implement some policies during the transition period, such as land market rules, urban planning controls, and population growth limits, contributed to urban sprawl in major Chinese cities. These findings are similar in Batticaloa, where urban sprawl arose due to ineffective government policies.

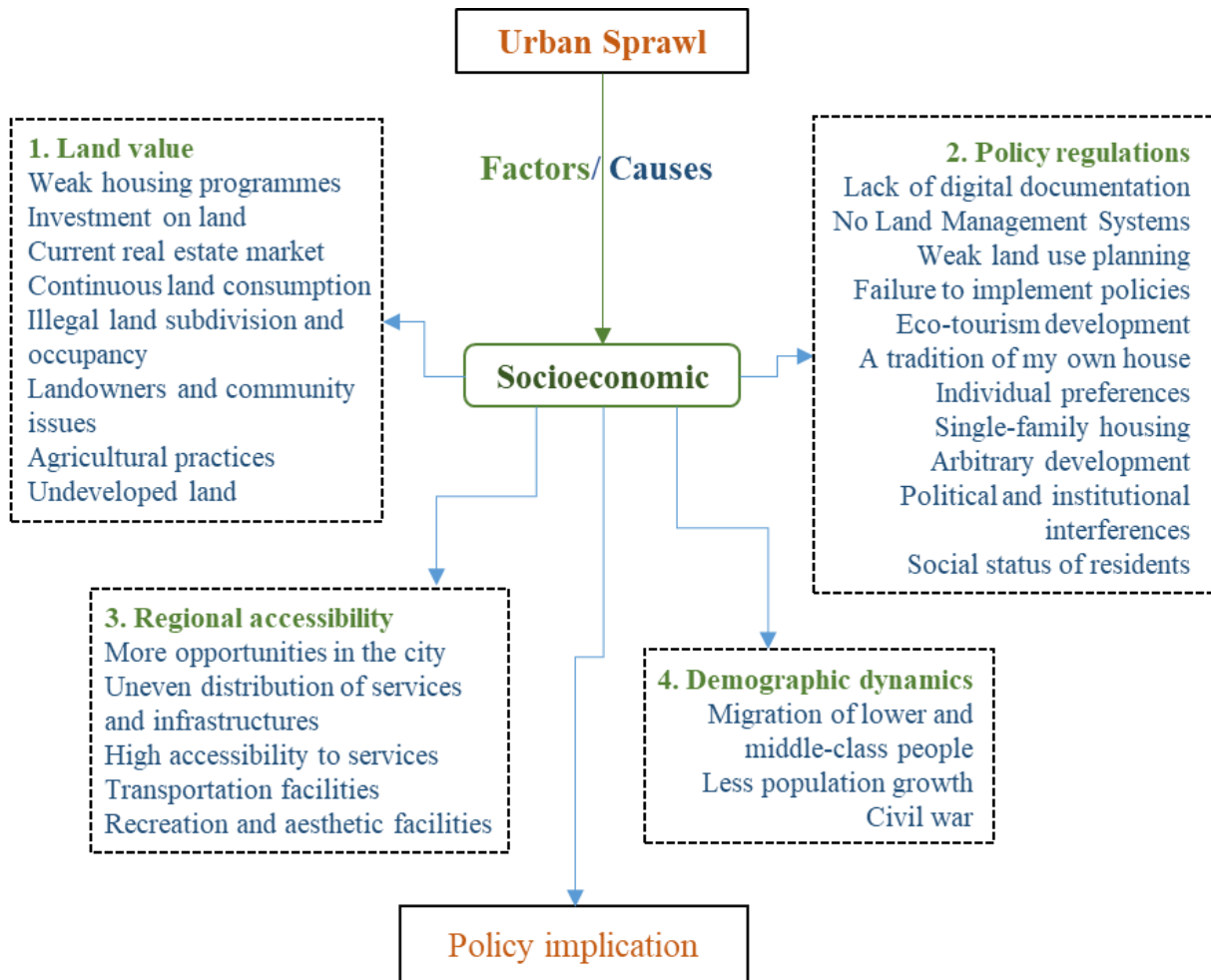


Figure 2. Conceptual framework.

One of the significant factors contributing to the urban sprawl in the municipality is regional accessibility. It all depends on how the service buildings and transportation are arranged concerning one other. According to Amarawickrama et al. (2015), urban sprawl in Colombo, Sri Lanka, has a strong link with built-up and proximity to services, including education and health, which has also been observed in the Batticaloa municipality. In Batticaloa district, the expansion of service infrastructure and industries is unevenly distributed, resulting in urban sprawl. This finding is consistent with Weilenmann and Schulz (2014). Compared to the areas around Batticaloa District, Batticaloa municipality has better access to all services,

like restaurants, banks, hospitals, universities, recreation, and administration. With all of these amenities, the municipality is attracting residents from all across Batticaloa District. People in the villages have poor economic or financial circumstances. Since their budgets don't allow them to purchase a house or property in the core city, they settle on low-cost lands or properties in the municipality, which are far from the city centre, including Thiraimadu, Paalameenmadu, and Thiruperunthurai areas.

Urban sprawl in Batticaloa is closely linked to and influenced by demographic dynamics. An increase in the population often accompanies land fragmentation in the municipality. As a result of a low population density, sprawling growth has occurred throughout the municipality. The population expansion in the municipality is a result of the internal migration of the neighbourhoods, which is comparable to Indian cities. Outbound commuters contributed more to urban sprawl in Switzerland's cities, whereas inbound commuters reduced the amount of urban expansion (Weilenmann & Schulz, 2014). Despite that, Batticaloa municipality seems to have an increase in sprawl due to inbound migration from nearby towns and villages in Batticaloa District. People from Western Batticaloa relocated to Eastern Batticaloa in 2007 because of the civil war, according to the International Organization for Migration (IOM). Simultaneously, Batticaloa and Chenkalady were both given 750 shelters in 2007, while another 700 were built, proving that migration was a significant factor behind urban growth in Batticaloa.

Further, Batticaloa has seen a steady rise in population since 1981. In 1981 and 2020, the population was roughly 51,037 and 94,785, respectively. An increase in the population of around 43,748 between the two periods significantly caused urban sprawl. The pressure of population growth encouraged the development of dwellings, shops, and other municipal infrastructure, which directly and indirectly resulted in the formation of urban sprawl in the municipality. These built-up developments generate a scattered and leapfrog pattern in the fringe areas, such as Kokkuvil, Thiraimadu, and Saththurukondan. This finding is similar to Hangzhou, China (Yue et al., 2013). Population growth in Batticaloa is not solely related to urban sprawl. Residential construction becomes increasingly spread as the population grows, putting further strain on the effective utility density. This finding is consistent with Saqui (2017); Weilenmann and Schulz (2014). According to Saqui, urban sprawl in Bangladesh is mainly caused by population increase and migration. In Dhaka, Barisal, Khulna, and Chittagong divisions of Bangladesh, population and density are significant contributors to urban sprawl (Saqui, 2017). This finding is parallel in Eastern China (Guangjin, Xinliang, Xiaojuan, & Lingqiang, 2016). It means that urban sprawl has a strong connection to population and human migration.

In addition, urban sprawl in the Batticaloa municipality is also influenced by land values, which have risen because of the current real estate market's growth. The municipality's population expansion is outpacing the purchasing of land. It can be found outside the city limits. Brody (2013) found similar results in cities across the United States. As a result of the increased demand for land, the population of the municipality is becoming more dispersed and less dense. At the same time, people are also purchasing plots outskirts of the city because of the rising demand for land in the municipality. This habit contributes to urban sprawl in the outskirts of the city. In addition, there is a significant pricing disparity between the city centre and its outskirts. For instance, core areas such as Arasady and Puliyanthivu are valued at between LKR 3,000,000 and LKR 4,500,000 per perch, while the value of land in urban outskirts such as Thiraimadu, Paalameenmadu, and Saththurukondan, is between LKR 200,000 and LKR

300,000 per perch (1 USD = 202 LKR) (UDA, 2015). The price disparity in land values encourages individuals to acquire lands outside the city centre, such as in the Koolavady, Punacholai, Amirthakali and Mamangam areas. As a result of the rising land value, many locals are buying more land to pass on to their children or to invest in for the future. Hence, these areas of the municipality are growing sprawl. Inadequate housing programmes in Batticaloa also increase the number of single-family residences in the city. According to Weilenmann and Schulz (2014), changes in societal patterns, such as single-household and age, have resulted in sprawl in Switzerland. This finding is parallel to Batticaloa. Land purchases are encouraged by residents' desire to build their own homes, regardless of their financial situation. In order to buy land and create their own home, they were drawn to the city limits because of the low land value.

However, income inequality, housing preference, employment and education were insignificant, and they were not taken into account in the study. Housing preference has spurred spatial growth in some preferred zones, such as the city centre and outskirts. This is also noted by Grigorescu and Kucsicsa, (2018). For instance, individuals are starting to build new residences in Kallady, Kokkuvil, Oorani and Navatkudah. According to Jetzkowitz, Schneider, and Brunzel (2007), the housing preferences of the general public are not contributing to urban sprawl. Social structures such as people's financial and local governments both play an essential role in promoting this idea. Income inequality creates uneven spatial separation between urban residents based on their income level. People in the lower and medium classes are more likely to be affected than those in the middle or upper classes (Lee et al., 2018). According to Wheeler (2006), raising the population's affluence reduces the density of cities, increasing the demand for land. However, 85.3% of Batticaloa citizens earn less than 50,000 LKR monthly. As a result of the high percentage of low-income residents, this area may have little effect on the expansion of the urban sprawl. Mehriar et al. (2020); Oueslati, Alvanides, and Garrod (2015) stated that raise of income is vital to the sprawl of cities like Nowshahr, Iran, and Chinese cities. However, according to Weilenmann and Schulz (2014), high wages lead to an increase in urban sprawl. In Batticaloa municipality, however, the regression analysis does not show it as a significant factor.

In addition, there are few educational options outside the city, including universities and colleges. However, the findings show that education did not impact the city's urban sprawl. This could be because students are temporarily migrating to the area. Further, employment opportunities differ between urban and rural areas, which contributes to rural-to-urban migration. The Batticaloa municipality is home to many government and private offices. People from all around the Batticaloa district come to work in this area. Due to the district's affordable public and private transportation options, employment may not have impacted urban sprawl growth. According to Mehriar et al. (2020), there was a strong link between work and urban sprawl in the Iranian city of Nowshahr. Besides government and non-government jobs, Batticaloa has seen a wide range of occupations in the municipality like small industries, agriculture, fishing, and commercial. Because of these employment categories, each area has a different distribution of settlements. As a result, urban sprawl may be at a relatively low level with employment. Generally, people prove their wealth to society through their living standards. The number of individual homes in a city increases due to advancements in building technology, which lowers the construction cost. The wealthy build high-priced dwellings to raise their living standards in society (X. Li et al., 2013). A wide range of socioeconomic statuses is represented among those who live beyond the core city.

However, there are fewer upper-class homes in those areas. As a result, it is possible that this factor could have a negligible impact on urban sprawl in the city.

5. CONCLUSIONS

Socioeconomic factors strongly drive the growth of urban sprawl in the municipality. The exploratory factor analysis identified nine (9) socioeconomic factors, including policy regulations, land value, demographic dynamics, regional accessibility, employment, education, housing preferences, income inequality, and living standards. As a result of Cronbach's Alpha, it was determined that the association between measured factors was strong enough to explore their influence on urban sprawl in Batticaloa. Further, four (4) models were created using the stepwise method for multiple linear regressions to identify the effect of socioeconomic factors on urban sprawl. Model 4 performed better than models 1, 2, and 3 in fitting the data. Land value, policy regulations, demographic dynamics and regional accessibility are the socioeconomic factors that influenced urban sprawl in Batticaloa. Thus, these factors should be focused on when developing policies to reduce urban sprawl in the future.

In order to implement the urban sprawl policy, the municipality and government should be considered its drivers and effects. Although Batticaloa is one of the growing cities in Sri Lanka, it receives little attention in policy-making. The findings show how municipal policy guidelines should be created considering the scope of the local level. To effectively deal with urban sprawl, the policy should consider various influencing factors holistically, which can enhance the municipality with less sprawling growth. Urban sprawl growth was not significantly influenced by all the socioeconomic factors studied in Batticaloa as a medium-sized city. Thus, several medium and large cities in Sri Lanka and the world should consider these factors, which may give significant findings. Future studies of urban sprawl may focus more on socioeconomic factors, such as drivers and effects, which could help lessen the long-term effects of urban sprawl.

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