Archives of Current Research International

Volume 24, Issue 1, Page 36-48, 2024; Article no.ACRI.111749
ISSN: 2454-7077

Measures of Urbanisation and Interrelationship between Factors Thereof in Tiruchirapalli District: A SEM Analysis

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/ACRI/2024/v24i1621

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/111749

Original Research Article

Received: 07/11/2023
Accepted: 12/01/2024
Published: 17/01/2024

ABSTRACT

Urbanization is a complex socio-economic process that transforms the built environment, converting formerly rural into urban settlements, while also shifting the spatial distribution of population from rural to urban areas. Urbanization was an important driving force in migration and commuting, because urban areas offer many economic opportunities to rural people through better jobs, new skills and cultural changes. The specific objective formulated for the study are to find out the various measures of urbanisation in the study area and to develop a structural equation model for depicting the interrelationship between these factors of urbanisation. A multistage random sampling technique was adopted. The tools of analysis for the study are Principal Component Analysis (PCA), Confirmatory Factor Analysis (CFA) using Structural Equation Model (SEM). The results revealed that the variables in the study had effect on urbanisation and the recommended fitness models and reliability test were achieved the required level for the study. The study concluded that the urbanisation has influence on the factors such as cropping pattern, land use pattern, growing employment and rural-urban migration in the study area.

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Keywords: Urbanisation; PCA; CFA using SEM.

1. INTRODUCTION

According to United Nations [1], "urbanization is a complex socio-economic process that transforms the built environment, converting formerly rural into urban settlements, while also shifting the spatial distribution of population from rural to urban areas". "It includes changes in the dominant occupations, lifestyle, culture and behaviour, and thus alters the demographic and social structure of both urban and rural areas.The process of urbanization in the developed countries has been very slow but steady and it has been accompanied by agricultural and industrial revolution, higher per capita income and high standard of living, whereas in developing countries the rate of urbanization is very fast and it is not accompanied by industrialization but rapid growth of service sector in the economies" [2].

"Depending on the relative magnitude of the different patterns (agriculture, land use pattern, rural-urban migration, remittances, technology transfer, labour supply) of the effect of urbanization, its impact on rural households' poverty is theoretically uncertain and may be negative or positive, especially in the context of rapid urbanization in developing economies" [3]. The agricultural land had been converted due to the growth in urbanization and industries, therefore urbanization was a threat to agricultural land as rapid economic growth shifted agricultural economies to non-agricultural economies. The rapid urban expansions had been mainly driven by a huge growth in industry, infrastructure development, population growth, increasing port-related activities and expansion of residential development, resulted in the consumption of agricultural land, vegetation cover, and hill encroachment [4-8].

With the above back drop, the specific objective formulated for the study are

1. To factorise the various measures of urbanisation in the study area.
2. To develop a structural equation model for depicting the interrelationship between these factors of urbanisation.

2. DESIGN OF THE STUDY

2.1 Methodology

A multistage stratified random sampling technique was adopted in this study. The nine taluks of Tiruchirapalli district have been classified as three gradients namely, Rural, Peri-urban and Urban, based on the proportion of urban population in the respective taluks (Census 2011) and also by referring geographical map of Tiruchirapalli district. One taluk has been randomly selected from each of the gradients, six villages have been randomly selected from each of the selected gradient and 15 respondents have been randomly selected from each of three villages. The ultimate sample consists of 270 sample respondents, which comprised of 90 sample respondents in each of the gradients, namely, Rural, Peri-urban and Urban. The primary data has been collected from the sample respondents of Rural, Peri-urban and Urban gradients using structured interview schedule. The nature of data collected, for the investigations focused on micro aspects, the primary data collected from the sample respondents of Rural, Peri-urban and Urban gradients of the Tiruchirapalli district have been utilized.

2.2 Tools of Analysis

2.2.1 Principal Component Analysis (PCA)

Principal Component Analysis is used to summarize most of the original information in a minimum number of factors for prediction purposes. In this study, principal component method of factoring was used to find out the major factors involved in urbanisation. However, the major difficulty of the analysis is based on the interpretation of results obtained. By extracting the maximum information, PCA aims to study the linear connections between variables and to identify homogeneous groups of variables from the correlation matrix or covariance. The principal component analysis (PCA), therefore, gives a description of the statistical units and observed variables based on the study of the correlation coefficients. Moreover, PCA highlights the similarities and contrasts between the analyzed units. The originally correlated variables are compressed and processed independent variables called principal components or axes. They allow to carry out a geometric representation that best explained the variability in the data. Thus, the PCA provides a system of orthonormal axes retaining all the distances between the variables, hence the delineation of groups of individuals with similar characteristics. PCA is used for heterogeneous data, while factor correspondence analysis (FCA) is used for contingency tables, but also allows analyses of qualitative data. The aim of the PCA is to group all the variables and facilitate the interpretation.

The PCA extracts the linear combination of these variables, which give the maximum variance and transform them into one index. The first principal component is the linear combination capturing the greatest variation among the set of variables. In other words, from an initial set of n correlated variables (X_1, X_2 … X_n), PCA creates m uncorrelated principal components, where each is a linear weighted combination of the initial variables as follows:

$$PC_m = a_{m1}X_1 + a_{m2}X_2 + a_{m3}X_3 + \cdots + a_{mn}X_n$$

where a_{mn} represents the weight for the m^{th} principal component and the n^{th} variable. The components are ordered, so that the first component explains the largest amount of variance in the data subject to the constraint that the sum of the squared weights ($a_{m1}^2 + a_{m2}^2 + a_{m3}^2 + \cdots + a_{mn}^2$) is equal to one. Each subsequent component explains additional, but less proportion of variation of the variables.

2.3 Confirmatory FACTOR ANALYSIS - Structural Equation Model (SEM)

“Structural Equation Modeling represents a combination of Factor Analysis and Path Analysis into one comprehensive statistical methodology. It is a family of statistical methods designed to test a conceptual (or) theoretical model. Structural equation modeling is a methodology for representing, estimating and testing a network of relationships between variables (measured variables and latent constructs). SEM is also known as Covariance Structure Analysis (CSA), Causal Models, Simultaneous Equations, Path Analysis, Confirmatory Factor Analysis, and Latent Variable Modeling. Examples include path analysis / regression, repeated measures analysis / latent growth curve modeling, and confirmatory factor analysis. Structural equation modeling can be portrayed as a model that uses particular configurations of the structures of four graphical symbols, that is, an ellipse (or circle), a rectangle, and a single or "double-headed arrow". Generally, squares (or rectangles) and circles (or ellipse) show observed and unobserved (latent) variables respectively, "single-headed arrows" (→) represent the direction of the impact of one factor on another, and "double-headed arrows" (↔) display correlations or covariance that take place between the variable or indicator pairs. Each of the four basic configurations is a vital component in the analysis process” [9].

2.3.1 Procedure for structural equation modeling

Structural Equation Modeling (SEM) has a two-step procedure, the first step is the measurement model validating and the second step is about the assumed structural model testing.

2.3.2 Phases of structural equation modeling

Validating the factors of the latent indicators or constructs, i.e., the scale of measurement,(CFA evaluated the measurement model). The structural model procedure is evaluated to judge the whole fitting model as well as the individual structural models.The phenomena or concepts of interest to human factors are often not directly measurable. In statistics, these abstract phenomena have been called latent variables, factors or constructs.

2.3.3 Measurement Model

“The measurement model is the part of a SEM model, which defines relations between the latent variables or constructs and their manifest variables. The manifest variables are often the items/questions of a questionnaire, but can be any type of measured data” [9].

2.3.4 Variables of SEM

“A measured variable is a variable that is directly measured, whereas a latent variable is a construct that is not directly or exactly measured. A latent variable could be defined as whatever its multiple indicators have in common with each other and are equivalent to common factors in factor analysis and can be viewed as being free of error of measurement” [9].

2.3.5 Parameters of SEM

“Parameters are constants which indicate the nature and size of the relationship between two variables in the population. Parameters in SEM can be specified as “fixed” (to be set equal to some constant like zero) or “free” (to be estimated from the data). Free parameters are estimated from the data, whereas the fixed parameters are not estimated from the data and their value is typically fixed as zero or one. Values of fixed parameters are generally defined based on requirements of model specification" [9].

2.3.6 Direct Effects

A structural model with a hypothesized mediating effect can produce direct and indirect effects. Indirect effects are those relationships that involve a sequence of relationships with at least one intervening construct involved.

The various packages namely, Amos, SAS PROC CALIS, R packages sem, lavaan, OpenMx, LISREL, EQS, and Mplus could be used to estimate parameters for a model, where the structure is well specified.

In order to estimate the adequacy of the measures to the present study and to carry out a preliminary evaluation and refinement of the measurement scales of the instrument, item total Correlations and Principal Component Analysis (PCA) was applied to check the construct validity. SPSS software version 16.0 was employed to conduct these analysis.

The responses of constructs that were perceived by the respondents were quantified in a 5 point Likert's scale continuum, namely strongly disagree, disagree, neither agree nor disagree, agree, strongly agree (from 1 for strongly disagree to 5 for strongly agree).

"Traditional statistical methods normally utilize one statistical test to determine the significance of the analysis. However, Structural Equation Modeling (SEM), CFA specifically, relies on several statistical tests to determine the adequacy of model fit to the data. The chi-square test indicates the amount of difference between expected and observed covariance matrices. A chi-square value close to zero indicates little difference between the expected and observed covariance matrices. In addition, the probability level must be greater than 0.05 when chi-square is close to zero" [10].

"The Comparative Fit Index (CFI) is equal to the discrepancy function adjusted for sample size. CFI ranges from 0 to 1 with a larger value indicating better model fit. Acceptable model fit is indicated by a CFI value of 0.90 or greater" [10].

"Root Mean Square Error of Approximation (RMSEA) is related to residual in the model. RMSEA values range from 0 to 1 with a smaller RMSEA value indicating better model fit. Acceptable model fit is indicated by an RMSEA value of 0.06 or less" [10].

"If model fit is acceptable, the parameter estimates are examined. The ratio of each parameter estimate to its standard error is distributed as a z statistic and is significant at the 0.05 level if its value exceeds 1.96 and at the 0.01 level it its value exceeds 2.56" (Hoyle, 1995). "Unstandardized parameter estimates retain scaling information of variables and can only be interpreted with reference to the scales of the variables. Standardized parameter estimates are transformations of unstandardized estimates that remove scaling and can be used for informal comparisons of parameters throughout the model. Standardized estimates correspond to effect-size estimates" [10].

List 1. The item measures which influence the factors are presented below:

Item No.	Variables
1.	Monsoon failure
2.	Increase in land values
3.	Labour Scarcity
4.	Increase in cost of cultivation
5.	Capital intensiveness
6.	Desire to enhance income
7.	Area available for cultivation
8.	Technology support for new crops
9.	Water scarcity
10.	Large family size
11.	Literacy Level
12.	Small size of holdings
13.	Alternative employment opportunities
14.	Rural welfare schemes
15.	Family obligations
16.	Indebtedness
17.	Income from agriculture
18.	Availability of alternative sources of income
19.	Lower wages at origin
20.	Urban proximity

A more accurate estimation of goodness-of-fit (GOF) between observed and estimated covariance matrices can be done using chi-square test. Software AMOS by IBM–SPSS can be used to create the model and estimate the parameters.

Keeping this in view, a structural equation model has been developed to show the interrelationship between factors of urbanisation. These variables were selected after conducting a detailed review of the past studies and also considering the suitability to the present study.

3. RESULTS AND DISCUSSION

3.1 Measures of Urbanisation

To study the different measures of urbanisation, Principal Component Analysis has been used in the study.

Principal Component analysis helps to reduce the innumerable variables into limited number of latent factors having inter-correlation. Bartlett's spherical test statistic was used to test whether the data is suitable for principal component analysis, KMO measure was used to measure the sample adequacy, the statistic values lies between 0 and 1 and it was also used to test the suitability of the correlation between the variables. Bartlett's sphere statistic was used to test whether the correlation matrix is the unit matrix, with significance level of 5 per cent. The results of KMO measures of sampling adequacy and the Bartlett's test of sphericity, which determines the factorability of the correlation matrix of urbanisation is presented in Table 1.

The results of the KMO and Bartlett's test would show that there was a higher KMO measure (0.869) and a significant Bartlett's test result (0.000). Hence, PCA has been attempted and the results are presented in Table 2 and 3.

The analysis was initially done with 20 variables, which were found to have effects on urbanisation. The principal component analysis (Table 2) revealed that the variables initially had a maximum of 97.954 cumulative per cent of variance.

The secondary loadings was done to extract the factors of urbanisation and as a result, four factors were extracted with more than one eigen values and the maximum cumulative percentage of variance of the four factors was around 54 per cent. And in the further loadings, the extracted factors obtained a maximum cumulative percentage of variance of 51.406 per cent, which reflects only minimal variation between the loadings.

"The correlations between the variable and the factor, with possible values range from -1 to +1 are shown as rotated factor loadings in Table 3. For a good factor solution, a particular variable should load high on one factor and low on all other factors in the rotated factor matrix" (Ajai and Sanjaya, 2006). It could be seen from Table 3 that all the variables were having more than 0.50 factor loadings. These variables were named and grouped as Land Use Pattern, Cropping Pattern, Occupational Pattern and Migration Pattern, which were the factors used for further analysis and influencedby urbanisation.

3.2 Interrelationship between the Factors of Urbanisation

From the above discussion, it was found that there exists interrelationship between land use pattern, cropping pattern, occupational pattern, migration pattern and urbanisation. Hence, a structural equation model has been developed in order to show the interrelationship between these factors of urbanisation.

3.2.1 Confirmatory factor analysis in structural equation modelling

The confirmatory factor analysis was done by using the factors extracted from PCA and Structural Equation Modelling (SEM) was run by using AMOS software. The model has been developed in order to show the interrelationship between land use pattern, cropping pattern, occupational pattern and migration pattern on urbanisation. This model included both observed and unobserved variable which are indicated in the Design of the Study. The estimates of the Structural Equation Model are presented in Table 4. The initial structure of CFA with SEM is given in Fig. 1. Having substantially achieved the required level of recommended fitness indices, the test results for reliability and convergent validity were found to be good for all the constructs. Hence, the structural model for the study was then assembled as shown in Fig. 2.

It could be seen from Table 4 that the estimates of regression weights of monsoon failure on land use pattern was 1.000, which represents partial effect of monsoon failure, holding the other path variables as constant. The estimated positive sign implies that land use pattern would increase by one time for every monsoon failure and this coefficient is significant at one per cent level.

Table 1. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.869
Bartlett's Test of Sphericity	Approx. Chi-Square	1.005E3
	Df	285
	Sig.	.000

Table 2. Total variance explained

Components	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	Percent of Variance	Cumulative Percentage	Total	Percent of Variance	Cumulative Percentage	Total	Per cent of Variance	Cumulative Percentage
1	4.963	24.814	24.814	4.963	24.814	24.814	2.772	13.860	13.860
2	1.293	6.466	37.281	1.293	6.466	37.281	1.971	9.856	30.716
3	1.236	6.179	48.460	1.236	6.179	48.460	1.826	9.130	42.846
4	1.087	5.435	54.895	1.087	5.435	54.895	1.712	8.560	51.406
5	.978	5.242	56.136						
6	.959	5.002	57.138						
7	.946	4.729	59.867						
8	.897	4.487	62.355						
9	.857	4.286	66.640						
10	.810	4.050	70.691						
11	.748	3.739	74.429						
12	.731	3.654	78.083						
13	.654	3.269	81.352						
14	.641	3.206	84.558						
15	.603	3.017	87.574						
16	.571	2.855	90.429						
17	.545	2.727	93.156						
18	.519	2.595	95.751						
19	.441	2.204	97.954						
20	.409	2.046	100.000						

Extraction Method: Principal Component Analysis

Table 3. Rotated component matrix

Variables Influencing Urbanisation	Components				Factors
	1	2	3	4	
Monsoon failure	0.571				Land Use Pattern
Increase in land values	0.748				
Labour scarcity	0.518				
Increase in cost of cultivation	0.649				
Capital intensiveness		0.568			Cropping Pattern
Desire to enhance income		0.574			
Area available for cultivation		0.586			
Technology support for few crops		0.514			
Water scarcity		0.723			
Large family size			0.548		Occupational Pattern
Literacy level			0.742		
Small size of holdings			0.667		
Rural welfare schemes			0.679		
Alternative employment opportunities			0.727		
Family obligations				0.643	Migration Pattern
Indebtedness				0.736	
Income from agriculture				0.662	
Availability of alternative sources of income				0.712	
Lower wages at origin				0.776	
Urban proximity				0.698	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 9 iterations.

Table 4. Estimates of CFA Model

Variables			Regression Weights	S.E	Factor Loadings	P-values
LU1	<---	Land Use Pattern	1.000	.095	0.801	***
LU2	<---	Land Use Pattern	.904	.100	0.899	***
LU3	<---	Land Use Pattern	1.109	.111	0.792	***
LU4	<---	Land Use Pattern	1.015	.106	0.858	***
CP1	<---	Cropping pattern	1.000	.086	0.744	***
CP2	<---	Cropping pattern	1.094	.175	0.779	***
CP3	<---	Cropping pattern	2.274	.322	0.878	***
CP4	<---	Cropping pattern	1.599	.228	0.742	***
CP5	<---	Cropping pattern	1.962	.275	0.924	***
OP1	<---	Occupational Pattern	1.000	.97	0.804	***
OP2	<---	Occupational Pattern	1.091	.107	0.919	***
OP3	<---	Occupational Pattern	1.066	.105	0.841	***
OP4	<---	Occupational Pattern	1.127	.100	0.872	***
OP5	<---	Occupational Pattern	.398	.065	0.901	***
MP1	<---	Migration Pattern	1.000	.101	0.797	***
MP2	<---	Migration Pattern	.928	.122	0.926	***
MP3	<---	Migration Pattern	.883	.119	0.812	***
MP4	<---	Migration Pattern	.866	.118	0.864	***
MP5	<---	Migration Pattern	.630	.098	0.972	***
MP6	<---	Migration Pattern	1.104	.134	0.892	***
U 1	--->	Land Use Pattern	.268	.173	0.073	***
U 2	--->	Cropping Pattern	.127	.239	0.134	***
U 3	--->	Occupational Pattern	.119	.192	0.041	***
U 4	--->	Migration Pattern	.252	.228	0.136	***

*(*** indicate significance at 1 per cent level)*

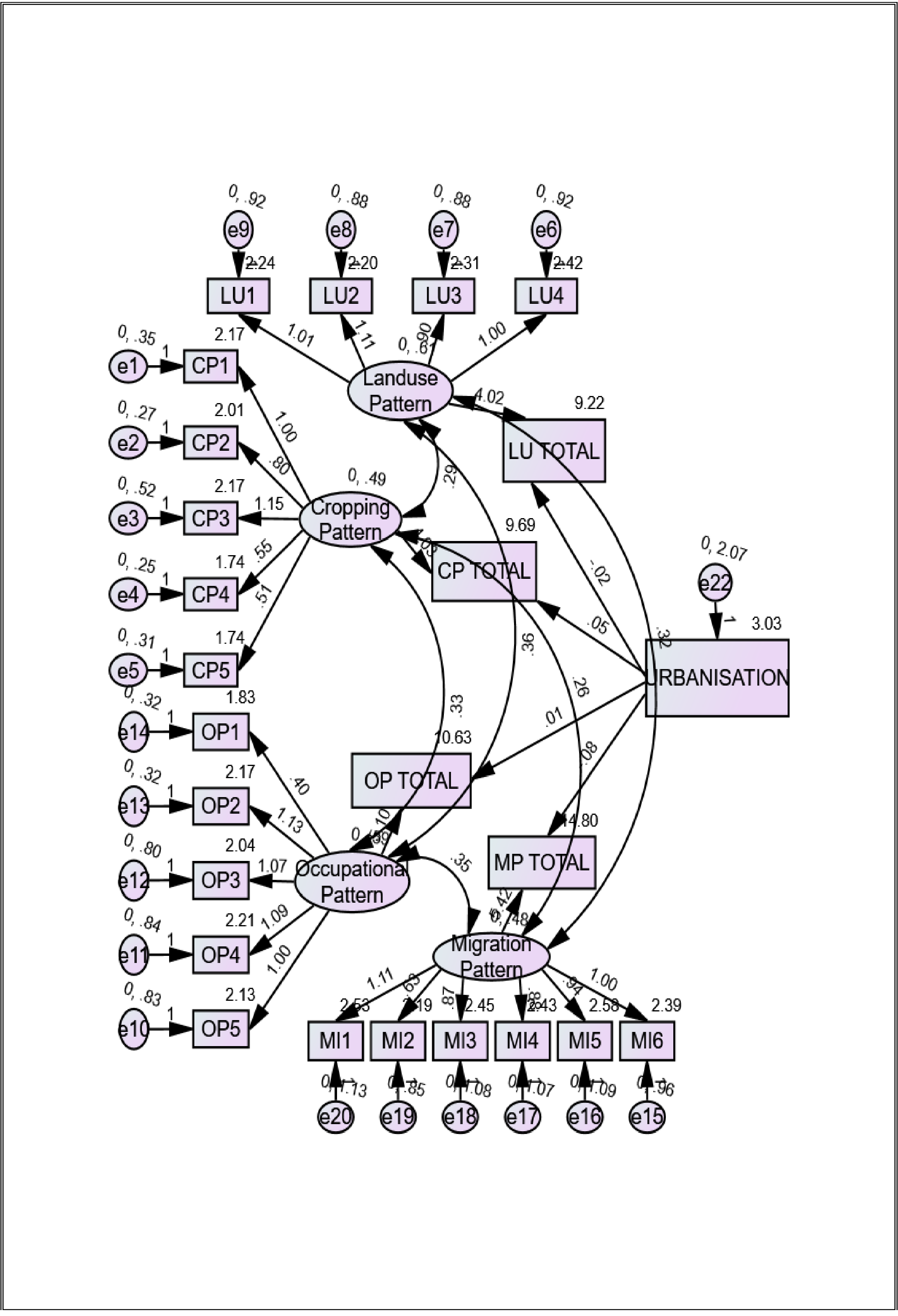

Fig. 1. Initial structure of confirmatory factor analysis with SEM

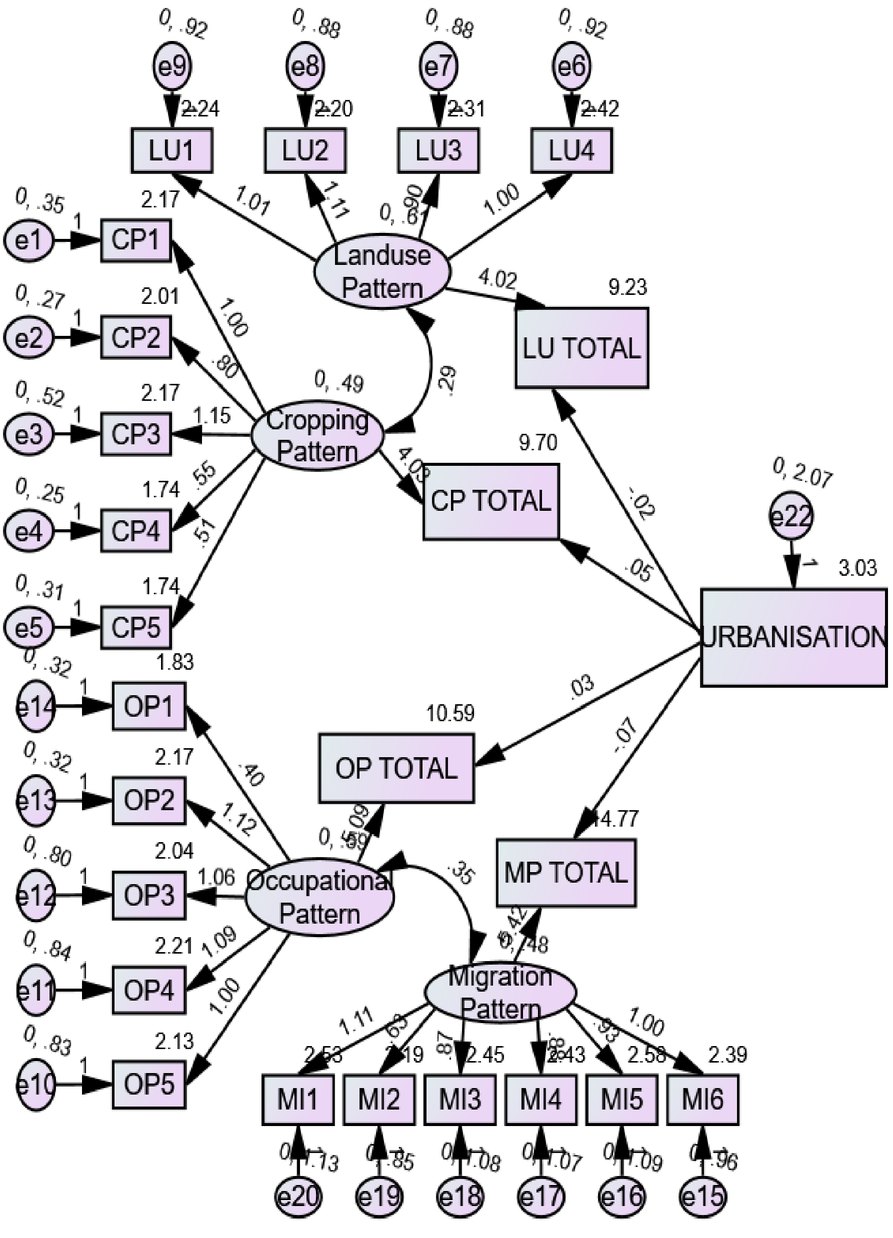

Fig. 2. Confirmatory Factor Analysis with SEM

The partial effects of increase in land values and labour scarcity on land use pattern were 0.904 and 1.109, holding the other path variables constant, implies that land use pattern would increase by 0.904 and 1.109 times, for every unit increase in land values and labour scarcity, respectively, the coefficients were significant at one per cent level.

The estimated positive regression weights of increase in cost of cultivation on land use pattern implies that land use pattern would increase by 1.015 times for every unit increase in cost of cultivation.

Among the land use pattern variables, the most important measure was increase in land value, which had a significant factor loading of 0.899, followed by increase in cost of cultivation with a loading of 0.858. However, monsoon failure and labour scarcity had a comparatively less effect with the factor loadings of 0.801 and 0.792, respectively.

The partial effects of capital intensiveness and desire to enhance income on cropping pattern were 1.000 and 1.094, holding the other path variables constant, implies that cropping pattern would increase by 1.000 and 1.094 times for every unit increase in capital intensiveness and desire to enhance income, respectively, the coefficients were significant at one per cent level.

The estimated positive regression weights of area available for cultivation and technology support for new crops on cropping pattern implies that cropping pattern would increase by 2.274 and 1.599 times, respectively, for every unit increase in area available for cultivation and technology support for new crop. The influence of change in water scarcity on cropping pattern was estimated at 1.962, which represents that cropping pattern would increase by 1.962 times, for increase water scarcity.

Of the various measures of cropping pattern, water scarcity was found to be the most influencing measures with the value of its factor loading being 0.924, followed by area available for cultivation with a factor loading of 0.878, desire to enhance income with 0.779, capital intensiveness with 0.744, and technology support for new crops had less impact with 0.742.

A further look at Table 4 revealed that the partial effect of large family size on occupational pattern was 1.000, holding the other path variables as constant. The estimated positive sign implies that the occupational pattern would increase by one time for every unit increase in the family size.

The estimated positive sign of the coefficient of literacy level and small size of holdings on occupational pattern were 1.091 and 1.066, respectively, which revealed that the occupational pattern would increase by 1.091 and 1.066 times, for every unit increase in literacy level and small size of holdings. The impact of rural welfare schemes and alternative employment opportunities on occupational pattern were 1.127 and 0.398, respectively, implies that the occupational pattern would increase by 1.127 and 0.398 times, for every unit increase in rural welfare scheme and alternative employment opportunities and this coefficient was significant at one per cent level.

Among the occupational pattern variables, literacy level was found to be the most influencing measures with a factor loading being 0.919, followed by alternative employment opportunities with the factor loading of 0.901, rural welfare schemes with 0.872, small size of holding with 0.841 and large family size had a less impact with 0.804 factor loadings.

The partial effect of family obligation on migration was 1.000, revealed that the migration would increase by one time, for every unit increase in family obligation. The effects of indebtedness and low income from agriculture on migration were found to be 0.928 and 0.883, respectively, representing the partial effect of these on migration, holding the other path variables as constant. The migration would increase by 0.928 and 0.883 times, for every unit increase in indebtedness and income from agriculture, respectively.

The effect of non-availability of alternative sources of income and lower wages at originon migration pattern were 0.866 and 0.630, respectively and implied that the migration would increase by 0.866 and 0.630 times for every unit increase in availability of alternative sources of income and lower wages at origin. The estimates of regression weights of urban proximity on migration was found to be 1.104. It could be interpreted that the migration would increase by 1.104 times for every unit increase in urban proximity and this coefficient was significant at one per cent level.

Of the various measures of migration pattern, the most important measure was the impact of lower wages at origin, which had a significant factor loading of 0.972, followed by indebtedness with a factor loading of 0.926, urban proximity with a factor loading of 0.892, availability of alternative sources of income with a factor loading of 0.864, income from agriculture with a factor loading of 0.812 and family obligations with a factor loading of 0.797, which had the least influence.

The estimates of regression weights of land use pattern on urbanisation was found to be 0.268. It would be interpreted that the urbanisation would increase by 0.268 times, for every unit increase in land use pattern and this coefficient was significant at one per cent level. The effect of cropping pattern on urbanisation was found to be 0.127, which revealed that the urbanisation would increase by 0.127 times, for every unit increase in cropping pattern and this coefficient was significant at one per cent level. The effect of occupational pattern on urbanisation was 0.119 and implied that the urbanisation would increase by 0.119 times, for every unit increase in occupational pattern. The estimates of regression weights of migration on urbanisation is 0.252 representing the partial effect of migration on urbanisation, holding the other path variables as constant. The estimated positive sign implies that the urbanisation would increase by 0.252 times, for every unit increase in migration.

Based on the interrelationship between the variables, it was observed that lower wages at origin (0.972) was the most influencing path in the structural equation model, followed by indebtedness (0.926), water scarcity (0.924), literacy level (0.919), alternative employment opportunities (0.901) and increase in land values (0.899).

The CFA addresses the issue of construct validity, when the recommended fitness indices reach the required level. The three model fit categories, *viz.,* absolute fit (RMSEA < 0.08; GFI > 0.90), incremental fit (CFI > 0.90; TLI > 0.90; NFI > 0.90), parsimonious fit (Chisq/df< 5.0) indices are presented in Table 5.

From Table 5, it was found that the calculated P value was 0.000. The Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI) values were 0.914 and 0.923, which are greater than 0.9, indicating a perfect fit of the model. The calculated Normed Fit Index (NFI) value (0.936) and Comparative Fit Index (CFI) value (0.961) indicated that the model was perfectly fit and also it was found that Root Mean Square Residuals (RMR) and Root Mean Square Error of Approximation (RMSEA) values were 0.072 and 0.077, which were less than 0.08 and indicated the perfect fit of the model.

Table 5. Fitness indices of structural equation model

S.No	Indices	Value	Suggested Value
1.	P value	0.000	< 0.05
2.	Chi-square value / DF	2.813	< 5.00
3.	GFI	0.914	> 0.90
4.	AGFI	0.923	> 0.90
5.	NFI	0.936	> 0.90
6.	CFI	0.961	> 0.90
7.	RMR	0.072	< 0.08
8.	RMSEA	0.077	< 0.08

To test the reliability and convergent validity, the Cronbach' Alpha coefficient (≥ 0.70), Value of Construct Reliability (CR ≥ 0.60) and also Average Variance Extracted (AVE ≥ 0.50) have been calculated and the results are presented in Table 6.

It could be seen from Table 6 that the factors involved in the model were fit for analysis by Cronbach's Alpha Reliability. It is noted that the CAR for Land Use Pattern (LU), Cropping Pattern (CP), Occupational Pattern (OP) and Migration Pattern (MP) were 0.798, 0.805, 0.807,

Table 6. Test results for reliability and convergent validity

Factors	Cronabach's Alpha Reliability	AVE	Sum of Factor Loadings	Sum of Delta	Construct Reliabilty
Land use Pattern	0.798	0.703	3.350	1.187	0.738
Cropping Pattern	0.805	0.667	4.067	1.664	0.710
Occupational Pattern	0.807	0.754	4.337	1.230	0.779
Migration Pattern	0796	0.773	4.371	1.157	0.791

0.796, respectively. The Average Variance Extracted (AVE) of the factors Land Use Pattern (LU), Cropping Pattern (CP), Occupational Pattern (OP) and Migration Pattern (MP) were 0.703, 0.667, 0.754 and 0.773, respectively, which are greater than 0.5. The Construct Reliability (CR) of the factors were also achieved by obtaining 0.738, 0.710, 0.779 and 0.791, respectively.

4. CONCLUSION

The study revealed that the variables used were found to have effects on urbanisation. The principal component analysis revealed that the variables initially had a maximum of 97.954 cumulative per cent of variance and in the further loadings, the extracted factors obtained a maximum cumulative percentage of variance of 51.406 per cent, which reflects only minimal variation between the loadings. All the variables were having more than 0.50 factor loadings. These variables were named and grouped as Land Use Pattern, Cropping Pattern, Occupational Pattern and Migration Pattern, which were the factors used for further analysis and had influence on urbanisation.

Based on the interrelationship between the variables, it was observed that lower wages at origin (0.972) was the most influencing path in the structural equation model, followed by indebtedness (0.926), water scarcity (0.924), literacy level (0.919), alternative employment opportunities (0.901) and increase in land values (0.899). The CFA addresses the issue of construct validity, when the recommended fitness indices reach the required level. The results achieved the required level of the fitness indices and reliability and convergent validity test.

Urbanisation has influence on the factors such as cropping pattern, land use pattern, growing employment and rural-urban migration in the study area. Urban conversion of agricultural land was intense and alarming in the study area and the loss of agricultural land to urbanisation has become inevitable, because of population pressure and migration of people to nearby towns.The policies concerned with urbanisation and urban development must pay special attention to increase the access of the poor to urban incomes and amenities, so that they can also take the advantages of urbanisation.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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