Assessing regional quality of life with an integrated framework: An application to district of Kozhikode in the state of Kerala (India), 2011

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The effects of urbanisation in developing countries like India call for measuring regional disparities in Quality of Life (QOL). Though there exists, several internationally recognized indexes to assess QOL, a regional QOL assessment is yet not studied in India. The study attempts to develop such an assessment framework for measuring objective QOL at the regional level using a composite index, taking the case of Kozhikode, Kerala, India, as a case example. Firstly, a set of 19 variables under five domains of QOL was arrived at through several steps of screening processes, refinement from a master list, and a final expert opinion survey. Secondly, a Composite Quality of Life Index (CQOLI) was formulated by conducting a series of statistical analyses on the data set, including Principal Component Analysis (PCA). Thirdly, a spatial analysis of QOL of the study area was conducted by mapping the CQOLI scores to understand the pattern and analyse inequities. Accordingly, the spatial study units were grouped into High, Medium, and Low QOL. Out of the total settlements, it was found that 20% fell in high QOL, 46.25% in medium QOL, and 33.75% in low QOL. The pattern was spatially analysed based on the topographical divisions, namely lowlands, midlands, and highlands, and it was found that the QOL decreased from lowlands towards highlands. Finally, solutions and strategies which may be used as policy directives were proposed for each QOL group. The insights from the study are helpful for planners and decision-makers while implementing interventions in the study region. The methodology adopted here can be replicated in other regions of similar scale by altering the variables suited to the context.

Keywords:
objective quality of life,
development disparities,
principal component analysis,
spatial mapping,
quality of life index,
human development

Introduction

In the context of rapid global urbanisation, development measured in terms of different indicators such as Gross Domestic Product (GDP), Human Development Index (HDI), or Genuine Progress Index (GPI) do not always represent the actual living conditions of people (Diener–Suh 1997, Hicks 2011, Mohit 2013, Puskorius 2015, Risser et al. 2017). The concept of Quality of life (QOL) becomes significant in this scenario. QOL measures the real-life conditions of people over and above a region's economic growth (Massam 2002, Turkoglu 2015). It includes all the factors influencing people's living beyond the material aspects (Eurostat 2017, Nanor et al. 2018, Young 2008). It is also interpreted as the overall satisfaction in several domains, such as finance, physical health, employment, family, education, religious beliefs, and the environment (Kolenikov 1998, Sores–Peto 2015). In the last few decades, scientists like Damen R, Chen Si, Diener E, and Suh Eunkook have offered many approaches to defining and measuring quality of life, mainly classified as Objective and Subjective QOL. Objective Quality of Life is based on quantitative statistics, which can be easily defined, recorded, and analysed, whereas Subjective Quality of Life measures the population's internal judgment of well-being (Chen et al. 2016, Damen 2014, Diener–Suh 1997, Discoli et al. 2014, Lee 2008). However, in many internationally recognised QOL indexes like Organisation for Economic Co-operation and Development (OECD) Wellbeing Index, both objective and subjective measures are combined to form a single index (Hakim et al. 2023, Kladivo–Halás 2012, Pál et al. 2021, Zagyi et al. 2021).

Apart from the globally recognised QOL indexes, researchers from different parts of the world have attempted to measure the QOL of regions, sub-regions or locales using a formulated or modified index. One of the earliest attempts at an area-specific QOL index was by Chan et al. (2005) by developing a QOL index for Hong Kong. At a regional scale, several studies have developed QOL indexes incorporating objective and subjective measures. For example, Chhetri et al. (2007) studied the perceived quality of life in the Brisbane-South East Queensland (SEQ) region. Giannias et al. (2010) tested the convergence of QOL indexes across the EU countries between 1970 and 1990. Lazim–Abu Osman (2009) developed a new Malaysian QOL index based on the fussy sets theory. Katumba et al. (2022) and Greyling–Tregenna (2017) developed a context-sensitive QOL index for South African provinces. Felix–Garcia-Vega (2012) assessed the QOL of southwestern Mexico using an index by applying the partial least square method. The latest study by Macků et al. (2022) attempted to construct a regional synthetic QOL index for the European administrative units. In recent years QOL at local scales, mostly at the city level, were assessed at different places by researchers such as Ledo et al. (2012) in Galicia, Floková et al. (2023) in the Czech Republic and Kamdar (2021) in India. Despite the prevalence of numerous regional QOL studies, the development of a QOL index at a regional scale has not yet been attempted in India. The QOL studies from India are mostly at the local scale capturing domains and addressing issues at the city level (Bardhan et al. 2011, Kamdar 2021). As far as India's governance system is concerned, a regional QOL assessment is required before the cities can be assessed for the same. The present study, therefore, attempts to fill this gap in the existing body of knowledge. Here, an objective QOL index at a regional scale is constructed and applied to a region in southern India.

The district of Kozhikode in the state of Kerala in southern India was taken here as the case study. Despite being part of a developing nation, Kerala is known for having high scores for social indicators such as HDI, demographic indicators, and health scores with decentralised governance mechanisms that assure social welfare (Firoz et al. 2014, Kallingal–Firoz 2023, Kundu et al. 2013, Tharakan 2006, 2008). Accordingly, Kerala is perceived to have a higher regional QOL. However, recent studies show disparities in social development even within Kerala (Kallingal–Firoz 2023. Zehba et al. 2021). Also, few studies have been conducted concerning QOL within Kerala. In addition, the state shows a rural-urban continuum pattern of development in which urban and rural areas cannot be differentiated (Cyriac–Firoz 2022, Firoz 2014, Krishnan–Firoz 2020, Paul 2017). A sub-regional level assessment of QOL can reveal the existing inequities and variations of QOL within the state. Hence, such a study also contributes to the knowledge domain of development disparities in Kerala, thereby aiding in sustainable development.

The original research is aimed to derive a spatial assessment framework for QOL at the regional level in developing countries like India. It is designed at three scales of QOL assessment, as shown in Figure 1. 'Tier 1' and 'Tier 2' analyses are carried out for regional and sub-regional scale studies (at the country, state, and district levels)[1] where only secondary data is used. This is because of the availability of secondary data and the difficulty in collecting primary data. Tier 1 and Tier 2 analyses help in identifying those significant sectors of urban development that require any regional-level interventions. This initial level of analysis also aids in deriving the settlements that need a detailed assessment of QOL from a larger context.

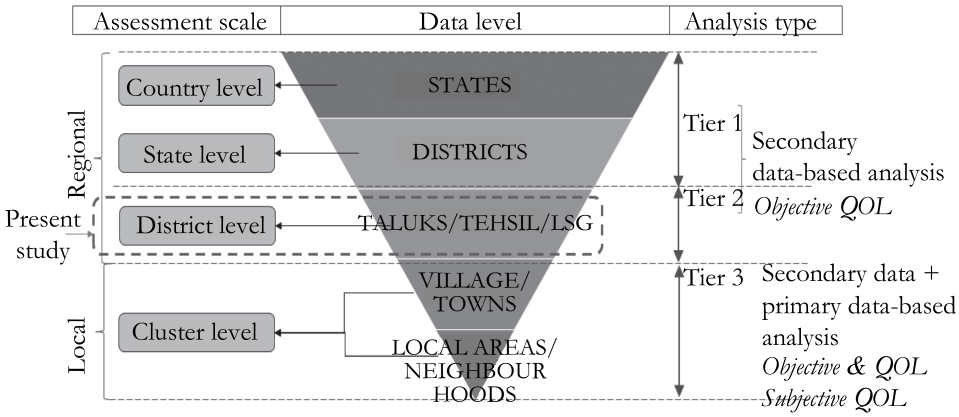
A 'Tier 3' analysis is carried out for local-scale studies, where both primary and secondary data can be used. At the local scale, the limited availability of secondary data and the higher feasibility of collecting primary data helps in conducting the Tier 3 analysis. As most studies look directly at local scales (Tier 3) without comprehensively deriving the study area from a larger region, the approach used in the present study is a need of the hour. A Tier 1 analysis was already conducted at the state level to understand the regional variability of QOL (Zehba et al. 2021). The analysis showed considerable variations in QOL across the state of Kerala, and QOL

[1] India is a union of states with a parliamentary system of government, which is federal in structure with certain unitary features. There are 28 states and 8 union territories (UTs), which are further divided into districts. A Taluk or Tehsil is an administrative district for taxation purposes comprising of several villages.

was high in highly urbanised regions. The present study focuses on Tier 2 analysis at the district level, considering the region with the highest QOL obtained from the results of Tier 1 analysis.

Figure 1

Scales of assessment of QOL



Measuring the progress of societies using a QOL index helps planners and administrators work for better living conditions for the region (Best 1996, Diener–Suh 1997). This has been practised in many developed and developing countries (Marans 2012, Mostafa 2012). However, applying any internationally accepted QOL index (e.g., OECD Better Life Index, Social Progress Index) directly to the Indian context was not considered adequate because of several limitations (Zehba et al. 2021). The variables in most of these indices were suited to a developed country and weren't completely addressing India's QOL problems due to social and demographical contextual differences. For example, some of the indicators used in the OECD Better Life Index, like social connections (social network support, social contact, time spent volunteering), may be considered irrelevant in an Indian context. Similarly, some indicators like personal security and housing conditions may require additional variables, like violence against women, water supply and sanitation facilities in houses, to be added to fit into an Indian context. In addition, there were limitations regarding data availability and the data set's nature. A formulated index considering the variables from all these global indices but suitable for the existing context thus became a necessity. Therefore, the study's primary objective is to construct a locally specific, valid and relevant index and interpret the results spatially to obtain inferences that aid policy recommendations. The study hypothesises that QOL scores do not vary across settlements, and the null hypothesis is expressed as objective QOL scores are equal in all the settlements of Kozhikode.

Assessment of QOL helps in understanding spatial inequalities, identifies areas requiring special focus, and in formulating policies and strategies for a balanced and sustainable development (Ranjan et al. 2022, Serag et al. 2013). Moreover, spatial mapping of QOL and analysis aid in a clearer understanding of QOL based on geographical factors and identifying its patterns (Bardhan et al. 2011, Delfim Santos–Martins 2014, Kallingal 2017, Krishnan–Firoz 2021).

The paper is organized as follows: review of literature (the background literature, including concepts, tools and techniques, QOL variables, and the final variable list), materials and methods used in the study (includes the study area, variable selection process, and QOL index construction), results (analysis and discussion of the results), and concluding remarks.

Review of literature

Literature on different approaches of measuring QOL, constructing a QOL index and selecting QOL variables were studied to select the most appropriate techniques for the study. It is found that two social indicators, namely Objective and Subjective well-being measures, are invariably used in the literature to evaluate the living conditions and wellbeing of a society (Diener–Suh 1997). The first one, Objective QOL, can be easily defined and quantified without relying heavily on individual perceptions, and it is technically convenient to make comparisons between regions or countries (Diener–Suh 1997, Patil–Sharma 2020, Psatha et al. 2011, Turkoglu et al. 2006). It reflects the normative ideals of a society and can capture important aspects of society that are not reflected enough in economic indices (Best 1996, Chen et al. 2016). However, it could be open to errors due to issues with input data and difficulties in measuring indicators across spatial regions. In addition, the chances of selection bias in indicators are high. (Delfim Santos–Martins 2014, Kironji n.d.).

Conversely, Subjective QOL measures are incomparable, intangible, and unstable as they are based on an individual's perceptions, satisfaction, and well-being (Santos–Martins 2014). They provide an additional essential assessment to evaluate the observations from objective indicators (Psatha et al. 2011). It is easier to modify in later studies and is more easily compared across domains having different units using a single dimension (Shoeibi et al. 2015). But the validity here is still questionable as it cannot be assumed that every individual's responses are valid and accurate (Lee 2008, Tuan Seik 2000).

Researchers have taken Objective QOL for regional comparisons of QOL and in policy and strategic decision-making (Chen et al. 2016, Guhathakurta–Cao 2011, Nanor et al. 2018, Martínez 2009). This approach aids in a better understanding of which sector to focus on for a better QOL (Chen et al. 2016). As a data-driven approach is more suitable to the present study as it is on a regional scale (Cyriac–Firoz 2022). In addition, owing to the entire research complexity in arriving at a composite indicator, comparing the two types of QOL, and validating the authenticity of subjective measures (Teklay 2012), only an objective-based QOL is considered for this study. While constructing a QOL index, the choice of indicators holds prime importance as it decides what domains of QOL are being measured based on the context of the study (Bardhan et al. 2011, Delfim Santos–Martins 2014). International agencies and scholars have identified several indicators reflecting people's living conditions. The major domains of QOL as identified by international agencies include the populations' socio-demographic characteristics such as sex ratio, literacy rate, housing conditions, employment conditions, infrastructure status for education, transport, and environmental conditions (Michalos et al. 2011, OECD 2011, Porter et al. 2017, World Bank 2013).

Literature agrees that the variables used in the index should be representative, simple, valid, policy-relevant, measurable, cost-effective, user-friendly, valid at all times, not be easily manipulated, reliable, and up to date at all times, for a better result and interpretation (Greyling 2013, OECD 2008). The selection of variables was from the available literature in most of the studies (Eurostat 2015, Michalos et al. 2011, Porter et al. 2017). Many studies use the WHOQol BREF[2] as a standard measurement tool for QOL assessment (Crea et al. 2015, Zhang–Li 2019). However, any such standard QOL measurement tool was not considered comprehensive enough to fit any region worldwide. Data availability also influenced the selection of variables in many studies (Afsar et al. 2013, Azad et al. 2015, Guhathakurta–Cao 2011, Tazebay et al. 2010), owing to which only secondary variables are focused in the present study. Since there was no set rule for the process of choosing variables, the selection from a holistic list after screening for contextual relevance and data availability was found to be a justifiable method.

Most literature used an already available international QOL index for the concerned case (Michalos et al. 2011, Porter et al. 2017). Researchers commonly agree that owing to the multidimensionality of the concept, it was essential to compute a composite index for measuring QOL (Ballas 2013, Costanza et al. 2008). For this, weights concerning the relative importance of variables need to be identified, which decides the authenticity of the index (Mazziotta–Pareto 2013, Puskorius 2015). Literature suggested various multivariate analysis methods for weighting and aggregation of the variables, such as factor analysis or Principal Component Analysis (PCA), analytic hierarchy processes (AHP), unobserved components models (UCM), data envelopment analysis, conjoint analysis (CA), and budget allocation processes (BAP) Even though such methods were used by many, PCA is preferred by the most (Erik–Marko 2011, Krishnan–Firoz 2020, Nardo et al. 2005, OECD 2008).

PCA explains the maximum variance and summaries a set of individual indicators while preserving the max possible proportion of the total variation (Abeyasekera 1995, de Senna et al. 2019, Egidi et al. 2021, Krishnan–Firoz 2020). Other approaches,

[2] WHOQoL BREF is a self-administered questionnaire consisting 26 questions covering four domains of QOL namely physical health, psychological health, social relationship and environment, to evaluate the health and well-being of individuals, valid across cultures, developed by the World Health Organization (WHO).

however, revealed many drawbacks. For instance, cluster analysis was purely descriptive (Weziak-Białowolska 2016), Delphi and AHP were time consuming (Bagheri et al. 2021, Olakitan Atanda 2019, Terano–Mohamed 2014), budget allocation was less reliable.

A few studies conducted spatial analysis with the help of a geographical database to analyse the disparities in QOL (Martínez 2009). Here, homogeneous groups were clustered to discover spatial association patterns, concentration areas, or hotspots (Ilic 2013, Santos–Martins 2014). PCA was the most prominent method used among many multivariate analysis methods in these studies.

The methodological approach used in each research was different and suited to the context's social, demographic, and geographical conditions. Accordingly, the indicators of QOL also varied. QOL indicators or variables hence formed the base of any such study.

Materials and methods

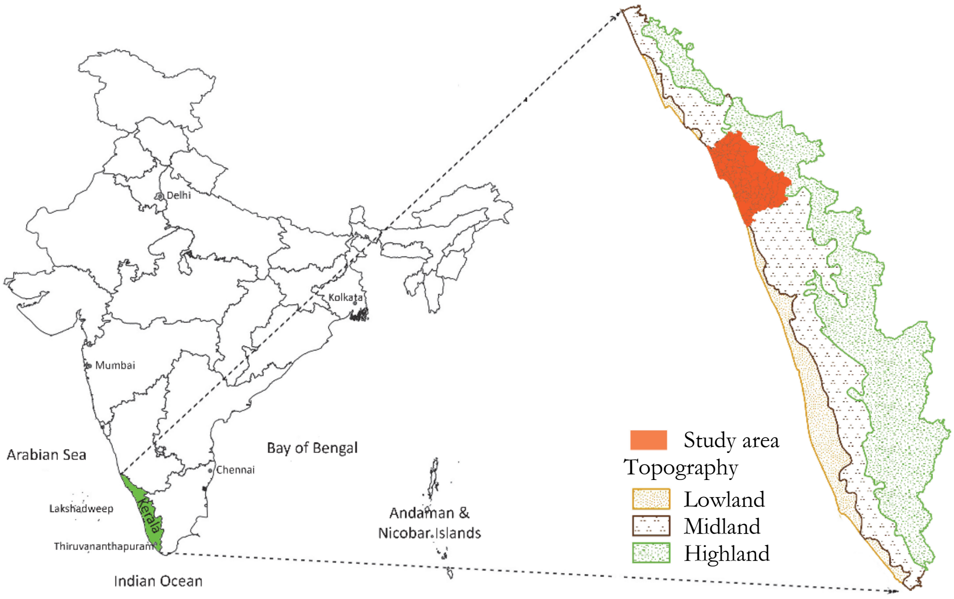
Study area

The study area is the Kozhikode District[3] located in the northern region of Kerala, India (Figure 1). Kozhikode is the most important urban services provider for all districts in northern Kerala (DTCP Kerala 2011, V.P. et al. 2021). A regional study of QOL assessment (Tier 1 analysis) in Kerala revealed that Kozhikode scored the highest in QOL (Zehba et al. 2021). Hence a detailed assessment of QOL is essential here to contribute to future decision-making processes. The spatial/geographical units of study were the local self-government bodies with either rural or urban designations, as these were the lowest administrative units for which secondary data was available. Local self-government bodies (LSG) are jurisdictions below the state level which has defined boundaries and socio-demographic data published by the respective administrative departments (Commonwealth Local Government Forum 2019). Geographically, Kerala state is divided into lowlands (coastal plains) in the west, midlands (rolling hills) in the centre, and highlands (rugged and cool mountainous terrain) in the east (Figure 2). Population density decreases from the lowlands towards the highlands, i.e., from west to east in the site.

[3] The administrative setup of India adopts a decentralized system comprising of the country at the apex, followed by the state and the local self-government. Each state is comprised of districts and each district is further divided into urban local bodies named Municipal Corporations or Municipalities and rural local bodies named Grama Panchayats.

Figure 2

Location of study area



Source: Adapted from Human development report Kerala 2005, Centre for Development Studies.

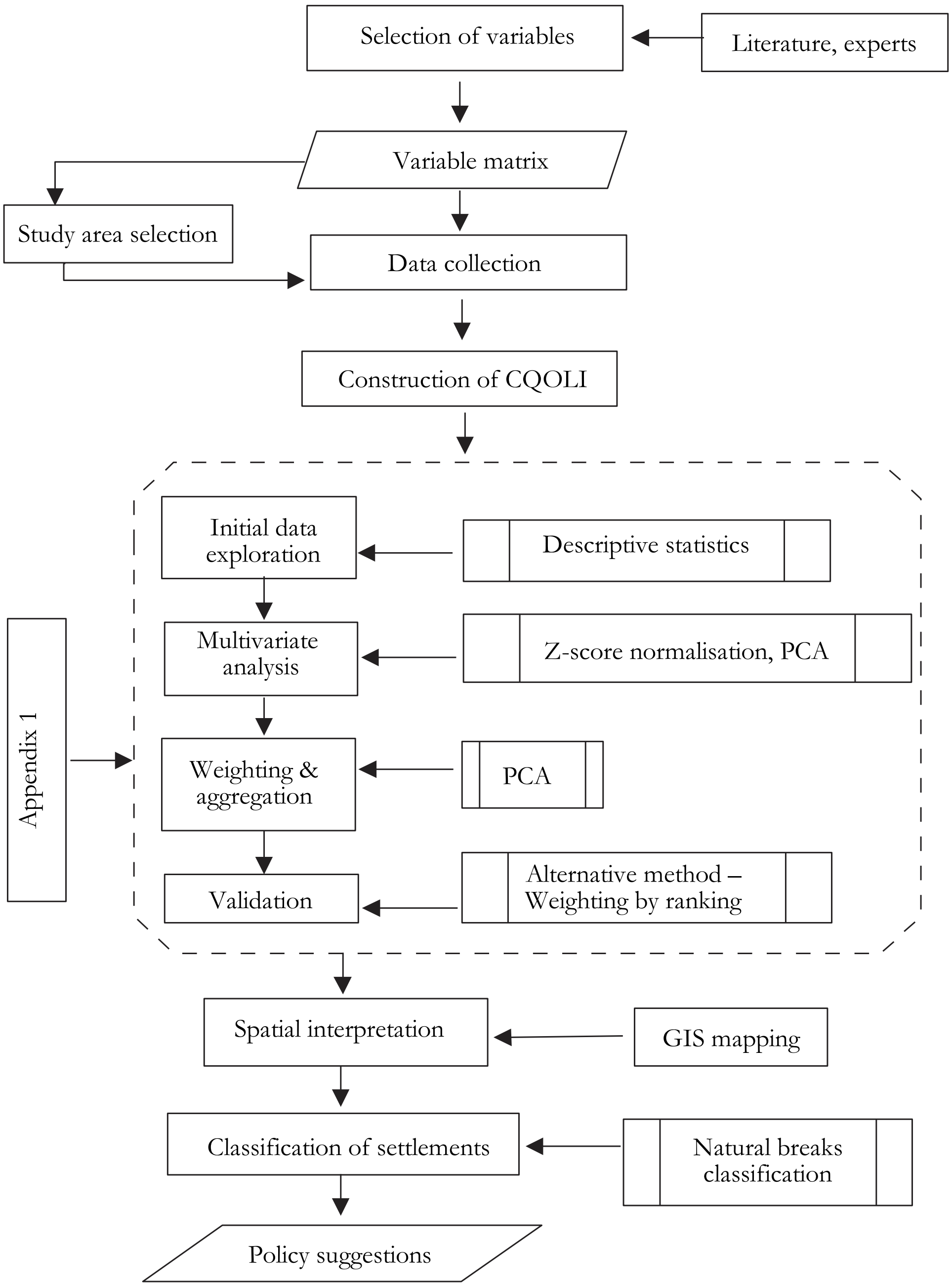
Methodology

The methodological framework followed in the study is explained in the flowchart (Figure 3). At first, variables were finalised, and the data were collected for all the settlements from various secondary sources such as the Census and panchayath statistics[4] (DCOP 2011, DEST Kerala 2011, MoHA 2011). Once data were collected, a variable matrix was formed for the same. The data matrix underwent a series of analyses to create a composite index. Scores for each study unit were calculated using this index and were spatially mapped and interpreted. Finally, policy suggestions were formed.

[4] Panchayat Statistics is published by the Department of Economics and Statistics – Thiruvananthapuram (DEST), the nodal agency of Government of Kerala responsible for the systematic collection, compilation and analysis of various socio-economic statistics of the state.

Figure 3

Methodological framework



Data source

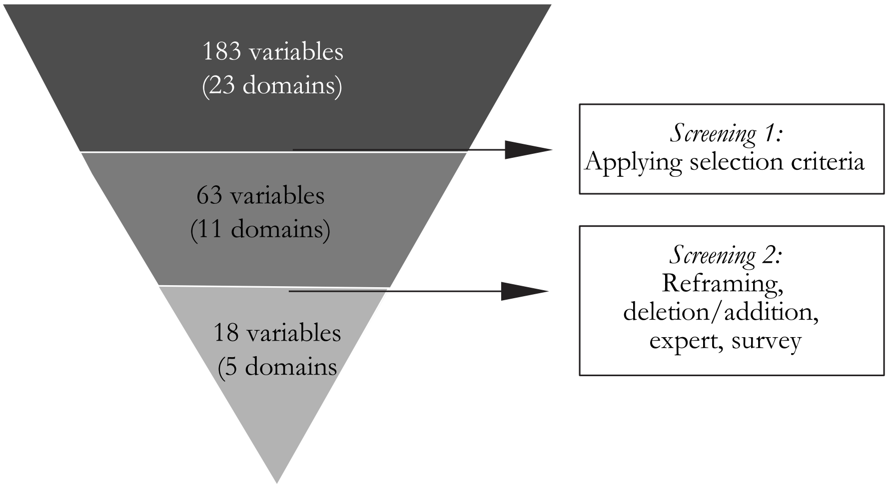
Data used for the study is from two major sources, namely the Census of India 2011 and the Panchayat Level Statistics 2011. The Census of India is the decadent data published by the Ministry of Home Affairs, Government of India (MoHA 2011). The latest available census data at the time of the study was from 2011, which is used here for the analysis. The Panchayat Level Statistics is the local level statistics collected and published by the Department of Economics and Statistics – Thiruvananthapuram (DEST), Government of Kerala (DEST Kerala 2011). It provides data regarding infrastructure at the local body level for each district in Kerala. The framework can be applied to future census data as and when it is published.

Selection of variables

The method of filtering globally used indicators to suit the context of a study, as in many studies (Firoz 2014, Krishnan–Firoz 2020, 2021), was adopted here. Initially, a holistic list of indicators/ variables was formed from the reviewed literature. This master list included variables used in several internationally recognised indicator systems such as OECD, Eurostat, United Nations Statistical Division (UNSTAT), World Bank Development indicators, Canadian Well-being Index, Social Progress Index, and City Livability Index by the Government of India, as well as selected research papers from Scopus and Web of Science database. Then the variables were screened in three steps. A selection criterion was applied in the first step. The variables were selected by checking their suitability, simplicity, validity, policy relevance, and data availability. The second screening was done to reframe the variable to suit the context, delete any irrelevant variable and add any variable to complement an existing one. The third step was a vetting process through an expert opinion survey. For this, an online expert opinion survey was conducted among planners, economists, social scientists, academicians, and professionals from different cities in India like Kozhikode, Thiruvananthapuram, Kollam, Hyderabad, Ahmedabad, Kharagpur, etc. An agreeance questionnaire was prepared in the Google form and mailed to the experts. In the form, they were asked to select those variables that were valid under each QOL domain and add any additional variable if needed. The response rate of the survey was 66%. The percentage of positive responses for each variable was recorded. The positive responses ranged from 60% to 97.5%. The variables with the highest positive responses were selected to modify the previous list, and the final variable list was obtained (Figure 4).

Figure 4

Variable selection process



Construction of Composite Quality of Life Index[5] (CQOLI)

The variables were weighted and aggregated to a composite index to get the overall character of quality of life (Michalos et al. 2011, OECD 2008). In this study, the process of formulation of the Composite Index of Quality of Life (CQOLI), as shown in Figure 3, followed the steps such as imputation of missing data, checking for normality, outliers and multicollinearity, data transformation, normalisation, Kaiser–Meyer–Olkin (KMO) test, and PCA (OECD 2008). Finally, the weighting and aggregation of indicators were carried out to form the composite index.

Spatial interpretation

Spatial analysis of QOL was carried out in the next stage, as described in the flowchart (Figure 3). The pattern of QOL was studied by spatially mapping the CQOLI scores of the settlements. The pattern of each component was also studied by considering its influence on CQOLI. Since any policy directive solutions should focus on where it is needed, the classification of settlements was required. It would help decentralised planning with focused service provisions and development initiatives (Krishnan–Firoz 2020). The settlements were classified into high, medium, and low QOL settlements using the natural breaks classification method in Geographic Information System (GIS) (Brewer–Pickle 2002, Krishnan–Firoz 2020). The characteristics of each group were studied based on the mean centers of variables. From the final inferences, policy recommendations were suggested for the betterment of QOL in each group.

[5] A detailed explanation of each of these steps, namely Initial data exploration, Multivariate Analysis, Principal Component Analysis, Weighting and aggregation and the Validation of the result, is provided in Appendix 1.

Results

Variables of quality of life

Table 1 shows the 18 variables of QOL under the heads of 5 domains with their descriptions, sign, and data sources.

Table 1

Variables of QOL

Domain	Sl. No.	Variable	Description	Data source	Reference
Population	1	POP DEN	No. of persons per sq. km	CEN	(Afsar et al. 2013, Michalos et al. 2011, UNDESA 1989, World Bank 2013)
	2	SEX RATIO	No. of females per 1000 males	CEN	(Afsar et al. 2013, Eurostat 2017, Michalos et al. 2011, UNDESA 1989, World Bank 2013)
Income, employment & wealth	3	WPR	Percentage of total main workers	CEN	(Dutt et al. 1986, Eurostat 2017, Firoz et al. 2014, OECD 2011, Posner 2010, Scott Stern et al. 2017, UNDESA 1989, World Bank 2013)
	4	HH ASST %	Percentage of households owning TV/ Computer/ Laptop	CEN	(Eurostat, OECD 2011, UNDESA 1989)
	5	BPL HH %	Percentage of BPL households	PS	(Eurostat 2017, OECD 2011, UNDESA 1989)
Housing conditions & services	6	DWL SPC	Average number of rooms per person	CEN	(Afsar et al. 2013, Firoz et al. 2014, OECD 2011, Scott Stern et al. 2017, UNDESA 1989)
	7	HH WS %	Percentage of households having water supply within their premises	CEN	(Afsar et al. 2013, Firoz et al. 2014, OECD 2011, Scott Stern et al. 2017, UNDESA 1989)
	8	HH DRG %	Percentage of households having closed drainage system	CEN	(Afsar et al. 2013, Firoz et al. 2014, OECD 2011, Scott Stern et al. 2017, UNDESA 1989)
	9	HH LAT %	Percentage of households having Flush/ Pour latrine	CEN	(Afsar et al. 2013, Firoz et al. 2014, OECD 2011, Scott Stern et al. 2017, UNDESA 1989)
	10	PUC HH %	Percentage of Pucca[a)] houses	CEN	(Afsar et al. 2013, Firoz et al. 2014, OECD 2011, Scott Stern et al. 2017, UNDESA 1989, Zehba et al. 2021)
	11	HH OWN %	Percentage of owned houses	CEN	(Afsar et al. 2013, Firoz et al. 2014, OECD 2011, Scott Stern et al. 2017, UNDESA 1989)

(Table continues on the next page.)

(Continued.)

Domain	Sl. No.	Variable	Description	Data source	Reference
Social infrastructure	12	HOS PER 1000	No. of hospital & health centers per 1000 population	PS	(El-Farouk 2018, Eurostat 2017, Firoz et al. 2014, Greenwood 2001, MoUD 2013, Scott Stern et al. 2017, UNDESA 1989, Zehba et al. 2021)
	13	SCH PER 1000	No. of LP/UP/HS Schools per 1000 population	PS	(El-Farouk 2018, Firoz et al. 2014, Scott Stern et al. 2017, Zehba M. et al. 2021)
	14	ELR	Percentage of literates among population above 6 years	CEN	(Afsar et al. 2013, Eurostat 2017, Michalos et al. 2011, OECD 2011, Scott Stern et al. 2017, UNDESA 1989)
	15	KG PER 1000	No. of Kindergartens per 1000 population	PS	(El-Farouk 2018, Firoz et al. 2014, Scott Stern et al. 2017, Zehba et al. 2021)
Civic infrastructure	16	SO-CUL PER 1000	No of Community halls and Sports/Arts club & Public libraries and reading rooms per 1000 Population.	PS	(Afsar et al. 2013, Firoz et al. 2014, MoUD 2013, Porter et al. 2017, Zehba et al. 2021)
	17	RD DEN	Total length of roads(m) per sq. km	PS	(Afsar et al. 2013, Firoz et al. 2014, MoUD 2013, Zehba et al. 2021)
	18	PO INT PER 1000	No of Post Offices and Private Couriers & Cyber Cafes / Akshaya centers per1000 Population.	PS	(Afsar et al. 2013, Firoz et al., 2014, MoUD 2013, Porter et al. 2017, Zehba et al. 2021)

a) The word 'Pucca' means 'Solid' or 'Permanent', mostly used in the Census of India vocabulary.

Source: Compilation of authors based on CEN – Census of India 2011 (DCOP 2011), PS – Panchayat statistics 2011 (DEST Kerala 2011).

Composite Quality of Life Index (CQOLI)

As explained in the methodology, a composite index was constructed for QOL using the data matrix through a series of statistical analyses. The results of each step are described in the further sections.

Initial data exploration

The collected data matrix was explored using descriptive statistics such as range, mean, median, standard deviation, variance, and coefficient of variation. Several initial inferences on the data matrix were drawn out from this. The CV (coefficient of variation) was highest for the variable, 'POP DEN' and was lowest for the variables, 'ELR', 'SEX RATIO', and 'HH OWN%'. This indicated that the variation in population density was very high, and that of sex ratio and percentage of people who own a house across the settlements was very low among the settlements. Variables like 'RD DEN', 'SO-CUL PER 1000', and 'BPL HH%' also showed comparatively higher variations. This meant that there were considerable disparities in infrastructure distribution among the settlements. After this process, missing values were discovered and replaced with the mean value of the group of concern (unconditional mean imputation).

Multivariate analysis

Once the descriptive statistics were found, the initial steps of multivariate analysis were carried out. In the normality check, it was found that seven variables were not normally distributed. This was possibly because of the presence of outliers. When checked for outliers, 'HH WS %', 'HH DRG %', and 'BPL HH %' were the variables having the highest number of outliers (6). This was treated through by the capping/ flooring method (Nardo et al. 2005). In addition, data transformation using box-cox method was done to normalise the variables (Kallio et al. 2018, Krishnan–Firoz 2020, Kumari–Raman 2022). Then, multicollinearity was checked on the dataset. The correlation matrix obtained showed variables having correlations of more than 0.3 but not more than 0.9. Hence no variables were deleted further. The highest correlation was found between 'HH WS %' and 'PUC HH %' (0.731). This indicated that households with water supply within their premises were most likely categorised as Pucca houses. Finally, the dataset was normalised using z-score standardisation.

Principal Component Analysis

PCA was conducted on the transformed set of 18 variables for all the settlements. KMO measure was calculated and obtained as 0.72, which was adequate (middling) to proceed with the analysis Nardo et al. 2005). The p-value obtained for Bartlett's test of Sphericity was 0.001, which was statistically significant. Five principal components were extracted, which showed eigenvalues greater than 1. Component loading of each variable, the correlation coefficients between the variable and the principal component, was obtained. Varimax rotation was carried out to improve the interpretability of the components. Here, the total variance explained by the five components was 70.73%. Each component explained 22.99%, 20.77%, 11.63%, 7.77%, and 7.55% variances. Table 2 shows the rotated component matrix.

Table 2

Rotated component matrix in district of Kozhikode, 2011

	Component				
	1	2	3	4	5
POP_DENS	0.39	0.768	–0.098	–0.128	0.086
SEX_RATIO	0.707	–0.227	0.378	0.109	0.092
WPR	–0.871	0.131	0.231	0.007	–0.004
HH_ASST%	0.314	0.688	0.376	–0.061	–0.047
BPL_HH%	–0.053	–0.112	0.023	0.103	0.885
DWL_SPC	0.059	–0.069	0.748	–0.067	–0.152
HH_WS%	0.76	0.26	–0.063	–0.034	0.161
HH_DRG%	0.845	0.002	–0.023	–0.104	–0.086
HH_LAT%	0.253	0.096	0.299	–0.651	–0.05
PUC_HH%	0.694	0.507	0.061	0.013	0.032
HH_OWN%	0.18	–0.838	0.184	0.104	0.126
HOSP PER 1000	–0.43	–0.489	0.418	0.262	–0.195
SCH PER 1000	0.26	–0.537	0.436	0.22	0.226
ELR	–0.173	0.795	0.013	0.075	0.08
KG PER 1000	–0.349	–0.054	0.73	0.035	0.291
SO_CUL PER 1000	0.127	–0.041	0.189	0.858	–0.019
RD_DEN	0.436	0.158	–0.031	–0.213	0.544
PO_INT PER 1000	–0.379	–0.606	0.347	0.026	0.07

Notes: Extraction Method: PCA. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 6 iterations.

Source: Output from SPSS software.

The five components were interpreted and shown in Table 3. Component 1 showed high positive correlations with variables SEX_RATIO, HH_WS%, HH_DRG%, PUC_HH% and negative correlation with WPR. This indicates that QOL increases when sex ratio, household water supply, household drainage and percentage of pucca houses increases, and work participation decreases. Component 2 shows high positive correlations with POP_DENS, HH_ASST%, ELR and negative correlations with HH_OWN%, HOSP PER 1000, SCH PER 1000 and PO_INT PER 1000. Similarly, component 3 showed high positive correlations with DWL_SPC and KG PER 1000. Component 4 showed a high positive correlation with SO_CUL PER 1000 and a negative correlation with HH_LAT%. Component 5 showed a positive correlation with RD_DEN and BPL_HH%.

Table 3

Components from PCA

Component				
1	2	3	4	5
SEX RATIO, WPR, HH WS %, HH DRG %, PUC HH %	POP DEN, HH ASST %, HH OWN %, HOS PER 1000, SCH PER 1000, ELR, PO-INT PER 1000	DWL SPC, KG PER 1000	HH LAT %, SO-CUL PER 1000	BPL HH %, RD DEN

Weighting and aggregation

The weighting of variables was carried out once components were interpreted from PCA. Then, the component scores were calculated for each Principal Component. This was done by multiplying the unit's standardised value on each variable with the corresponding component loading of the variable for the given principal component and finally summing up these products (OECD 2008). The weight of each component was taken as the proportion of explained variances for the corresponding component. The final weights obtained for each component are shown in Table 4.

Table 4

Component weights in district of Kozhikode, 2011

Rotation sums of squared loadings				
component	eigenvalues total	% of variance	cumulative %	weight
1	5.129	22.996	22.996	0.325
2	3.259	20.776	43.772	0.293
3	1.819	11.638	55.41	0.164
4	1.295	7.776	63.185	0.109
5	1.231	7.551	70.737	0.106

CQOLI was calculated using these weights on the factor scores and summing up the values for each component using Equation 1 in the Appendix, i.e., CQOLI for settlement 1 = (0.325 x Component 1 Score) + (0.293 x Component 2 Score) + (0.164 x Component 3 Score) + (0.109 x Component 4 Score) + (0.106 x Component 5 Score).

The final scores were then standardised to get values from 0 to 100, shown in the second column of Table 5.

Validation of results

Validation by an alternate method was done using the computation of QOL scores with the help of the 'weighting by ranking' method. For this, six sub-indices were formed by redefining the QOL domains. These are,

1. **Social Characteristics Index (SCI):** POP DEN, SEX RATIO, WPR, HH ASST %, BPL HH %
2. **Housing Conditions Index (HCI):** DWL SPC, HH WS %, HH DRG %, PUC HH %, HH OWN %, HH LAT %,
3. **Social Infrastructure Index (SII):** HOS PER 1000, SCH PER 1000, ELR, KG PER 1000
4. **Civic Infrastructure Index (CII):** SO-CUL PER 1000, RD DEN, PO INT PER 1000

Using Equation 2 in the Appendix, weights were calculated for all the variables. The final weights obtained are shown in Table 5.

Table 5

Weights by ranking in district of Kozhikode, 2011

Sub-index	Sub-index weight	Variable	Variable weight
SCI	0.19	POP DEN	0.12
		SEX RATIO	0.16
		WPR	0.2
		HH ASST %	0.15
		BPL HH %	0.2
HCI	0.22	DWL SPC	0.16
		HH WS %	0.2
		HH DRG %	0.15
		HH LAT %	0.16
		PUC HH %	0.16
		HH OWN %	0.18
SII	0.31	HOS PER 1000	0.5
		SCH PER 1000	0.25
		ELR	0.26
		KG PER 1000	0.23
CII	0.13	SOCUL PER 1000	0.32
		RD DEN	0.33
		PO INT PER 1000	0.34

Through linear aggregation, final CQOLI scores were obtained from the weighted mean of all the sub-indices.

CQOLI = 0.19 SCI + 0.22 HCI + 0.13 HI + 0.18 EI + 0.13 CII + 0.14 EWI

The final scores were standardised to get values from 0 to 100, shown in second and fourth columns of Table 6 (only for the top 10 settlements as a representation).

Table 6

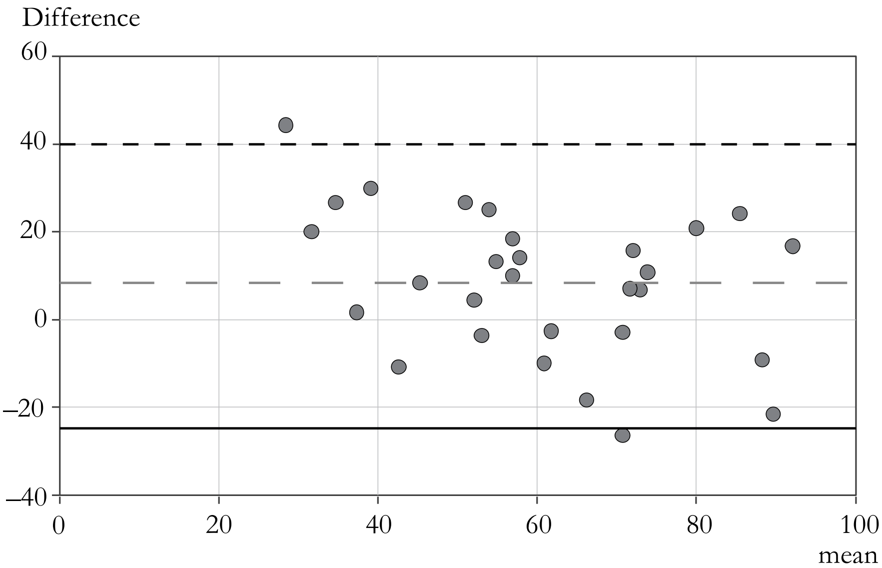
QOL score and QOL category of top 10 settlements in district of Kozhikode, 2011

Settlement	CQOLI score (PCA)	Settlement	CQOLI score (ranking)
Onchiam	100.00	Nanmanda	100.00
Azhiyur	99.66	Thalakkulathur	96.89
Vadakara (M)	93.94	Kakkodi	90.14
Kozhikode (M Corp. + OG)	91.02	Ramanattukara	82.90
Beypore	88.45	Kakkur	78.92
Nanmanda	88.38	Kozhikode (M Corp. + OG)	78.06
Edacheri	84.60	Narikkunni	77.65
Quilandy (M)	83.62	Cheruvannur-Nallalam	74.67
Eramala	83.22	Kuruvattur	74.07
Ramanattukara	82.54	Beypore	67.57

It was required to compare the scores from PCA and the ranking method to validate the same. The Bland Altman's plot obtained is shown in Figure 5.

Figure 5

Bland Altman's Plot in district of Kozhikode, 2011



It was seen in the plot that the points were scattered all over between the upper and lower limits, suggesting no consistent bias for one approach over the other. Also, a correlation coefficient of 0.745 showed a significant correlation between the two results (Krishnan–Firoz 2021). Hence, there was no significant variation between the results from the two methods, which shows that the results are valid.

In addition, it was observed that settlements with good housing and civic infrastructure conditions showed the highest CQOLI. Where population density was low compared to the average, there was medium CQOLI. Most densely populated settlements showed higher scores of BPL Household, lower scores on Housing conditions, and lower scores of CQOLI. Hence it was clear that the CQOLI status of the settlements was linked to their actual housing conditions, population density, infrastructure, etc. Thus, the results are validated qualitatively.

Spatial interpretation

The final scores of CQOLI for all the settlements were calculated and tabulated. Then the pattern was studied through spatial mapping of scores with the help of GIS. Spatial analysis aided in understanding the data in a broader view and identifying stressed areas.

Pattern of CQOLI

To map the index scores spatially, the study units were classified into high, medium, and low QOL based on their CQOLI scores. The natural breaks classification method was used in GIS to get this output (Brewer–Pickle 2002, Krishnan–Firoz 2020). Figure A1 in the Appendix shows the site's CQOLI pattern and high to low QOL areas. It can be seen that 20% of settlements were in high QOL, 46.25% in medium QOL and 33.75% in low QOL categories.

The pattern was also analysed based on the topography and the rural/urban classification of the settlements of the site (Refer to Figure A1 in the Appendix). It was observed that QOL decreases from the coastal areas towards the highlands. A combination of high and medium QOL was found in the lowlands, medium and low in the midlands, and mostly low in the highlands. The low QOL scores in highlands could be associated with the low per capita infrastructure availability due to the difficulty in construction raised by the land's topographical characteristics. Highly undulating plains and soil structures in highlands hinder the easier construction of housing and road infrastructure.

QOL was found to be lower in areas of low population density. Most of the variables are based on the per capita availability of infrastructure. Hence, when population density decreases, the per capita value increases, and accordingly, CQOLI increases. Despite this trend, Kozhikode Municipal Corporation and its outgrowths, with high population density also being the highest urbanised settlements, had high values of QOL. As observed from Figure A2 in the Appendix, most of the settlements designated as urban showed either high or medium scores, and those designated as primarily rural showed low scores. Since the categorisation of urban or rural is heavily dependent on the population density parameter in India, this trend can be explained using a similar association of QOL with population density.

Discussion

The study attempted to construct a composite index to quantify the objective QOL in the district of Kozhikode, India. The proposed index can also measure the variations of QOL among different spatial study units. It was derived through a systematic statistical process and was validated so that the results obtained from the index are reliable. Moreover, spatial interpretation of the index scores helped draw many inferences. Topographically, the general trend observed in the overall QOL in the study area was that the QOL decreases from lowland to highland, i.e., from west to east. The components extracted through PCA were found to be positively related to urbanisation and negatively associated with population density.

Once the patterns were studied, the characteristics of the low, medium and high QOL groups were analysed separately using a radar diagram with the mean centres of all the variables in the high, medium, and low QOL groups (Figure 6) (Donadieu et al. 2019). It was found that settlements having variables' z-scores above +0.5 had formed the first group of high QOL, between +0.5 and –0.5 had formed the second group of medium QOL and –0.5 had formed the third group of low QOL. However, for some variables, the trend was different. From this, inferences could be drawn out regarding the development areas requiring intervention. The characteristics of each group were summarised and shown in Table 7. This can be considered while deciding on the sector that needs intervention.

Figure 6

Mean centres of all groups in district of Kozhikode, 2011

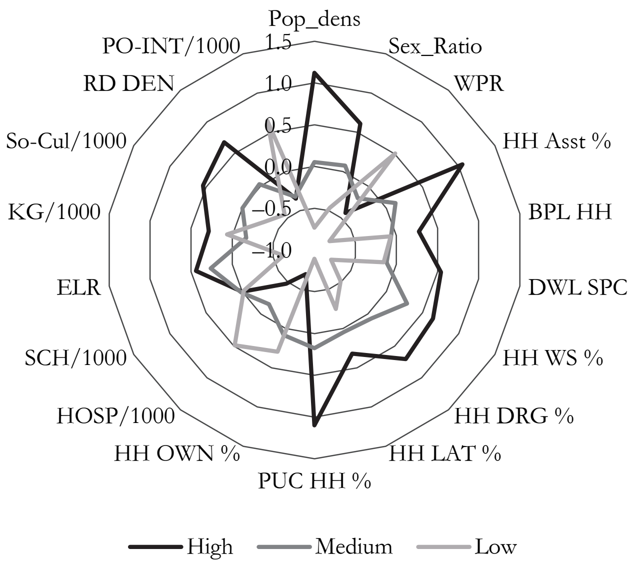


Table 7

Characteristics of groups of QOL in district of Kozhikode, 2011

Domain	Variable	Group 1 (High QOL)	Group 2 (Medium QOL)	Group 3 (Low QOL)
Population	POP DEN	High	Average	Low
	SEX RATIO	High	Average	Low
Income, Employment & Wealth	WPR	Low	Low	High
	HH ASST %	High	Average	Low
	BPL HH %	Average	Low	Low
Housing Conditions & Services	DWL SPC	High	Low	Low
	HH WS %	High	Average	Low
	HH DRG %	High	Average	Low
	HH LAT %	Average	Average	Low
	PUC HH %	High	Average	Low
	HH OWN %	Low	Average	Average
Social Infrastructure	HOS PER 1K	Low	Low	High
	SCH PER 1K	Low	Average	Average
	ELR	Average	Average	Low
	KG PER 1K	Average	Low	Average
Civic Infrastructure	SO-CUL PER 1K	High	Average	Low
	RD DEN	High	Average	Average
	PO INT PER 1K	Low	Low	High

Planning recommendations

It was inferred from the detailed analysis of the pattern of QOL that there exist considerable disparities/ inequities in living quality among the settlements of the study area. Broad planning recommendations are suggested to dissolve these disparities and improve the living conditions of the residents. Low and medium QOL groups should be dealt with the highest priority with all possible interventions to improve living conditions. In a group with higher social characteristics, it can be utilised by enhancing community participation in the decision-making process. More income-generating employment opportunities should be prioritised in the group where income & employment domains scored low or average. Also, skill development programs that would benefit the educated population can be focused in this group to improve workforce participation. Wherever this domain scored high, it will be useful if the high-income population is encouraged in investments beneficial to infrastructure development. A prioritisation of government housing programs is needed to increase household ownership in groups where the housing conditions domain scored low. The community can be made responsible for the improvement and maintenance of infrastructure through awareness programs. Policies should be introduced to improve the workforce's working conditions wherever the variable 'work hours' scored high. Health initiatives should be prioritised to improve the population's physical health by utilising good environmental conditions available. Similarly, the number of public schools and quality of education should be increased in groups where the education domain scored low.

Table 8

QOL intervention areas in district of Kozhikode, 2011

QOL group	Variable that needs intervention	Planning recommendation
Group 1 (High QOL)	Work Participation Rate Household ownership Hospitals/ 1000 population Schools and Kinder-gartens /1000 population Post offices & internet cafes/ 1000 population	Skill development programs like PMKVY[a] and institutions like KASE[b] shall be implemented. More housing programs like NSHS[c] and financial aids for housing shall be introduced. The number and the quality of public health centers shall be increased and more programs like KASP[d] shall be introduced to make private hospitals more accessible. More public schools with high-quality curriculum shall be focused. More communication infrastructure shall be installed.
Group 2 (Medium QOL)	Work Participation Rate Below Poverty Line Household Hospitals/1000 population Schools and Kinder-gartens/1000 population Post offices & internet cafes/1000 population	Skill development programs like PMKVY[a] and institutions like KASE[b] shall be implemented. The number and the quality of public health centers shall be increased and more programs like KASP[d] shall be introduced to make private hospitals more accessible. More public schools with high-quality curriculum shall be focused. More communication infrastructure shall be installed.
Group 3 (Low QOL)	Sex ratio Household assets Below Poverty Line Household Dwelling Space Household Water supply, Drainage, Latrine Pucca houses Effective Literacy Rate Socio-cultural infrastructure/ 1000 population	Active research and household level intervention shall be conducted in women and newborn health and schemes like PMMVY[e] shall be implemented. More income-generating employment opportunities shall be introduced. Space requirement studies shall be conducted and open spaces shall be provided in housing programs. Water supply and drainage infrastructure shall be emphasized in development plans, programs like Individual Household Latrine (IHHL) shall be implemented. More housing programs like NSHS[c] and financial aids for housing shall be introduced More adult literacy programs shall be implemented. More public community halls, public libraries, arts, and sports clubs shall be opened.

a) PMKVY – Pradham Mantri Kaushal Vikas Yojana is an initiative by the Ministry of Ministry of Skill Development and Entrepreneurship, Government of India, implemented through National Skill Development Corporation (NSDC) to enable the youth to achieve skills that are industry relevant. b) KASE – Kerala Academy for Skills Excellence is a non-profit company by the Kerala Government for facilitating and coordinating skill development programs among the youth. c) NSHS – New Suraksha Housing Scheme is a housing financial aid scheme by the Kerala Government for the EWS in urban and rural areas. Other such programs are 'Parasparyam' Projects, 'Saphalyam' Housing Scheme and, 'Grihasree' Housing Scheme. d) Karunya Arogya Suraksha Padhathi (KASP) is the health care scheme which aims at providing a health cover of Rs. 5 lakhs per family per year for secondary and tertiary care hospitalization to over 42 Lakhs poor and vulnerable families (approximately 64 lakhs beneficiaries) that form the bottom 40% of the Kerala population. e) PMMVY – Pradhan Mantri Mathru Vandana Yojana is a maternity benefit scheme by the Government of India, implemented in Kerala through 'Anganawadi's (public kindergartens), with an aim to improve health seeking behavior among pregnant mothers.

The classification of settlements used in this study can aid in providing better interventions in required areas. Settlements of low, medium and high QOL can be dealt with separately. Using the characteristics of each group from Table 7, variables which are needed to be addressed can be identified. Also, manipulating each variable score to check its effect on overall QOL can be done to establish which sector needs intervention. Table 8. describes areas that need intervention in each group of QOL.

Conclusions

The study aimed to form a spatial assessment framework for assessing the quality of life at the regional level in Kerala using a composite QOL index. Nineteen objective variables under five domains of QOL were formed, and a Composite Quality of Life Index (CQOLI) was constructed using PCA. It was inferred from the spatial mapping of the scores that geographical and topographical characteristics influence QOL. Here, CQOLI decreased from coastal to highlands and was higher in highly urbanised areas. The quality of infrastructure and services affects the overall QOL within the settlements. Moreover, high population-density areas showed higher QOL and vice versa. Solutions needed were proposed in all the domains of QOL to resolve the inequities among settlements.

The QOL assessment in this research uses a formulated index applicable in similar analysis contexts. The methodology proposed can be replicated in any scales of similar analysis, and output can be generated with appropriate changes in variables. A major limitation of the present study is that the data source had a longer period of gap, which was inevitable since these are the nearest data period available at the time of the study. Further, the availability of specific data at settlement levels has limited the selection of variables and the analysis. Also, it should be noted that the QOL variations inferred in the current research are a relative depiction of QOL conditions. This does not mean that low QOL areas are highly backward in development.

The authors put forward a Tier 3 assessment system to be conducted at three different spatial scales (Figure 1). The Tier 1 assessment considers a broader regional scale (Zehba et al. 2021). The present study is attempted at an intermediate level (Tier 2) based on the result obtained from the Tier 1 analysis. A Tier 3 analysis shall be further conducted at the local level (neighbourhood level) based on the output from the present research using the same or different variables. This Tier 3 analysis forms the future scope of the study. Subjective well-being variables using primary data can be incorporated Tier 3 framework for an inclusive and elaborate assessment. The present Tier 2 analysis can also be conducted in a different region within Kerala using the same framework. Such a comprehensive analysis and assessment framework would aid policymaking and spatial planning and can help planners, administrators, and decision-makers.

Appendix

1. Construction of Composite Quality of Life Index (CQOLI)

Initial data exploration

At first, the data matrix was explored using descriptive statistics such as Range, Mean, Median, Standard Deviation, Variance, and Coefficient of Variation. This helped to understand the dataset's characteristics and derive some initial inferences like which variables are interconnected, which show similar attributes, etc. Next, missing values were treated adequately, as these would hinder the robustness and results of any statistical analysis (Erik–Marko 2011). Out of the three methods studied for imputation (OECD 2008), case deletion (the other two were Single Imputation and Multiple Imputation) was not possible since it would delete data of the entire settlement. The method adopted was unconditional mean imputation in explicit modelling of single imputation (Nardo et al. 2005), in which the missing values were replaced with the mean value of the group of concern. Once this was done, the matrix was ready for proceeding with multivariate analysis.

Multivariate Analysis

Multivariate analysis was carried out as an exploratory analysis to investigate the overall structure and suitability of the data set, which can also aid in deciding the methodology for weighting and aggregation (OECD 2008). It was checked if the data were normally distributed. Outliers were detected using the Box Plot diagram in SPSS software. The capping/Flooring method was adopted here to treat these outliers and carried out in the data transformation stage. Then data were checked for multicollinearity by examining the correlations between the variables using Pearson's correlation. For PCA, there should be more than 0.3 correlations between variables (Erik–Marko 2011). Also, variables having correlations of more than 0.9 should be avoided (Nardo et al. 2005). Then, data transformation was carried out through the capping method. Data was capped (top) or floored (bottom) by setting the lowest and highest values at the 5th and 95th percentiles, respectively (OECD 2008). For Normalisation, Standardisation using Z-scores[6] was adopted.

Principal Component Analysis

PCA is a dimension reduction technique to present a large dataset using a smaller number of variables (Erik–Marko 2011). The benefits of PCA over other methods are that it does not require large computations, is adopted by many international Indices, and reduces the dimension of data without losing much information

[6] The Z- scores were calculated using the following formula.
$z_i = \frac{x_i - \bar{x}}{\sigma}$ where, $x_i = i^{th} value, \bar{x} = mean\ value\ and\ \sigma = standard\ deviation$.

(Abeyasekera 1995, de Senna et al. 2019, J.S.N.P et al. 2015). Therefore, PCA was chosen for this study (Erik–Marko 2011). First, KMO measure was conducted on the data set before doing PCA to determine the adequacy of samples. A KMO value of 0.6 or above was needed to perform PCA (Greyling 2013; Nardo et al. 2005). The Bartlett test of sphericity was then carried out to check if the correlation matrix is an identity matrix. Here, the p-value obtained should be significant, i.e., <0.05 (Greyling 2013; Nardo et al. 2005). Finally, PCA was carried out using SPSS software. The input for PCA in this study was the transformed and normalised variable matrix. Principal components were extracted, and component loadings for each variable, which were the correlation coefficients between the principal components and the variables, were obtained. This was rotated using Varimax rotation to get a better interpretable result. Here, the first component accounts for the maximum possible proportion of variance of the dataset, the second maximum of the remaining variance, and so on. Eigenvalues were the variances of the principal components. Several studies suggest that an eigenvalue greater than 1 is the criterion for deciding the number of principal components (Erik–Marko 2011, Nardo et al. 2005).

Weighting and Aggregation

For obtaining weights for each variable, component scores of each settlement on each principal component were calculated first. Then, weights were assigned for each component which were taken as the proportions of the explained variances of each corresponding variable in the dataset (Nardo et al. 2005). An index was finally calculated by using these weights on the component scores and summing up these values for each component. The component score for each settlement was multiplied by the corresponding weight, which was summed up to compute the index (Nardo et al. 2005). A standardised index was then calculated using the following formula (Equation 1) to interpret the results better.

Equation 1

$$Composite\ Quality\ of\ Life\ Index\ (non\ standardized) = \left(\frac{Var1}{tot\ var}\right) \times (Component\ 1\ score) + \left(\frac{var2}{tot\ var}\right) \times (Component\ 2\ score) + \left(\frac{var_n}{tot\ var}\right) \times (Component_n\ score)$$

$$Standardised\ Composite\ Quality\ of\ Life\ Index\ od\ Settlement\ 'A' = \frac{Index\ of\ settlement\ 'A' - Min\ index}{Max\ index - Min\ index} \times 100$$

Validation

Validation of the results obtained was required to assess the quality and reliability of the index. Here, validation was done by checking the results with an alternate method. For this, weighting by ranking was chosen as the alternate method. Initially, sub-indices of QOL were first defined by considering the principal components obtained from PCA and the characteristics of variables of QOL. Ranks were assigned to the variables concerning their value for a particular settlement. Similarly, 30 rankings were formed for each variable. Then a score for each variable was computed. If there were 'n' settlements ranking 'a' variables with ranks '1 to b', where '(b ≤ a)', scoring was performed by giving the reciprocals of ranks '(1/b)' into scores ' (s)' and 'n_{xy}' represented the number of settlements given rank 'y' (where 'y' = 1 to b) to the variable 'x'(where x=1 to a). The total score for variable x is calculated as (Chithra et al. 2015; Stillwell et al. 1981)

$$\sum_{y=1}^{b} NySy$$

and the total score for all the variables is calculated as

$$\textstyle\sum_{x=1}^{a}\sum_{y=1}^{b} NxySxy.$$

Then the weightage of each variable is worked out as

$$\textstyle\sum_{y=1}^{b} NySy \;/\; \sum_{x=1}^{a}\sum_{y=1}^{b} NxySxy.$$

Weights were calculated for each variable and each Sub Index (by adding the scores of variables under each sub-index). Linear aggregation was carried out to produce the final CQOLI (Royuela 2002). The weighted mean of each sub-indicator was found first. Then the weighted mean of all the sub-indicators was taken as the composite indicator.

Equation 2

$$SI_1 = w_1v_1 + w_2v_2 + w_3v_3 + w_nv_n$$

$$CQOLI = W_1SI_1 + W_2SI_2 + W_nSI_n$$

$$where, SI_1 = Sub - index\ 1, w_1 = weight\ of\ variable\ 1, v_1 = value\ of\ variable\ 1\ and\ W_1 = weight\ of\ sub - index\ 1$$

The results from this method were compared with that of PCA using Bland Altman's plot. First, the mean value and the difference between each score for the two results were computed. This was plotted against each other (Giavarina 2015). Here, an agreement interval was set within which 95% of the differences between the second and the first methods fall. This graph measured the bias of the result towards any of the two methods.

In addition, QOL results were compared with the already-known information about the settlements. The characteristics of each settlement were compared with their QOL score. For example, if a settlement shows a low QOL score, it was seen if it scores less in individual indicators. Thus, it was checked whether the QOL status of the settlements was linked to their actual housing conditions, population density, infrastructure, etc.

Figure A1

Pattern of CQOLI in district of Kozhikode, 2011

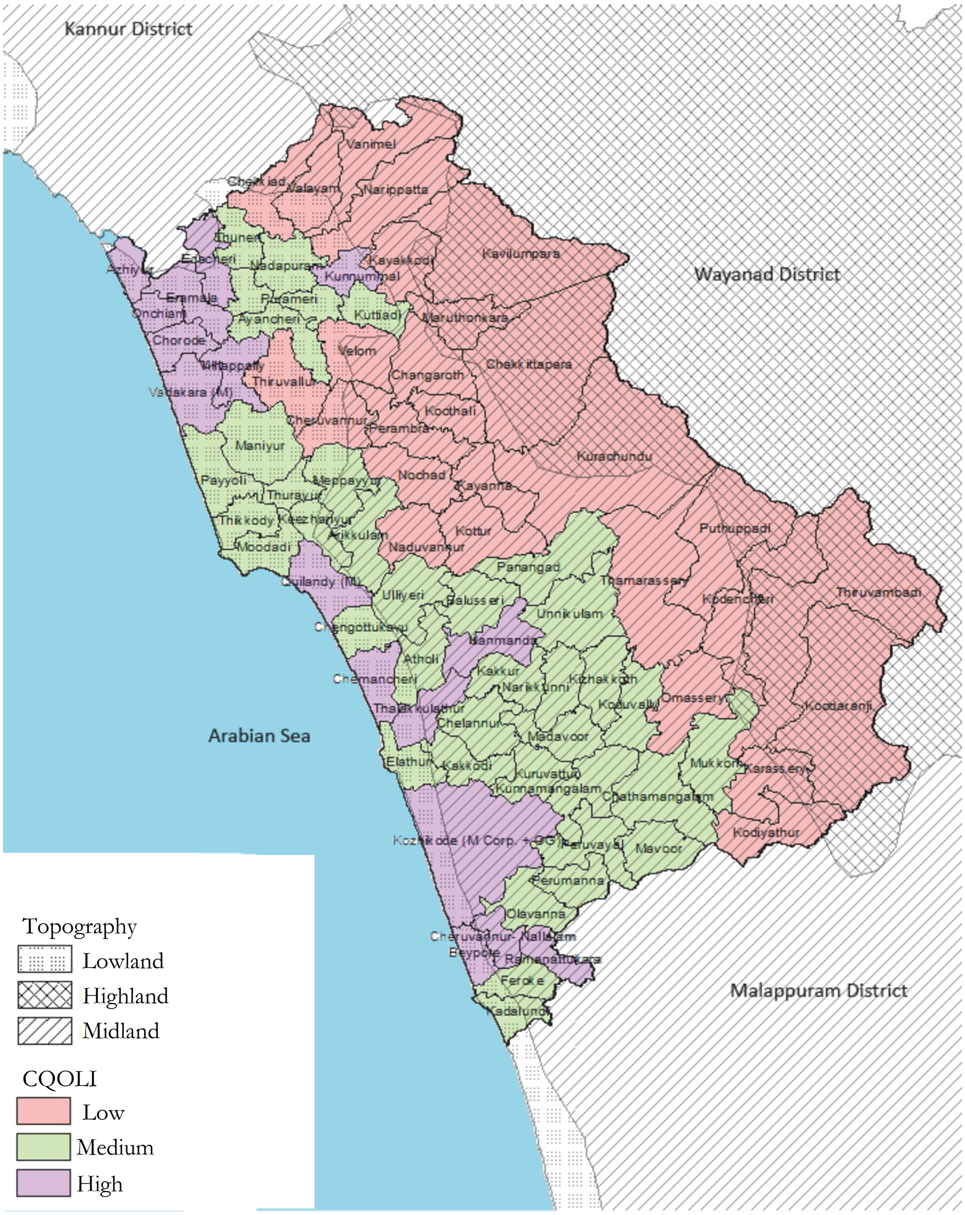
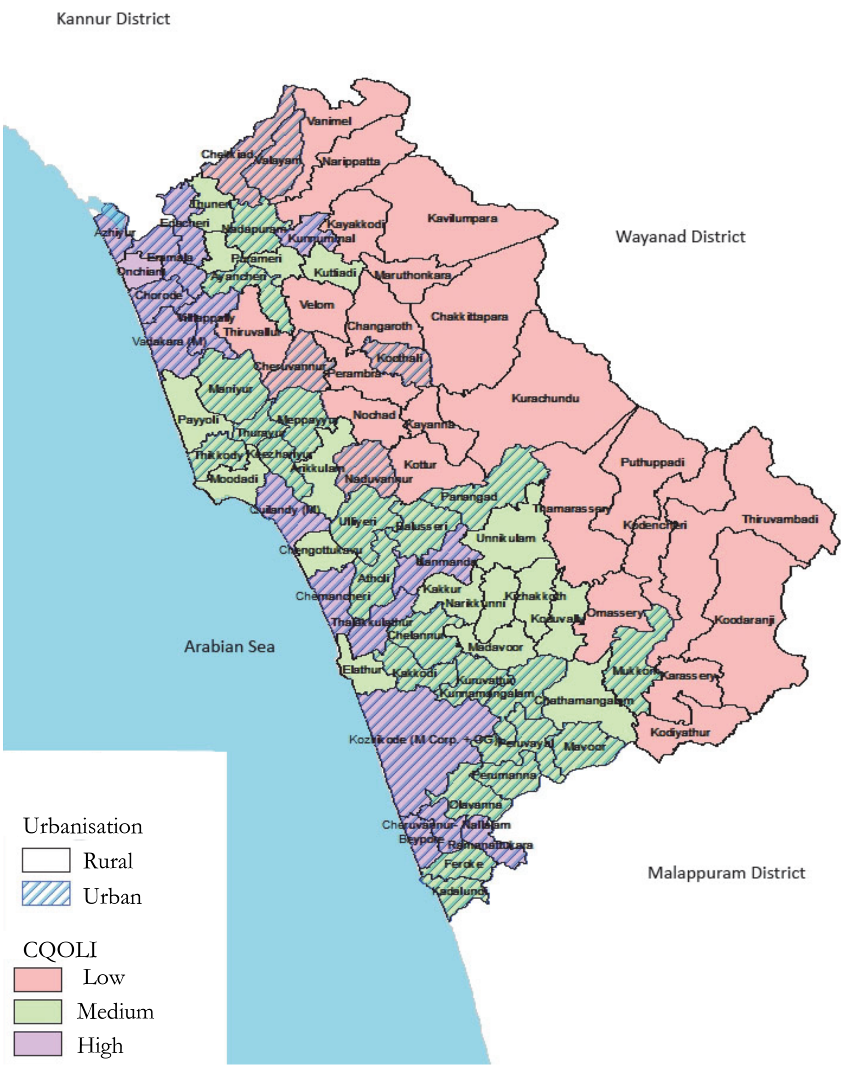


Figure A2

Urban/rural classification of settlements in district of Kozhikode, 2011



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