BUILT ENVIRONMENT AND NON-COMMUNICABLE DISEASES

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DECLARATION BY THE STUDENT

CERTIFICATE

I, **JOANNA SARA VALSON,** hereby certify that I had personally carried out the work depicted in the thesis entitled, "Built environment and non-communicable diseases".

No part of the thesis has been submitted for the award of any other degree or diploma prior to this date.

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The thesis entitled, "Built environment and non-communicable diseases" was carried out under my direct supervision. No part of this thesis was submitted for the award of any degree or diploma prior to this date.

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LIST OF ABBREVIATIONS

BE	Built Environment
DA	Discriminant Analysis
DALY	Disability Adjusted Life Years
DEM	Digital Elevation Model
GIS	Geographic Information System
LMIC	Low-and-middle-income country
MAUP	Modifiable Areal Unit Problem
MET	Metabolic Equivalent Task
NCD	Non-communicable disease
NDBI	Normalized Differentiated Built Index
NDVI	Normalized Differentiated Vegetation Index
OSM	Open Street Map
PA	Physical Activity
SD	Standard Deviation
sq.km.	Square kilometre
US	United States
USGS	United States Geological Survey
WHO	World Health Organization

GLOSSARY

PHENOMENON	MEANING
Built environment	Human-made structures, features, and facilities viewed collectively as an environment in which people live and work.
Built-up density	Refers to density of built-up properties.
Choropleth map	Type of map in which a set of predefined areas is coloured in proportion to a statistical variable.
Coordinates	Latitude and longitude data associated with positions on earth (geographic position).
Data processing	The operation carried out on data to retrieve, transform or classify information.
Discriminant analysis	A statistical procedure that classifies unknown individuals and the probability of their classification into specific groups.
Discriminant function	A function of several variables used to assign items into one of two or more groups.
Geocode	Providing geographical coordinates for a location.
Geospatial	Indicates that each record in the dataset has information on geographic location, such as coordinates, address, city, or postal code.
Greenness	Refers to green vegetation, grass, or the like.
Group centroid	They are group means of variables considered for discriminant analysis.
Interpolation	Method of constructing new data points within the range of a discrete set of known data points.
Kriging	An interpolation method to find values for a point based on neighbouring values.

Neighborhood	Defined by a circular buffer of a defined radius centred on an address.
Raster calculator	Menu that allows one to perform calculations based on existing raster pixel values.
Raster image	Images which are grids of individual pixels/cells that collectively compose a image.
Shapefile	One of the geospatial data storage formats for storing geometric location and attribute data.
Spatial cluster	A geographically bounded group of occurrences of sufficient size and concentration, unlikely to have occurred by chance.
Study cluster	Groups divided into a population for research using the probability sampling technique.
Terrain	The term for an area of land. It can be flat plains/ mountains/ forests, etc.
Walkability	The extent to which the built environment is friendly to the presence of people living, shopping, visiting or relaxing in an area.

SYNOPSIS

The prevalence of non-communicable diseases and their risk factors continue to rise rapidly among high and low-and-middle-income-countries (LMICs). About 336 million people with diabetes are now living in LMICs. Kerala, the south-western state, has been a forerunner in the rise of non-communicable diseases in India. Intervention studies in India included modifications in dietary behavior, physical activity, social participation, the necessity of social support networks, clinical management, health service delivery re-organnization, etc. There is a need to move beyond risk-factor identification and primary prevention strategies at the individual level. We have emphasized the community level/ neighborhood influences on non-communicable diseases and their risk factors in Kerala.

This thesis involved secondary data analysis and its main focus was on the built environment characteristics in the neighborhood and its influence or relationship with the prevalence of non-communicable diseases and their risk factors. This was also an attempt to incorporate Geographical Information Systems (GIS) and use open-source data to capture built environment characteristics for the state. We hypothesized that if spatial clusters of high and low prevalence of diabetes and physical inactivity could be identified using spatial analysis, we could distinguish built environment characteristics between the high and low spatial clusters. For this reason, we tried to identify spatial clusters within a sample population selected across the expanse of Kerala. Moreover, we postulated that certain built environment characteristics in the neighborhood could be significant contributors to the prevalence of diabetes or physical inactivity.

The first objective was primarily to study the distribution of built environment variables across districts and subdistricts in Kerala. This was fulfilled by estimating the built environment variables of interest for both districts and subdistricts and the creation of choropleth maps. Moreover, the correlations between these variables among districts and subdistricts were analyzed.

The second objective was to identify spatial clusters of high and low rates of diabetes and physical inactivity among the sample population and evaluate built environment characteristics within those spatial clusters. (A spatial cluster was defined as an excess of case counts within a geographical space unlikely to have occurred by chance) Spatial clusters were identified by comparison of expected and observed cases within and outside the pre-determined radii. This comparison, called Likelihood Ratio (LR), determined how likely a cluster occurs due to more than chance alone. The scanning window with the maximum likelihood ratio was flagged as the most likely or primary cluster. The other significant ($p<0.05$) clusters were flagged as secondary clusters. A 1600m circular buffer was defined as a neighborhood around each participant location based on previous literature, and since we had a minimum of five participants within each survey site, we employed a spatial cluster analysis with windows of 5 km, 7.5 km, 10 km, and 15 km radii to ensure consistent results. The overall prevalence of diabetes and physical inactivity in urban and rural locations in Kerala were set as cut-off levels for detecting high and low spatial clusters. These were 21.3% and 19.1% for diabetes, whereas 26.1% and 20.1% for physical inactivity among urban and rural locations, respectively. Hence, those scanning windows with a significantly higher or significantly lower prevalence of diabetes/ physical inactivity as compared to the cut-off rates were reported to be primary and secondary clusters.

The final objective was to find those built environment characteristics within the neighborhood that could significantly contribute towards participants being physically inactive or having diabetes. We could achieve this by employing the discriminant analysis of the built environment variables of interest for both outcome groups (those with and without diabetes, those who were physically inactive and active) and by assessing the classification accuracy of the discriminant function.

The built environment variables of interest in the study were population density, residential density, safety from crime, safety from traffic, greenness, built-up density, land slope, and intersection density. The data sources included (a) Census 2011, (b) State Crime Records Bureau, (c) Satellite data, (d) OpenStreetMap (OSM) and (e) Survey data. Population and residential density were captured from the 'village and town release data' from Census 2011. Population and residential density were defined as the total number of inhabitants and households per square kilometer respectively in each unit (district/ subdistrict/Panchayat) of study. Safety indicators from crime and traffic were captured as crime rates and pedestrian accident rates, defined as the total number of crimes and the total number of pedestrians involved in road traffic accidents, respectively, per total population in each unit of study. Crime rates and pedestrian accident rates were acquired from the State Crime Records Bureau.

Variables captured from Satellite data included greenness, built-up density, and land slope. Normalized Differentiated Vegetation Index (NDVI) was used to estimate greenness, while Normalized Differentiated Built Index (NDBI) estimated built-up density. Both NDVI and NDBI were accessed from Landsat8 OLI (Operational Landsat Imagery) images derived from United States Geological Survey (USGS) archives. The land slope was estimated from the Digital Elevation Model (DEM) data retrieved from Shuttle Radar Topography Mission (SRTM) 90m resolution images from Consortium for Spatial Information (CSI). Meanwhile, intersection density was calculated as the number of three-way intersections per square kilometer, captured from the road network layer using Open Street Map (OSM).

The 'Survey data' on non-communicable diseases and their risk factors were accessed from 'Prevention and control of non-communicable diseases in Kerala' Project after obtaining due permission. This survey was done in 2016-17 among 12,012 participants selected from 1393 cluster sites across urban and rural areas in Kerala. Anonymity was maintained throughout data handling and analysis. Variables included sociodemographic profiles, diet patterns, tobacco use, activity patterns, and other measurements. Outcome variables of interest were diabetes and physical inactivity, which were extracted as binary variables. Diabetes was defined as being on an oral hypoglycemic agent or insulin for the past two weeks or had a fasting blood glucose $\geq$ 126 mg/dL, as recommended by the Centers for Disease Control and Prevention (CDC). Total metabolic equivalent (MET) minutes for a week were estimated from self-reported time taken to engage in vigorous physical activity, time to walk/cycle, vigorous sports, moderate sports, and sit/recline. Those participants who had total

MET minutes of less than 600 in a week were considered to be physically inactive, as recommended by the World Health Organization (WHO).

We found distinct patterns of built environment characteristics being distributed across districts and subdistricts in the state. Thiruvananthapuram district was the most populous and had the highest density of housing units per square kilometre. Crime rates were the highest in Ernakulam and lowest in Malappuram districts. Pedestrian accident rates were reported to be highest in Kollam and lowest in Malappuram. Ernakulam had the highest built-up density and lowest greenness, while Kozhikode had the lowest built-up density and highest greenness. Idukki had the highest land slope, while Alappuzha recorded the lowest. Intersection density per square kilometre ranged from 10.9 in Ernakulam to 1.7 in Wayanad district.

Among the subdistricts, Cochin in Ernakulam was found to be the most populous with the highest residential units, while Pirmed in Idukki was the least populous with the least residential units per square kilometre. Cochin city also recorded the highest built-up density and lowest greenness, while Kuttanad in Alappuzha had the lowest built-up density, and Ranni in Pathanamthitta recorded the highest greenness. Land slope among subdistricts was the highest in Devikolam (Idukki district) and lowest in Aleppey (Alappuzha district). Kanayannur and Cochin subdistricts of Ernakulam district ranked the lowest and highest for both crime and pedestrian accident rates, respectively.

Correlation between the built environment variables across districts showed nearly perfect correlation ($r = 0.98$, $p<0.01$) between population density and residential density. Population density was positively related to intersection density ($r = 0.57$, $p<0.05$) and inversely related to land slope ($r = -074$, $p<0.01$). A similar trend was illustrated for residential density. Pedestrian accident rates within the districts were directly related to density of residential units ($r = 0.54$, $p<0.01$), crime rates (0.78, $p<0.01$), road intersection density ($r = 0.60$, $p<0.05$) but inversely related to greenness ($r = -0.70$, $p<0.01$). The density of road intersections per square kilometer had a tendency to decline with higher land slope ($r = -0.68$, $p<0.01$).

A total of five spatial clusters of high rates and four spatial clusters of low rates of diabetes were identified among both urban and rural sample sites. The primary clusters of high rates of diabetes (Changanassery in urban setting and Aruvikkara in rural setting), had about three times higher likelihood of being a high spatial cluster of diabetes as compared to other sites both in urban (relative risk [RR] = 3.14, log-likelihood ratio [LLR] = 104.04, $p<0.01$) and rural (RR = 2.68, LLR = 40.48, $p<0.01$) settings. Similarly, the primary cluster identified for low rates of diabetes had 70% likelihood (Kasaragod city, RR = 0.30, LLR = 23.45, $p<0.01$) and 81% likelihood (Vazhakulam, RR = 0.19, LLR = 15.65, $p<0.01$) for being a low spatial cluster of diabetes as compared to other sites in urban and rural settings respectively.

About 10 and 7 spatial clusters of high rates and 13 and 9 spatial clusters of low rates of physical inactivity were found in urban and rural settings, respectively. The primary spatial cluster of physical inactivity (Changanassery in urban setting and Punnapra in rural setting) had thrice the risk of being a spatial cluster with a higher rate as compared to the sampling sites in both urban (RR = 3.21, LLR = 152.73, $p<0.01$) and rural (RR = 3.87, LLR = 88.9, $p<0.01$) settings. Meanwhile, the primary clusters of low rates of physical inactivity were found to have about 100% likelihood for being a spatial cluster with low rates of physical inactivity as compared to other sampling sites in both urban (Chittur, RR = 0.05, LLR = 61.37, $p<0.01$) and rural (Kinanoor, RR = 0.0, LLR = 30.20, $p<0.01$) settings. There were significant differences in the sociodemographic characteristics of participants in spatial clusters of high and low rates of diabetes in the urban setting except for gender, while only age ($p<0.05$) and marital status ($p<0.01$) showed a significant difference in the rural setting. However, educational status ($p<0.01$) and occupational status ($p<0.01$) of participants within high and low spatial clusters of physical inactivity showed significant differences in both urban setting and rural setting.

Comparison of built environment characteristics within the neighborhoods in high and low spatial clusters of diabetes and physical inactivity were performed. In the urban setting, participants belonging to spatial clusters of low rates of diabetes were located within neighborhoods with significantly higher population density, residential density, built-up density and intersection density, and lower crime rates, pedestrian accident rates, greenness and land slope. Moreover, participants belonging to spatial clusters of low rates of physical inactivity were also within neighborhoods with significantly lower crime rates, pedestrian accident rates, intersection density, and greenness but with higher built-up density and land slope. However, in the rural setting, participants belonging to spatial clusters of low rates of diabetes were within neighborhoods with significantly higher population density, residential density, crime rates, pedestrian accident rates and built-up density and lower greenness and land slope. On the contrary, those neighborhoods found to be spatial clusters of physical inactivity had significantly lower population density, residential density, built-up density, intersection density, crime rates and pedestrian accident rates, and significantly higher greenness and land slope.

Finally, the relationship between built environment characteristics in the neighborhood and the prevalence of diabetes and physical inactivity were assessed using discriminant analysis. The discriminant function could clearly demarcate between the outcome groups (diabetes/ no diabetes and physically active/ inactive). The group centroids demonstrated that those with the outcome scored on the positive end, while the others scored on the negative end. The discriminant function could also achieve about 78.7% and 73.9% overall classification accuracy for diabetes and physical inactivity, respectively, in the urban setting, while the accuracies were 81.0% and 79.6%, respectively, in the rural setting. The significant discriminating variables were crime rates, pedestrian accident rates, intersection density, built-up density, and land slope for diabetes, while they were crime rates, pedestrian accident rates, intersection density, and built-up density for physical inactivity in the urban setting. In the rural setting, built-up density and land slope emerged to be significant discriminators for diabetes, while those were crime rates, built-up density, and land slope for physical inactivity. These findings were congruent with the significant differences found in neighborhoods within spatial clusters of low rates of diabetes and physical inactivity in both urban and rural settings.

This study could demonstrate regional differences in the built environment characteristics across Kerala. The findings could reiterate that the built environment characteristics within an individual’s neighborhood do matter, and it does contribute significantly to his/her ability to be physically active. This substantiates the importance of exploring the role of place on the prevalence of non-communicable diseases in low-and-middle-income countries. Urban-rural differences of built environment characteristics that are conducive for being physically active indicate the need for customized interventions. This study also establishes the utilization of spatial data analysis as a necessary tool for tailor-made interventions by both public health professionals and policymakers.

CHAPTER 1

INTRODUCTION

1 INTRODUCTION

1.1 Research Context

The twenty-first century's greatest pandemic causing a substantial public health challenge is the rising mortality and morbidity due to non-communicable diseases (NCDs). The United Nations had identified non-communicable diseases as a significant threat to international health (Phan et al. 2020). Mainly four categories of NCDs, namely cardiovascular diseases, cancer, diabetes and chronic respiratory diseases, account for 41 million deaths annually, out of which 16 million deaths occur in the age group of 30-70 years (World Health Organization 2017). Globally, the prevention of NCDs continues to be an evolving issue, while the burden predominantly lies in developing countries which represent 82% of premature deaths due to NCDs (World Health Organization 2018a). There is an urgent call to reduce the modifiable risk factors of NCDs by creating health-promoting environments. The impetus is to make macro-level changes in the design and planning of residential areas, recognising the importance of residential density, street connectivity, easy access to destinations and access to public transport.

Physical activity is the cardinal risk factor proven to prevent and treat non-communicable diseases (World Health Organization 2018b). However, in this decade, one in four adults and three in four adolescents have insufficient physical activity globally. Inadequate physical activity or physical inactivity are characterised when physical activity levels are lower than prescribed based on the World Health Organization recommendations for adults and adolescents. The risk of death escalates by 20-30% for those physically inactive compared to those who meet the recommended levels of physical activity (World Health Organization 2020a). The global target resolved in 2013 for all member countries of WHO was to aim for 25% relative reduction of premature mortality from cardiovascular diseases, cancer, diabetes and chronic respiratory diseases. Furthermore, global targets also included a 10% reduction in the prevalence of physical inactivity and curbing diabetes.

Nevertheless, there has not been any significant improvement in the global levels of physical activity since 2001 (World Health Organization 2013a). Besides, about 12% of men and 24% of women are physically inactive among the low-and-middle-income countries (LMIC). The WHO has raised the alarm on less evidence from LMICs on potential steps to curb the rise in physical inactivity prevalence. One of the major action plans for low resource countries is to teach new technologies, innovations and research to generate cost-effective approaches (World Health Organization 2020b). In 2015, the United Nations General Assembly decreed on 'Transforming the World: The 2030 Agenda for Sustainable Development', known as the '2030 agenda'. The sustainable development goals (SDGs) 2030 for developing countries involve policy development to promote walking, cycling, sport and play. The global action plan charts out four objectives: creating active societies, creating active environments, creating active people and creating active systems to promote physical activity. This plan begins with changing mindset towards engaging in physical activity, maintaining an environment that fulfils individuals' fundamental rights, providing physical activity opportunities and transforming governance or multisectoral policy-making strategies.

The challenge among LMICs is the substantial switch of individuals to personalised motorised transport from the former walking and cycling behaviours. This is mainly because of the transformation of developing countries from solely agriculture-driven to industrialised sectors (Giles-Corti et al. 2016). With no regulations or safety frameworks in curbing transport and traffic-related injuries, the unstructured rise in transport adds to the burden of physical inactivity in LMICs. The built environment in the neighbourhood is considered a structural determinant affecting physical activity patterns (Phan et al. 2020). The urban environments within LMICs bear the most brunt of overladen traffic volume and incidence of crimes. Insufficient planning and lack of evidence-based practice in LMICs pose a more threatening environment for residents to engage in physical activity (Reis et al. 2016). However, there is a tremendous gap in the evidence from LMICs for sharing lessons on structured housing, transport and legislation, or planning environments that encourage physical activity.

Although India is one of the LMICs, India accounts for higher age-specific mortality rates from chronic diseases than the high-income countries (Mehdi et al. 2016). There is a substantial rise in individuals' socioeconomic status, which has contributed to a leap in the prevalence of physical inactivity and obesity in India (Patel et al. 2011a). Also, rapid motorisation and lack of efficient policies have a glaring impact on the rise in NCDs and traffic-related injuries.

The National Programme for Prevention and Control of Diabetes, Cardiovascular diseases and stroke (NCPCDS) has focussed upon capacity building and infrastructure development for early diagnosis and treatment of those with non-communicable diseases. However, dialogue on the importance of safe neighbourhoods or creating neighbourhoods favourable for physical activity has rarely carried the weight to influence policymakers in India. Although interventions on dietary modifications and physical activity behaviours have provided a base for a paradigm shift among the Indians, there seems to be a glaring deficiency in studies related to the importance of the Indian context's neighbourhood environment.

Therefore, there is a need to gather evidence on the importance of 'space' or 'place' in the occurrence of physical inactivity or non-communicable diseases in India. The millennium years have witnessed rapid strides in technological advancements and software development. Therefore, this evolution has bestowed public health researchers in LMICs and India to spearhead studies on the influences of the neighbourhood environment. Availability of accessible software, open-data systems and open-source platforms has been beneficial for the researchers in resource-poor settings. Therefore, this research aims to use open-source solutions to generate evidence on the influence of the neighbourhood environment on physical activity and diabetes in India. We have focussed on one state, namely Kerala, which has NCDs contributing to about 90% of premature mortality (within ages 15-69 years) (Sarma et al. 2019).

Hence, the major objectives of this research are to:

1. To determine the geographical distribution of built environment variables across districts and subdistricts of Kerala

2. To evaluate the relationship between built environment variables and the prevalence of diabetes and physical inactivity in Kerala
3. To identify spatial clusters of diabetes and physical inactivity and evaluate built environment characteristics within low and high spatial clusters.

1.2 Outline of the thesis

have outlined this research in six chapters. The second chapter describes the literature review on neighbourhood-level capture of the built environment and its relationship to non-communicable diseases or its risk factors, particularly diabetes and physical inactivity.

The third chapter of this thesis deliberates on the research methodology. This section begins by detailing the geographical context of the research. It discusses data collection methods, data capture and processing of datasets accessed for this research. It also delineates the steps of data analysis performed.

The fourth chapter in this thesis presents the results of this research. It begins by describing the distribution of built environment variables across the districts and subdistricts of Kerala. The following section details the spatial clusters identified across Kerala among a sample population. The final section describes the results regarding the most critical contributors toward diabetes and physical inactivity.

The fifth chapter discusses the results of this research with previous findings and emphasises this research's importance. It also delineates the limitations and hurdles faced during this research. Another section in this chapter portrays the implications of the findings and essential areas of further investigation.

The final chapter provides a summary of this thesis. It provides the conclusions drawn from this research.

CHAPTER 2

LITERATURE REVIEW

2 LITERATURE REVIEW

2.1 Introduction

The purpose of this chapter on the review of literature was to identify various ways of defining the built environment and find methods to capture the built environment in a low-and-middle-income country. We also aimed to establish relationships between non-communicable diseases (NCDs) and built environment characteristics to identify patterns in both high-income countries and LMICs. This chapter gives an overview of the review of published articles to illuminate the main characteristics to be captured and the probable relationships that arise from previous studies.

This review summarises definitions of terms, findings from previous literature, gaps in the literature and rationale for this research. We have summarised literature published in the English language and those published in peer-reviewed journals. The search databases used for this review was mainly PubMed and ScienceDirect. The search terms for this review included, but were not limited to, "built environment", "built environment variables", "built environment measures", "built environment analysis", "healthy living", "built environment design", "built environment effects", "built environment features", "health", "non-communicable diseases", "physical activity", "physical inactivity", "obesity", "overweight", "walking" and "diabetes".

The inclusion criteria placed for including literature in this review were: (a) built environment measured as an exposure, (b) outcome measures of risk factors/

prevalence/ prevention of non-communicable diseases and (c) community-based studies.

In this chapter, we begin with the burden of non-communicable diseases, define the built environment, delineate the built environment's measures, define outcome variables physical activity and diabetes, and define the neighbourhood and how it is delineated. We then proceed to document the relationship between the built environment and physical activity/ walking and diabetes.

2.2 The scenario of non-communicable diseases

2.2.1 Global Scenario

Two-thirds of deaths worldwide are attributed to non-communicable diseases and is a cause of high public health and economic concern. Heart and lung diseases, cancers, and diabetes cause 38 million deaths annually, and about 82% of premature deaths occur in developing countries (World Health Organization 2018a). Tackling the prevention of NCDs is crucial for the economic development of nations. Presently, 25% of the adults and three in four adolescents fall short of the recommended physical activity levels by the World Health Organization. Also, a downward trend is projected for 2030, with a very high rise in sedentary behaviour and lack of exercise globally (Laddu et al. 2021).

2.2.2 Indian Scenario

India is experiencing a non-communicable disease epidemic with rapid rates of obesity, diabetes mellitus and associated chronic and co-morbid NCDs (Prabhakaran et al. 2018). India also inhabits the largest diabetic population in the world, projected to reach 100 million by 2030 (Adlakha et al. 2016a). In the global status report, the World Health Organization (WHO) pinpoints the prevalence of insufficient physical activity in India to be 12.1% and premature NCD mortality rates to be 26.2% in 2014. NCDs contribute to 60% of all deaths (about 5.87 million), cardiovascular diseases (coronary heart disease, stroke and hypertension) contribute to 45% of all NCD deaths in India. The age-standardised prevalence of obesity and overweight has increased by 22% in 44 years. As per WHO standards, two-thirds of the adolescents aged 11-17 years and 13% of the adults are physically inactive in India (World Health Organisation 2014). The burden of NCDs is known to cause a considerable loss of \$237 billions of national income in 2015 (Deepa et al. 2011). The epidemiologic transition explains the differences in the occurrence of diseases with and between the country.

Urbanisation has fast advanced beyond basic health services and regional infrastructure, thus causing compounded health threats from NCDs (Adlakha et al. 2016b). Increased affluence and urbanisation has led to an epidemiological transition, which has led to a high prevalence of hypertension and diabetes (Gupta et al. 2012). Also, India's rapid rise in socioeconomic conditions has contributed to a higher risk of NCDs (Suchday et al. 2006; Patel et al. 2011b; Kulkarni 2013). Prevalence of diabetes has shown a positive gradient with higher social structure, with high prevalence in the educated and affluent strata (Samuel et al. 2012). In recent times, several physical activity barriers include lack of time, motivation, lacunae in the built environment, and lack of inexpensive facilities for physical activity (parks, walking paths and accessible recreational facilities) (Mathews et al. 2016).

2.2.3 Kerala Scenario

Being highly literate (about 90%), Kerala is undergoing a demographic and epidemiologic transition, and 76% of the 33 million population reside in non-urban areas (Daivadanam et al. 2013a). Keralites have a high prevalence of non-communicable diseases and their risk factors such as physical inactivity and overweight (Krishnan et al. 2016; Mathews et al. 2016). A survey in 2016 among rural women in Thiruvananthapuram reported 26.6% of physical inactivity, much higher than reported by urban women in 2006. Access to facilities emerged as an essential correlate for physical activity in the study (Thankappan et al. 2015). Other determinants identified for Kerala's lifestyle change were less than ideal accessibility and availability of health services, cultural values and norms, optimistic bias, and other misconceptions related to risk (Daivadanam et al. 2013b).

2.3 Neighbourhoods

2.3.1 Defining the neighbourhood

The association between neighbourhood built environment and health outcomes have been researched in previous literature with specific definitions of the physical neighbourhood. Operationalising the neighbourhood has been based on various definitions defined by the researchers depending upon the research question. An ancient definition by an urban planner was "a unit that contains four basic elements: a primary school, small parks, small shops, and buildings and streets configured to allow all public facilities to be within safe pedestrian access".

The Oxford English dictionary states the neighbourhood as "the area of a town that surrounds someone's home" or "the people who live in this area". This definition means that the neighbourhood can be both spatial or social in nature (Lupton 2003). However, in health, neighbourhoods are characterised as purely spatial units (Macintyre et al. 2002; Dietz 2002; Guo & Bhat 2007; Spielman et al. 2013). One comprehensive definition of spatial nature states that the neighbourhood is the bundle of spatially based attributes associated with clusters of residences, sometimes in conjunction with other land uses" (Galster 2001). Hereafter, in this thesis, neighbourhoods are considered as spatial units only.

Another definition practically compatible with public health research is a person's surrounding environment, which is unique to each participant in the study (Boruff et al. 2012). When the outcome of the investigation is to study walking behaviour, we might have to capture constant contact of the participant with the environment while on the move or during transport. There are also evidences that the interaction between the environment while walking or engaging in physical activity depends solely on the participant. It is a product of both environmental and individual-level factors.

A neighbourhood captured using the GPS (global positioning system) is considered ideal but can be exhaustive in time and resources (Kwan 2004). GPS measurements can capture actual exposure with accuracy but can be impractical in large samples because the participants themselves need to be data collectors. However, the researchers met compromise by selecting spatial units that best suit the study participants.

Yet another hurdle in research involving the built environment and health is the concept of 'exposure'. The term 'neighbourhood' and 'exposure' are used interchangeably in research, but these terms denote different concepts. When 'neighbourhood' signifies an area surrounding the residence in a residential neighbourhood, 'exposure' signifies external influences on an individual in a particular location. As previous research has acknowledged, the residential neighbourhood does not truly capture the total exposure for an individual (Mathews et al. 2015). Many places may not be visited or rarely visited by an individual. Hence the actual exposure might be different from potential exposure. Therefore, the measurement of the neighbourhood is of great importance in the relationship between built environment measures and outcome of interest.

2.3.2 Capture of neighbourhood

The neighbourhood defined using GIS includes the creation of buffers around the residence of participants or using pre-destined administrative boundaries. The size of the buffer or the type of buffer does not seem to be uniform across studies. Besides, there is no consensus on the most appropriate one, either. Census tracts or geographic boundaries have been used in studies with physical activity and walking behaviour as an outcome. When we analyse exposure across an administrative area, all the participants within that area may be considered to have similar exposure. But there can be differences based on their location within the said geographical boundary.

The scale and boundary decisions are considerably crucial in neighbourhood level research. These decisions are essential because of a phenomenon called 'modifiable areal unit problem' (MAUP) (Jelinski & Wu 1996). There are two concerns within MAUP which are 'scale problem' and 'zoning problem'. They are inter-related but are separate problems involved in spatial data analysis. The scale problem arises if the same set of areal data is broken down into several sets of units, which will cause varying values and inferences for each combination. The zoning problem emerges depending on the boundaries we place on a given data, which can also cause variation in data values, hence differing conclusions.

These decisions can be difficult for researchers studying neighbourhood relationships because the choice largely depends on the levels at which the environmental data and outcome data are captured (Flowerdew et al. 2008). The primary step in defining the neighbourhood is to identify the residential location of the participants. The majority of the studies have residential location identifiable to administrative boundaries; in such cases, the neighbourhood can be defined only at the administrative boundary level or higher. Data on built environment measures are also often available in summarised formats at the administrative boundary level (Cummins et al. 2005).

However, summarised measures will not capture variations within the administrative boundaries because variations are 'ironed out' in summary values. Hence when the boundaries are too large, it will be impossible to detect within-area differences, which is the scaling problem mentioned before. In such a scenario, the relationship between environment measures and the outcome of interest will be more challenging to detect. On the other hand, it is not sufficiently proven that smaller units are the best choice for environmental measures (Moudon et al. 2006).

Therefore, the most optimal definition will depend upon the hypothesised effect of the environmental measure on the outcome of interest. While examining the relationship between physical activity or walking with the built environment measures, it is relevant to deal with smaller units than a large administrative boundary; because physical activity or walking is frequently hypothesised to be dependent on areas closer to home. Even though the scaling problem is dealt with, the zoning problem can still exist. This problem is because the zoning issue will lie with the shape of the area defined, and there can be infinite choices for determining the shape of the boundary (Wong 2004). Few other researchers tried to identify the possible difference caused by the zoning effect on walking and self-rated health. They concluded that the differences did not necessarily affect the estimates (Stafford et al. 2008). Coulton and colleagues tried to figure if the administrative boundaries would underestimate the effect of relationships engaging environmental measures (Coulton et al. 2001). They used participant-defined boundaries, which were mostly different from the census boundaries. This method is, however, impractical in large samples. Therefore to find a compromise, researchers take decisions to define neighbourhoods by using GIS to delineate neighbourhood buffers.

For a personalised measure of exposure, buffers around the participants' residences are considered helpful. Previous research has included buffer sizes extending from 400 to 3200 metres (Brownson et al. 2009). The type of buffer can be circular in nature or network-based buffers, as shown in Figure 2.1. Circular buffers may be convenient to create but can cover areas inaccessible to the participants, such as rivers or hills. Such a buffer may not be the accurate representation of the spatial area that influences walking (Oliver et al. 2007).

Network buffers can be polygon-based or line-based. Polygon-based network buffers are formed along with the road network in all possible directions for a specified distance from a participant's residence and then creating a polygon across the endpoints. This method may be more accurate to identify spatial areas that affect walking behaviour but requires dense and regular grid street patterns (Frank et al. 2005). A line-based network buffer is a buffer of a predetermined width around a road network. These line-based buffers were commonly used in studies related to hospital travel times (Schuurman et al. 2006). The network buffers require complex and intensive computational capacities and have been attempted only in high-income countries.

Figure 2.1. Depiction of different kinds of buffers (Eriksson 2013)

However, the alternative method of delineating a neighbourhood is derived from a mix of residential and commercial zoning. Also, neighbourhoods can be defined by the homogeneity of population or housing characteristics. Nevertheless, determining neighbourhoods for research can be challenging for researchers, and any definition may be disputed.

2.4 The built environment

2.4.1 Defining the built environment

The built environment has been defined in many ways in published writings. "*Built environment includes urban design factors, land use, and available public transportation for a region, as well as the available activity options for people within that space*" (Booth et al. 2005). Another author states, "*the built environment encompasses the structural features, the social processes and relationships among community members, and the characteristics that the individual adds to the environment*" (Adams et al. 2014).

More specific definitions state that "*built environment refers to the man-made structures and surroundings and includes roads, neighbourhoods, recreational facilities such as parks and playgrounds, food sources, buildings and houses in which people live and perform activities of eating, playing educating and working*" (Qazi 2011). Adding to the above definition, "*built environment encompasses land-use mix, proximity to home, street connectivity, pedestrian infrastructure, safety in the neighbourhood, access to recreational or non-recreational destinations*" (McCormack & Shiell 2011). Additionally, "*built environment features include the residential density, walking and cycling environment, aesthetic quality and safety*" (Durand et al. 2011a).

Furthermore, the built environment has three major dimensions: land-use patterns, transportation systems, and services that provide spatial links or connectivity among activities (Anjana & Pradeepa 2017). The physical characteristics of areas where people live can be summarised as the built environment, namely the buildings, streets, open spaces, and infrastructure (Amuda & Berkowitz 2019). These characteristics can be operationalised in different levels, which can be Macro, Meso or Micro levels. The macro-level operates at a large metropolitan area (at the Panchayat in the Indian context), meso-level works at the particular metropolitan area (within the ward/ Grama Panchayat) and micro-level refers to the participant neighbourhood.

2.4.2 Measurements of the built environment

Three types of data are used for measuring environment characteristics: perceived (subjective- measured by personal interview/ questionnaire), observational (objective- measured by systematic scans or audits), and archived datasets that are analysed using GIS (Su et al. 2014a).

2.4.2.1 Objective measures of the built environment

Objective assessment of the built environment is usually performed using Geographical Information Systems (GIS). GIS involves computer-based systems composed of hardware, software and data to create, store, manage, display and analyse location-based data. Mainly these data are accessed from national or local data providers or accessible datasets with spatial reference. GIS measures also do have limitations as in other measures. GIS assessment of environment variables requires competence to handle datasets that are not designed for research and demand substantial data management skills. The neighbourhood may be defined differently for each research question, either using the administrative boundaries or creating buffers around participants' residence. There is no consensus available on the best approach and the size of buffers.

The various objective measures of built environment characteristics captured in previous literature are summarised in the Table 2.1.

Table 2.1. Measurements of objective built environment

Sl. No	Measure
1.	**Population density**
	a. The number of people per square mile in a county (Hipp & Chalise 2015).
	b. The number of persons per square kilometre of the area within the buffer (Villanueva et al. 2013a; Tamura et al. 2014).
	c. Population per square mile within a 1-mile Euclidean buffer of a participant's home (Hirsch et al. 2014).
2.	**Building/ Residential density**
	a. The number of housing units per square kilometre for a census tract (Duncan et al. 2014).
	b. The number of single-family units per buffer area/ total squared kilometres of residential land use in buffer area (Salvo et al. 2014).

c. Number of dwellings calculated (detached, semi-detached, condos and apartments) and divided by the total area of the buffer zone (de Sa & Ardern 2014).

d. The ratio of the number of residential dwellings to the residential area in hectares (Müller-Riemenschneider et al. 2013).

3. Land-use mix

a. Score buildings within the buffer were categorised as residential, recreational, retail, office or institutional. A sum of each building category was calculated, and the total score ranges between one and five. Score one denotes residential area only, while five denotes high land-use mix (Bringolf-Isler et al. 2015).

b. Using five categories (food, retail, services, cultural/educational, and physical activity), diversity was calculated with an entropy formula. Possible scores ranged from 0 (no diversity) to 1 (maximum diversity) (Duncan et al. 2014; Tamura et al. 2014).

c. Facility density was computed by dividing the number of facilities by kilometres of road within each 1200 meter buffer (Tamura et al. 2014).

d. Euclidean distance from a participant's residential address to the nearest area zoned for commercial (not including industrial or institutional) use (Michael et al. 2014a).

e. The proportion of area that is covered by each land use type divided by the number of land-use classes (Müller-Riemenschneider et al. 2013).

4. Intersection density

Intersection density is derived by dividing the number of three-way or greater intersections by the total length of roads within the buffer (Duncan et al. 2014; Tamura et al. 2014).

5. Traffic density

a. Average daily traffic x length of roads in metres in 800m line-based network buffers divided by buffer area in square kilometres (Duncan et al. 2014).

b. The number of cars registered per day in several street stations within the area (0.01 square kilometres) of each district (Gose et al. 2013).

6. Sidewalk completeness

Sidewalk completeness within 800m buffer calculated for the road without medians (Duncan et al. 2014).

7. Zoned land-use patterns

Percentage of the area zoned for retail/residential use in a one-mile Euclidean buffer around a participant's home (Hirsch et al. 2014).

8. Access to destinations

a. Percentage of census tracts (census blocks) where 33% of the population lives far from a supermarket or grocery store (Hipp & Chalise 2015).

b. The density of social/ walking destinations (count per square mile) within a one-mile buffer around a participant's home (Hirsch et al. 2014).

c. The number of fast-food restaurants/ supermarkets/ sports facilities and playgrounds within the two km buffer were counted to create standardised scores, which were summed to obtain an overall 'destinations score' (Van Dyck et al. 2013).

d. It is calculated by summing the number of grocery stores, convenience stores, fast-food restaurants and parks within each tract and 20-m buffer (Carroll-Scott et al. 2013).

e. Access to destinations: food retail, general retail (newsagent, shopping centre); medical care services (doctor, medical centre); financial services (bank, post office); general services (hairdresser, pharmacy) and social infrastructure (restaurant, church or place of worship) (Nathan et al. 2012).

f. Neighbourhood Destinations Accessibility Index (NDAI): a measure of walking access to 31 types of community service and amenity destinations- educational, transport, recreation, social and cultural, food retail, financial, health, and other retail destinations (Witten et al. 2012).

9. Public transportation

a. The Euclidean distance (in miles) between a participant's home and the nearest bus route (Michael et al. 2014a; Hirsch et al. 2014).

b. The number of bus public transit routes intersecting the buffer (Salvo et al. 2014).

10. Street connectivity

a. The area of a one-mile network buffer divided by a one-mile Euclidean buffer around a participant's home. The ratio has a value between 0 and 1, with zero meaning none of the areas can be reached through the road network and one meaning the entire area can be reached through the street network. (Hirsch et al. 2014).

b. The density of intersections in a quarter-mile radius around each participant's residence (Michael et al. 2014a).

c. The ratio of the number of three-way or more intersections to the area per square kilometre (Müller-Riemenschneider et al. 2013; Villanueva et al. 2013a).

d. A standardised z-score of the number of three- or more- way intersections within the two km buffer (Van Dyck et al. 2013).

11. Walkability

Sum of weighted z-scores of population density, road connectivity and land-use mix (Gose et al. 2013).

12. Green space area

a. It can be the number of hectares of green spaces and of wooded areas calculated for the neighbourhood (Bringolf-Isler et al. 2015).

b. The total area of parks/ green space calculated around each centroid (de Sa & Ardern 2014).

c. Based on NDVI- an indicator of relative biomass and greenness. The value ranges from -1 to +1. Negative values depict the presence of water. Variation in vegetation is derived from the standard deviation of NDVI for all green space within each neighbourhood (Pereira et al. 2013; Gong et al. 2014a).

d. Percentage of the area which is covered by tree canopy within each 30m pixel (Kowaleski-Jones & Wen 2013).

13. Park access and quality

a. Distance in metres to the nearest park (Michael et al. 2014b; Salvo et al. 2014).

b. The proportion of buffered zip code area defined as park space (Stark et al. 2014).

c. Park cleanliness score is based on litter, glass, weeds, and graffiti provided by Park Inspection Program (Stark et al. 2014).

d. Data on parks, recreation, and trees (Carroll-Scott et al. 2013).

e. Population-weighted distance (in miles) from the neighbourhood centroid to the nearest seven parks (Kowaleski-Jones & Wen 2013).

14. Reach

Street distance covered when walking one mile from the residents' block in all possible directions (Schulz et al. 2013).

15. Land slope

a. Slope measures the on-ground terrain or topography. Digital Elevation Model (DEM) data with a cell size of 90m x 90m were used to calculate slope values. The mean of this slope measure was calculated for all cells that intersected the road network in each participant's 1600m service area using zonal statistics. The mean slope was used as a measure of hilliness or terrain in the service area (Villanueva et al. 2013b).

b. Elevation data obtained from Digital Map 50m Grid (Hanibuchi et al. 2011).

16. Safety

a. The number of homicides per 10,000 persons for each Zip code, the total number of homicides were averaged and divided by Census 2000 population estimate (Stark et al. 2014).

b. Average crime rates calculated for each district and related to the average number of inhabitants (Gose et al. 2013).

2.4.2.2 Perceived measure to capture the built environment:

The majority of the research on neighbourhood environments and physical activity has been based on self-reported measurements. Though there are many questionnaires to capture perceived environment, the most frequently used questionnaire is the Neighbourhood Environment Walkability Scale (NEWS) and its abbreviated form (NEWS-A) (Bracy et al., 2014; Carlson et al., 2012; Jack and McCormack, 2014; Pelclová et al., 2014; Zwald et al., 2014). NEWS and NEWS-A were designed to assess perceived environmental attributes that are related to physical activity. They contain 67 and 54 items, respectively. There are eight subscales that capture perceived residential density, proximity to non-residential land uses, ease of access to non-residential land uses, street connectivity, infrastructure for walking and cycling, aesthetics, traffic safety, and crime. Most items are rated on a four-point Likert scale where one denotes "strongly disagree", and four denotes "strongly agree". There are limitations for subjective measures, too, mainly with recall bias regarding how much one can recall their exposure to the items mentioned in the questionnaire (Adams et al. 2009). There are also issues with overestimating the exposure, with difficulties in accurately identifying distances or conceptualising access to various destinations, like the parks, restaurants, etc. (Dewulf et al. 2012).

2.4.2.3 Audit tools to capture the built environment:

The audit tools also provide an objective measure of the neighbourhood environment. Researchers use them to survey various variables in the environment. These tools demand training of those involved in data collection (Pikora et al. 2002; Bedimo-Rung et al. 2006). They are majorly attempted in research studies where few neighbourhoods are sampled and when the information is unavailable as spatial datasets.

Those that have been used concerning physical activity are summarised below:

1. **CHESS- Community Health Environment Scan Survey (Wong et al. 2011)**: This tool was developed by Community Interventions in Health (CIH) evaluation team to systematically document, map and assess the environments in which people normally engage themselves to shop, live, work, and play. It includes eight assessment tools that list inventory streets, stores, restaurants, street vendors, recreational facilities, parks/gardens, vending machines, and the information environment.

2. **Systematic Pedestrian And Cycling Environment Scan (SPACES) (Witten et al. 2012):**
   This is a streetscape audit tool developed by Pikora et al., in 2004. This tool captures items that support walking, such as physical infrastructure, street-level aesthetics, and traffic safety. This audit was used to capture data over 1987 kilometres of road in Perth, Western Australia.

3. **SPOTLIGHT Virtual Audit Tool (S-VAT) (Bethlehem et al. 2014):**
   This tool is a virtual audit to assess neighbourhood characteristics that are potentially associated with physical activity and dietary behaviours.

4. **Environmental Profile of a Community Health (EPOCH) (Chow et al. 2014)**
   EPOCH was developed to evaluate features of the built environment of communities using a standard set of photos. This was a novel methods to capture

environmental assessment utilising a set of photos taken according to the standardised method and applying a standard data extraction form to analyse each photo set for features of the community environment.

5. **Wisconsin Assessment of the Social and Built Environment (WASABE) (Malecki et al. 2014):**

   This tool was developed to capture a range of social and built environment features in urban and rural communities. This audit-based tool is both reliable and valid and can be used in a variety of settings.

2.5 Spatial techniques and analysis

2.5.1 Interpolation

Interpolation is a technique of using points with known values to estimate values at other unknown points. The Interpolated surface, called the statistical surface, is a smooth surface containing values at all points within the surface. Method to produce this smooth surface include approaches that include regression analyses and distance-based weighted averages. The criteria used to weight values in relation to distance can be simple distance relations (e.g., inverse distance weighting), minimization of variance (e.g., kriging and co-kriging), minimization of curvature, and enforcement of smoothness criteria (splining) (Hartkamp et al. 1999).

The most commonly used techniques for interpolation in environmental sciences are kriging and Inverse Distance Weighting (IDW) (Yao et al. 2013). IDW has been previously used to interpolate crime data in Trivandrum city, Kerala and in

Aurangabad city (Ansari & Kale 2014; Achu & Rose 2016). Also, IDW has aided in the interpolation of traffic accident datasets. In IDW, the value at a point is estimated using the nearest sample points. Weights by a power proportional to the inverse of their distance are applied from the estimated point. The power calculated will determine the influence of the closer sample points (Kurtzman & Kadmon 1999).

2.5.2 Spatial cluster analysis

Spatial statistics are used to detect and evaluate clusters of cases in either purely temporal, purely spatial or space-time setting. Clusters are by gradually scanning a window across time and/ or space, with a comparison of the observed and expected number of cases inside the window at each location. In SaTScan, the scanning window is circular or elliptical to capture spatial clusters. The analysis is repeated for many window radii. The window that has maximum likelihood ratio is the most likely cluster, that is, the cluster least likely to be due to chance. A p-value is assigned to this cluster.

Different probability models are incorporated to assess the outcomes of different nature. (Kulldorf 2018) A Bernoulli model is used to count data such as the number of people with asthma; a multinomial model is used for categorical data such as cancer histology; an ordinal model for ordered categorical data such as cancer stage; an exponential model for survival time data with or without censoring; and a normal model for other continuous data such as birth weight or blood lead levels.

The standard purely spatial scan statistic imposes a circular window on the map. The window is in turn centred on each of several possible grid points positioned throughout the study region. For each grid point, the radius of the window varies continuously in size from zero to some upper limit specified by the user. In this way, the circular window is flexible both in location and size. In total, the method creates an infinite number of distinct geographical circles with different sets of neighbouring data locations within them. Each circle is a possible candidate cluster. Each data location is a potential cluster in itself.

For each analysis, the alternative hypothesis is that there is an elevated risk within the window as compared to outside. The likelihood function is maximized over all window locations and sizes, and the one with the maximum likelihood constitutes the most likely cluster. This is the cluster that is least likely to have occurred by chance. The likelihood ratio for this window constitutes the maximum likelihood ratio test statistic. Its distribution under the null hypothesis is obtained by repeating the analysis on a large number of random replications of the data set. The p-value is obtained through Monte-Carlo hypothesis testing by comparing the rank of the maximum likelihood from the real data set with the maximum likelihoods from the random datasets. The SaTScan program scans for areas with high rates (clusters), for areas with low rates, or simultaneously for areas with either high or low rates.

2.6 Physical Activity

2.6.1 Defining physical activity

Physical activity is often defined as 'any bodily movement produced by skeletal muscles that require energy expenditure' (World Health Organization 2020a). They can be moderate- or vigorous- intensity, both of which can avert and manage non-communicable diseases. The major domains of physical activity are classified as leisure/ recreation/ exercise, occupation, transport and household (Pratt et al. 2004). Physical inactivity is termed for not meeting physical activity levels as recommended for each age category (children/ adolescents/ adults/ older adults) by the World Health Organization (World Health Organization 2020a).

2.6.2 Ecological pathways between physical activity and built environment

Physical activity is mainly related to multiple factors, including individual, social, institutional, built environment and policy. The multi-level and multi-sectoral linkages in the physical activity phenomenon require coordinative effort and interventions (Sallis et al. 2012). Physical inactivity or less than recommended physical activity levels is the critical pathway by which the built environment affects non-communicable disease epidemiology (Frank et al. 2003; Frumkin et al. 2004).

Walkability, a phenomenon that determines the ease to walk, is closely related to physical activity. Building designs, open spaces and a variety of land use are also elements of the built environment linked to walkability (Durand et al. 2011b; Bauman et al. 2012). Street designs and connectivity within a neighbourhood is beneficial toward transportation-related physical activity (Wendel-Vos et al. 2007). However, leisure-time activity levels are related to bike paths, cycling paths, road and sidewalk conditions (Owen et al. 2018). Also, highly dense neighbourhoods with high public transport density and easy access to parks are positively related to higher physical activity levels and lower sedentary time (Sallis et al. 2016; Wong 2018).

Safety within the neighbourhood is yet another anchoring factor that affects physical activity behaviours (Boslaugh 2004). Fear or lack of safety is closely related to perceived risk and constraints walking (Loukaitou-Sideris 2006). Fear can be due to the actual crime rates or perceived fear of harm, both of which are related to neighbourhood safety (Tamayo et al. 2016; Foster & Giles-Corti 2008). Also, high road traffic levels, lack of pedestrian safety and infrastructure has contributed toward neighbourhoods being unsafe to walk or engage in physical activity.

Policy initiatives have greater impacts on walking behaviour and lifestyle changes. Recent municipal policy to create pedestrian walkways, crossings and cycling infrastructure in Ottawa, Canada, showed higher work commutes following policy implementation (Arnason et al. 2019). Urban planning and design depend heavily on policy initiatives to enhance healthy and active lifestyles. The most common policies include increasing urban sprawl (Resnik 2010) (uncontrolled growth and development in the outskirts of a city) and land-use mix (Spears et al. 2014) (measures the diversity of buildings – residential/ office/ retail services and parks/ open spaces).

2.7 Diabetes Mellitus

2.7.1 Defining diabetes mellitus

The American Diabetes Association has defined diabetes mellitus as a group of metabolic diseases characterised by hyperglycaemia resulting from defects in insulin secretion, insulin action, or both. Type 2 diabetes mellitus is a combination of resistance to insulin action and inadequate compensatory insulin secretory response. (American Diabetes Association 2004). South Asians have shown a tendency to have diabetes despite lower body mass index (Narayan & Kanaya 2020).

Several epidemiological studies point towards south Asians having less compensatory reserves due to low ability to secrete insulin. This tendency of high prevalence of diabetes in those with low body mass index, has forced the WHO to recommend lower BMI cut-offs for obesity in South Asians (Misra 2015; Caleyachetty et al. 2021). The underlying cause might be that the Asians, and South Asians have more severe inflammation, insulin resistance and liver fat even when they are classified as non-obese by BMI standards for the Caucasian population (Misra & Dhurandhar 2019).

2.7.2 Pathways concerning diabetes and built environment

Various linkages of built environment and diabetes show a direct relationship with walkable neighbourhoods, green space in the neighbourhood and safety within communities. Pieces of evidence show pathways related to low levels of ambient air pollution and low susceptibility to stress, which facilitates a lower risk for diabetes (Tsai et al. 2020). The other pathway is through the food environment, where a high density of fast-food restaurants and supermarkets are directly linked to a higher risk of diabetes (Hsieh et al. 2014). Moreover, socioeconomic conditions within neighbourhoods have a high impact on grocery stores, recreational facilities, and access to services (Piccolo et al. 2015). These mechanisms of availability and access influence food behaviours and healthy diets, which in the long run, influences the risk for diabetes.

On the other hand, economically deprived neighbourhoods have infrastructural deficiencies with higher insecurities to walk and engage in physical activity (Park et al. 2020). Also, those with diabetes living in high-crime neighbourhoods were found to have decreased odds of treatment adherence (McDoom et al. 2020). Moreover, in neighbourhoods with a high density of fast-food restaurants, detrimental effects on weight status have been found (Piccolo et al. 2015).

2.8 Relationship of diabetes and physical inactivity with objective built environment characteristics

Recent years has shown a growing body of evidence on the role of the built environment in the neighbourhood as an important determinant in causing both physical inactivity and sedentary behaviour (Laddu et al. 2021). Though most of these factors do not lie within the purview of healthcare, they are significantly related to the prevalence of NCDs in general (Sallis et al. 2012).

2.8.1 Urbanicity, including population and residential density

Population density refers to the number of individuals or households in a defined area closely associated with high urbanicity. Denser neighbourhoods encourage active transportation and have easy access to services (Saelens & Handy 2008; Durand et al. 2011b). Since more people reside in a small area, all accessible destinations such as shops, restaurants, and schools may be available close (Sallis et al. 2012). Urban neighbourhoods may have many of the built environment characteristics co-existing together and hence suggests that isolating effects of each characteristic are impossible.

Spatial cluster analysis of physical activity was attempted in the US to reveal that clusters of physical activity and obesity existed in California, Massachusetts and Pennsylvania (Tamura et al. 2014). Population density and intersection density were significantly different within and outside clusters of physical activity, which are expected to be associated with walkability. Though the results were not consistent, some of the high physical activity clusters had built environment factors like availability and condition of sidewalks, aesthetics, outdoor recreational facilities, etc. However, the study among the Nurses' Health Study cohort from 2004 provided evidence that the population density, intersection density and facility density were associated with greater odds of meeting physical activity recommendations. Canadian residents living in high residential areas were involved in active modes of transport (de Sa & Ardern 2014).

Active travel among young adolescents in the US showed a similar association with perceived street connectivity, perceived pedestrian safety around the home, objective street connectivity and residential density around the home (Carlson et al. 2014). Physical activity among older women (participants of NHS cohort) showed association with population density, intersection density and facility density. A higher proportion of physical activity facilities nearby showed a higher prevalence of obesity among older women (Troped et al. 2014).

2.8.2 Street Connectivity

Street connectivity is linked to ease of transportation within neighbourhoods and can determine walkability. The higher the connectivity within neighbourhoods, the more accessible will the residential areas and destinations be (Sallis et al. 2012). The use of public transport has been associated with people being more active and encouraged physical activity (Moudon et al. 2007; Sallis et al. 2009). Systematic reviews have proven the presence of walking paths and bicycling infrastructure to encourage walking and cycling among youth and adults (Giles-Corti et al. 2009; Faulkner et al. 2009). Though not consistent, evidence shows that walking is higher in walkable neighbourhoods (Heath et al. 2006).

Canadian residents living in neighbourhoods with higher intersections were found to engage in greater leisure-time walking and cycling (de Sa & Ardern 2014). Pedestrian safety was associated with physical activity among two cross-sectional studies in the US involving about 3000 participants (Gong et al. 2014b). One study conducted in Mexico, representing low-and-middle-income-countries showed contrasting results from that of high-income countries (Salvo et al. 2014). Here, results showed that walkability was inversely related to minutes of moderate and vigorous physical activity. Moreover, the number of transit routes within the 500-m buffer was also related inversely to the minutes of physical activity. Communities who were involved in active living in the US showed the presence of more sidewalks, better connectivity to other places and access to public and civic destinations, and thus they were beneficial for the inhabitants (Oliver et al. 2014).

2.8.3 Safety

One of the major concerns for physical activity and walking is the lack of safety from crime and traffic. High crime rates cause less likelihood of walking in the neighbourhood (Piccolo et al. 2015). There is also evidence showing crime rates playing a mediator for the risk of diabetes (Tamayo et al. 2016). Also, violent crime rates have shown area-level influences on the prevalence of diabetes (Foster & Giles-Corti 2008).

Findings also show that patients with diabetes in unsafe neighbourhoods had difficulties in treatment adherence (Tung et al. 2018). Evidence also points out that certain neighbourhoods can be disadvantaged and appear to be found in low socioeconomic settings. Such neighbourhoods had higher crime rates and less traffic safety (Casagrande et al. 2009; Sallis et al. 2011).

2.8.4 Green space

The possible mechanism by which greenness is related to diabetes, though very unclear, is by lowering ambient air pollution, increased rates of physical activity and lowering stress susceptibility (Tsai et al. 2020). Greenness in the environment is considered to decrease the risk of developing diabetes by modulating immune functions. Studies showed lowering risks is due to a naturally occurring organic compound called terpenes, which have anti-inflammatory and anti-cancer properties (Cho et al. 2017). Meanwhile, elderly men who were part of the Caerphilly Prospective study demonstrated that living near neighbourhoods with higher green space would help in regular participation in physical activity (Gong et al. 2014a).

2.8.5 Policy initiatives to tackle diabetes and physical inactivity

The Robert Wood Johnson Foundation's Active Living by Design program had a set of changes in the physical environment in Michigan, including installing a rail trail and policy that all streets must accommodate bicyclists and pedestrians. These interventions manifested an increase in active transportation among the residents (TenBrink et al. 2009).

The 'Shape-Up Somerville' trial also significantly impacted child overweight/obesity prevalence and increased physical activity among the population. The trial focussed on a comprehensive intervention across all levels. The major directions are installing infrastructure for walking, initiating walk to school campaigns and setting up new school play equipment (Economos et al. 2007; Chomitz et al. 2010). Another initiative was the Communities Putting Prevention to Work (CPPW) by the CDC, which involved grants to change environments to aid physical activity and prevent obesity (Sallis et al. 2012).

Policy analysis among rural communities in Southern United States showed that multi-level interventions are needed to address physical activity issues, beginning with introducing built environment features (sidewalks), town programs and policy initiatives and community-wide amenities (Robinson et al. 2014). A similar case study in High Point Neighbourhood, Seattle, showed the effectiveness of a community readiness model. This retrospective study demonstrated that physical activity increased with newer housing policies (Buckner-Brown et al. 2014). However, analysis of a sample of legislative policies related to the built environment in Minnesota showed that 88% of them were based on non-research evidence (Kite et al. 2014).

Three longitudinal studies looked at the change in the built environment and the difference in walking behaviour in the United States, Hong Kong and Australia (Sun et al. 2014; Knuiman et al. 2014; Hirsch et al. 2014). A GIS-based study among participants of *Multi-ethnic Study of Atherosclerosis* assessed walking behaviour at baseline, and three follow-up visits showed that high levels of population density, area zoned for retail, social destinations, walking destinations and street connectivity were associated with an increase in walking for transportation over time.

The seven-year follow-up RESIDE (Residential Environment) study in Australia among people building homes in 73 new housing developments showed similar results. The number of public transit stops and the diversity of destination types accessible from home were related to higher amounts of walking for transportation. The longitudinal study at a University campus in Hong Kong among the University students provided an opportunity to assess change in walking behaviour over time. The assessment was done at baseline and follow-up at the tenth month. Change in bus timings raised the walking behaviour of the students. Increasing the frequency of bus timings had an inverse relationship with walking.

2.9 Relationship of diabetes and physical inactivity with perceived built environment characteristics

Perception of the built environment is closely related to one's experience within or the exposure to the 'actual' built environment (Jack & McCormack 2014). Reliability has been established between perceived built environment characteristics and objectively-determined factors. However, both measures are to be considered. The attitudes, beliefs, self-efficacy, preferences, habit, past experiences, health and socioeconomic status, can influence one's perception of the environment. Perceptions are understood to act as mediators in the physical activity-built environment causal pathway.

Working women in the United States reported use of the built environment, self-regulation, perception of higher land-use mix diversity, and perception of lower infrastructure and safety to be associated with meeting PA recommendations (Gell & Wadsworth 2014). Also, high perceived safety of the environment was associated with the highest PA, as documented by data from two cross-sectional studies (Bracy et al. 2014).

Traffic speed and perceived crime rates were significant correlates of public transportation and walking (Zwald et al. 2014). Residents living in high-walkable neighbourhoods tend to perceive higher built environment characteristics. Transportation walking was also associated with perceived access to services, street connectivity, motor vehicle safety and a mix of recreational destinations (Jack & McCormack 2014). Similarly, older adults in the *Cardiovascular Health of Seniors and Built Environment Study* reported a greater association of transportation walking with the proportion of commercial and residential areas. At the same time, a negative correlation was found with greater access to bike paths. The proportion of commercial and residential areas were associated with walking. Moreover, a higher density of bus transit stations was also associated with higher walking prevalence (Hino et al. 2014).

Aesthetics seem to have a highly significant relation to greater odds of walking. Park quality, cleanliness, maintenance and safety also attributes to walking behaviour. Factors such as safety of the neighbourhood and crime issues were associated with recreational walking. Proximity to parks is related closely to recreational walking. Street connectivity, with fewer intersections, has been associated with greater walking. It is mostly related to transport-related walking. Higher residential density seems to be related to greater odds of walking. Land-use mix, determining easily accessible locations is also related to recreational and transport-related walking (Sugiyama et al. 2014). Findings have shown that self-reported and objectively-determined factors were independently associated with transportation-based walking among Calgary residents (Jack & McCormack 2014). Perceived accessibility and aesthetic quality of the environment has shown significant associations with leisure-time physical activity in Hangzhou, China. Here, about 3% of the variability in leisure-time physical activity was attributed to the neighbourhood-level differences. Neighbourhood density was inversely associated with walking for women, and those who perceived greater scores for aesthetic quality had greater physical activity (Su et al. 2014b).

2.10 Research gaps

While we encapsulate the review of published literature, many gaps seem to be unaddressed yet. We find very sparse literature from low and middle-income countries, which is the first goal of this research to add evidence from our country. There is a need to bring empirical evidence on capturing built environment characteristics within an LMIC and in resource-poor settings. Also, we see that a perceived built environment can largely influence risk factors of non-communicable diseases, which was not addressed in this research. We additionally find the majority of the studies based on large databases and robust databases exist only in high-income countries. We tried to address this lacuna by using data from a cross-sectional survey extending across the state within our country.

Again we see that the outcome measure, such as the prevalence of non-communicable diseases, was not explored. We attempted to cover this void by evaluating built environment characteristics within spatial clusters of the high and low prevalence of diabetes and physical inactivity. There is also a need to decipher the relationship between the built environment characteristics and non-communicable diseases in India, which we have explored in this research. Moreover, we have applied novel techniques harnessing advanced geographical information systems and spatial epidemiological methods

CHAPTER 3

MATERIALS AND METHODS

3 MATERIALS AND METHODS

3.1 Introduction

This chapter depicts an overview of the study setting, details of the data sources and the methods used to define and describe neighbourhood and neighbourhood characteristics. The methods we have undertaken to access, download and process satellite data are also described here.

3.2 Objectives of this study

The major objectives of this study were:

1. To determine the geographical distribution of built environment variables across districts and subdistricts of Kerala
2. To evaluate the relationship between built environment variables and the prevalence of non-communicable diseases in Kerala
3. To identify spatial clusters of non-communicable diseases (NCDs) and evaluate built environment characteristics within low and high spatial clusters.

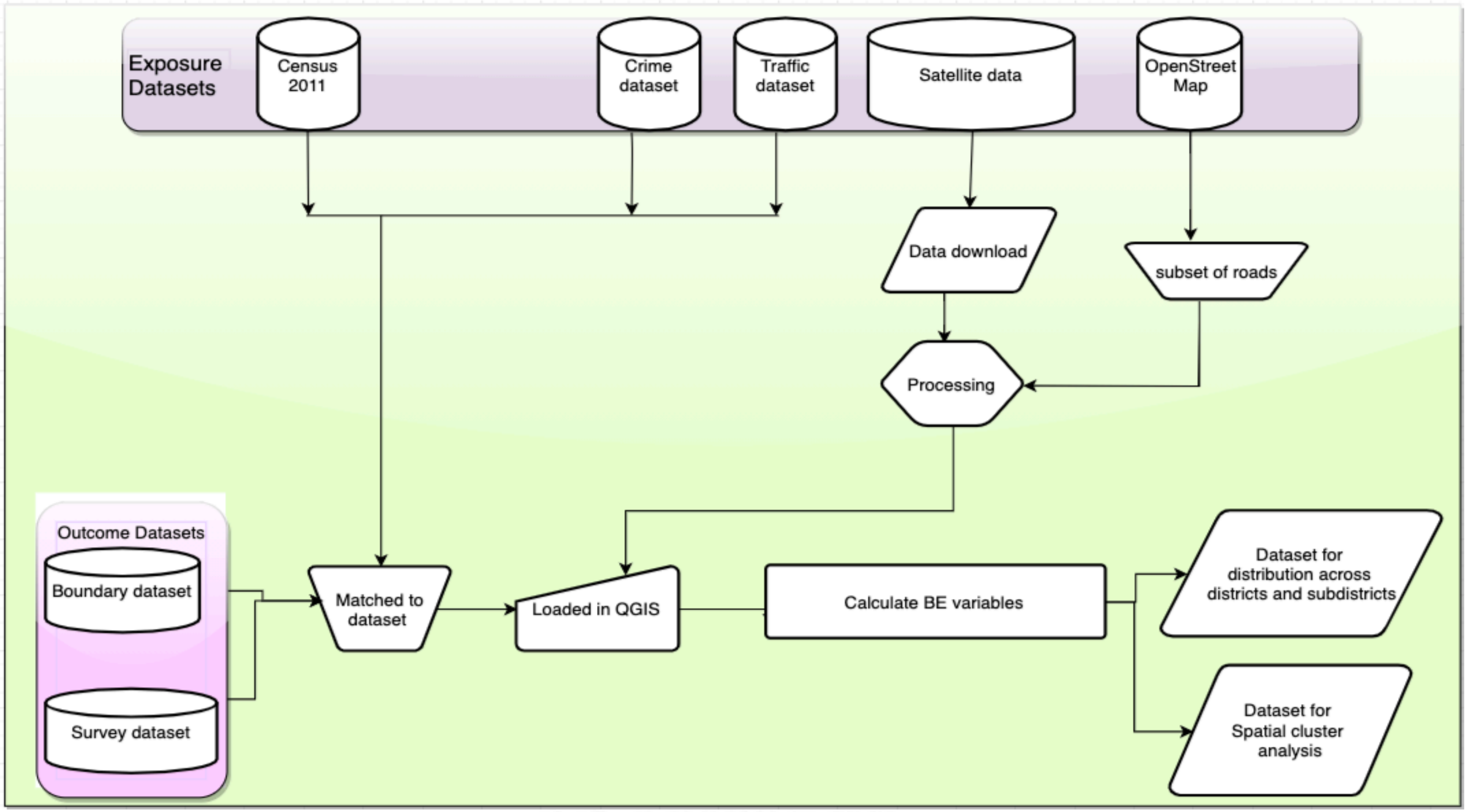
3.3 Study design

This research was cross-sectional in nature, which involved secondary data analysis following the capture of data from different sources. Geospatial techniques were employed in assimilating and linking datasets. Spatial analysis was undertaken to meet the research objectives. The flowchart of the research process is shown in Figure 3.1.

3.4 Study setting

The study setting is the state of Kerala, which lies on the south-western border of India. It is located between 8°18′ and 12°48′ north latitude and 74°52′ and 77°22′ east longitude (National Science Academy et al. 2001). This state has the Western Ghats running in the eastern border, with the Arabian sea surrounding the western border and the neighbouring states of Karnataka and Tamil Nadu sharing its northern and southern borders, respectively.

Figure 3.1. Flowchart showing process of data capture and processing



With respect to population, Kerala ranks 12th among the Indian states and contributes 2.76 per cent of the total population in India. The urban population in Kerala has doubled in ten years from 8 million in 2001 to 16 million in 2011, such that rural population constitute only 52.3% in 2011 as opposed to 74.0% in 2001 (World Bank Group 2017). A high disparity of distribution of towns across the state predisposes towards varied environmental conditions in each district. About 85% of the towns are located within eight districts, namely, Kannur, Kozhikode, Malappuram, Thrissur, Ernakulam, Alappuzha, Kollam and Thiruvananthapuram (Praveen Lal C.S. & Nair 2017). These eight districts also contribute to 87.7% of the total urban population in the State. The two hilly districts, Wayanad and Idukki, have no Census towns but have one statutory town each. Hence, each district has distinct land-use features, with the most urbanised district being Ernakulam and the least being Wayanad.

Kerala is at the forefront in literacy rates (94.0%), way higher than the national rate of 72%. It has also made remarkable progress in terms of health indices like infant mortality rate, death rates, birth rates and life expectancy at birth (State Planning Board 2016). Yet, it faces a double burden of non-communicable diseases, namely, diabetes, coronary heart disease, renal diseases, cancer, etc. and of infectious diseases, namely, chikungunya, dengue fever, swine flu (H1N1) and leptospirosis.

The topography of this state is asymmetrical and has three distinct elevation zones, namely, the lowland, midland ad highland zones, which lie parallel to each other from North-west to South-east (Simon & Mohankumar 2004). The transport infrastructure in the state includes 2.43 lakh kilometres of the road network. The road density in Kerala is 390 km per 100 square kilometres (sq.km.), while the national average is 131 km per 100 sq.km. However, the traffic rates have had a yearly growth of 10-11% and thus have resulted in excessive pressure on the road network (Government of India 2016a).

3.5 Data sources and variables

Here, an overview of the datasets used to capture the built environment and the survey data on the prevalence of diabetes and physical inactivity is given. The flowchart showing the process of accessing data, processing and analysis is given in Figure 2.

3.5.1 Census Data

Census 2011 data, including Village and Town Release data, were accessed.

Population and number of households were data of interest.

The following variables were estimated:

Population density

The population density was defined as the total number of inhabitants per sq.km. for each district, sub-district, Panchayat and Municipality.

Residential density

Residential density in this study was calculated as the total number of households per sq.km. in each district, sub-district and Panchayat/ Municipality. This dataset was obtained from the Census of India, 2011.

3.5.2 State Crime Records Bureau

Dataset on the total number of crimes and pedestrian accidents in 2016 were obtained from the State Crime Records Bureau (SCRB) on due permission from the Director-General of Police. SCRB is the licensed data holder of crime records, established under the directive of the Central Government of India. This data was available at the Police station level for all the 498 police stations across the State. The police stations were mapped to the corresponding district and subdistrict based on the jurisdiction details provided for each police station in their respective 498 Kerala Police websites. Crime rates were calculated for each district and subdistrict.

Pedestrian accident rates were captured as a proxy indicator of safety from traffic, as has been mentioned in former research. Total pedestrian involved in traffic accidents in 2016 were obtained from the SCRB since the Road Accident Information System (RAIS) within SCRB is the authorised data holder for traffic accidents. This data on pedestrian accidents were available for 400 police stations. These police stations were mapped to the corresponding district, sub-district and Panchayat/ Municipality as mentioned for the safety from crime dataset.

The variables captured were:

Safety from crime

Crime rates were taken as indicators for 'Safety from crime'. Safety from crime was defined as the total number of crimes per total population for each district and subdistrict.

Safety from traffic

Pedestrian accident rates were taken as indicators of 'Safety from traffic'. Pedestrian accident rates were calculated as the total number of pedestrian accidents reported per total population within the district and subdistrict.

3.5.3 Landsat 8

Landsat 8 satellite data resources were accessed to capture 'Greenness (Normalized Differentiated Vegetation Index) and Built-up density (Normalized Differentiated Built Index).

This satellite program provides retrospective portraits of the land surface across the globe. These have been used in a variety of government, public, private and national security applications. Examples of Landsat data application include land and water management, global change research, agricultural yield forecasting, pollution monitoring, land surface change detection and cartographic mapping.

3.5.3.1 Selection and download of raster images

The Landsat8 mission collects image data for nine short-wave spectral bands as given in Table 3.1 and the steps undertaken to download data is given in Table 3.2. We have accessed images of three bands, namely, Band 4, Band 5 and Band 6, for this research. The images accessed are shown in Figure 3.2 to Figure 3.7.

Table 3.1. Landsat8 OLI and TIRS Bands

Band	Resolution	Wavelength (m)
Band 1	30m Coastal/ Aerosol	0.435-0.451
Band 2	30m Blue	0.452- 0.512
Band 3	30m Green	0.533-0.590
Band 4	30m Red	0.636-0.673
Band 5	30m NIR	0.851-0.879
Band 6	30m SWIR-1	1.566-1.651
Band 7	30m SWIR-2	2.107-2.294
Band 8	15m Pan	0.503- 0.676
Band 9	30m Cirrus	1.362-1.384
Band 10	100m TIR-1	10.60-11.19
Band 11	100m TIR-2	11.50-12.51

Table 3.2. Steps to download data from Earth Explorer

Criteria	Selection	Results
1.Search criteria	Kerala, India	Path:144, Row:52,53
	Kasaragod, Kerala, India	Path:145, Row:51 Path:145, Row:52
	Thiruvananthapuram, Kerala, India	Path: 144, Row: 54
	Kanyakumari, Tamil Nadu, India	Path: 143, Row: 54
2.Date range	01.01.2016 to 31.12.2016	
3.Dataset search	Landsat 8 OLI/ TIRS C1 Level-1	
4.Additional criteria	Land cloud cover (less than 10%) Scene cloud cover (less than 10%)	
5.Select for download (with least cloud cover)	Path 144, Row 53	3 images
	Path 144, Row 52	4 images
	Path 145, Row 51	7 images
	Path 145, Row 52	5 images
	Path 144, Row 54	4 images
	Path 143, Row 54	2 images

Figure 3.2. Landsat OLI image in path 143 and row 54

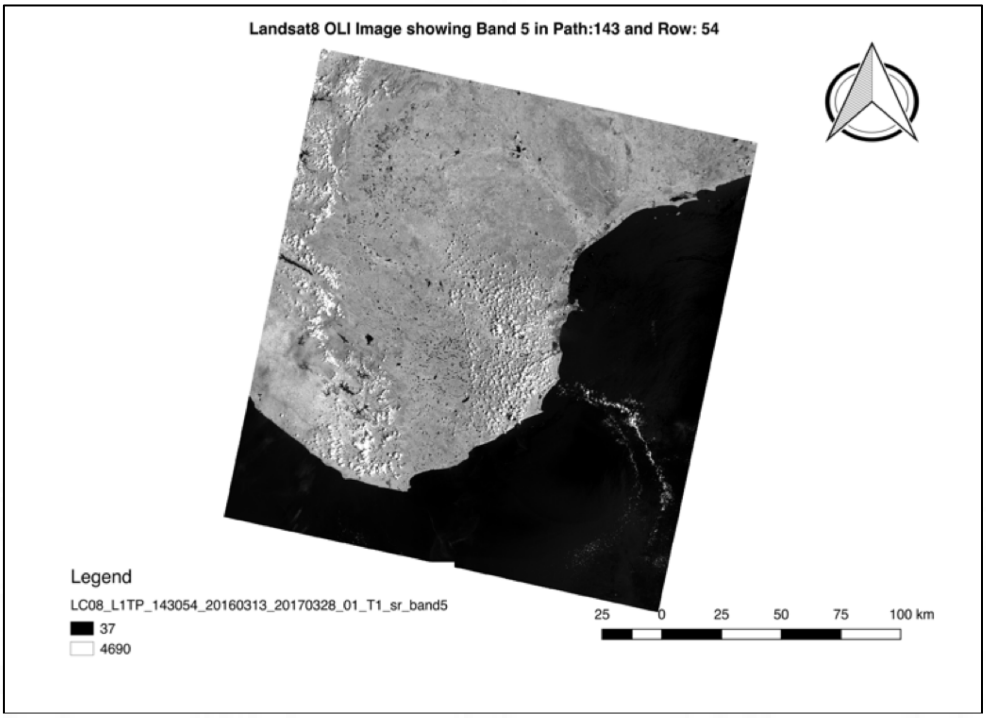


Figure 3.3. Landsat OLI image in path 144 and row 52

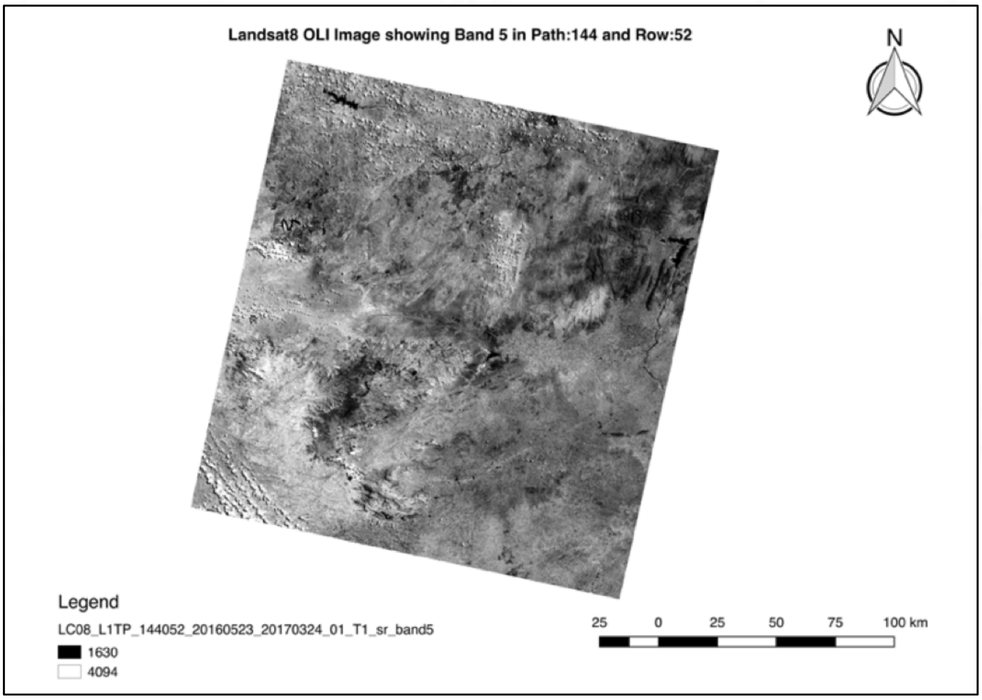


Figure 3.4. Landsat OLI image in path 144 and row 53

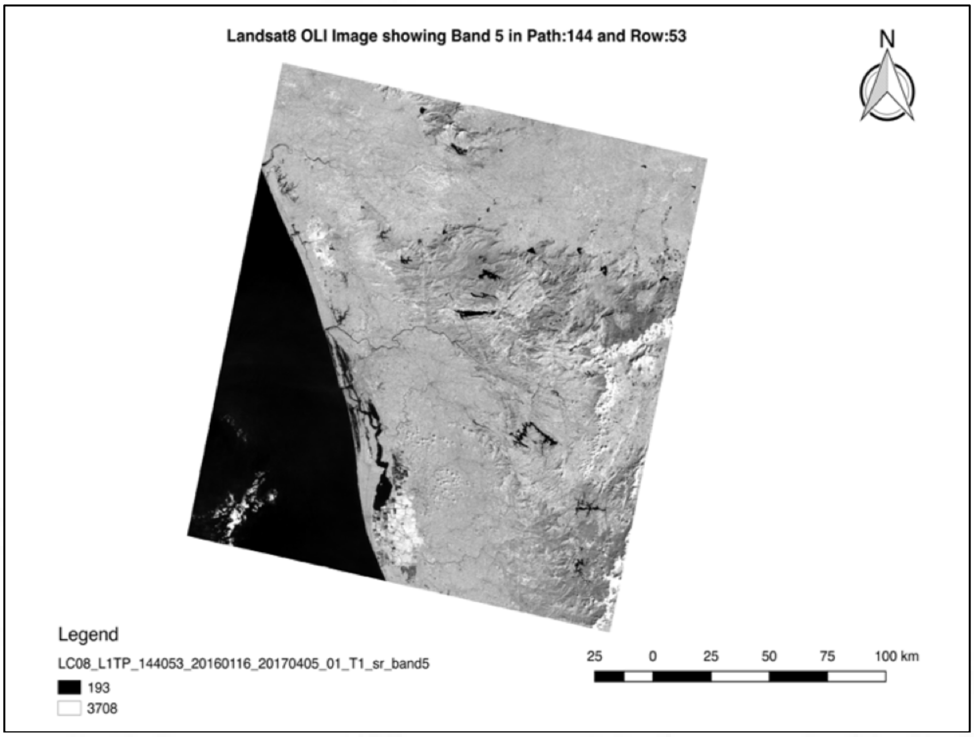


Figure 3.5. Landsat OLI image in path 144 and row 54

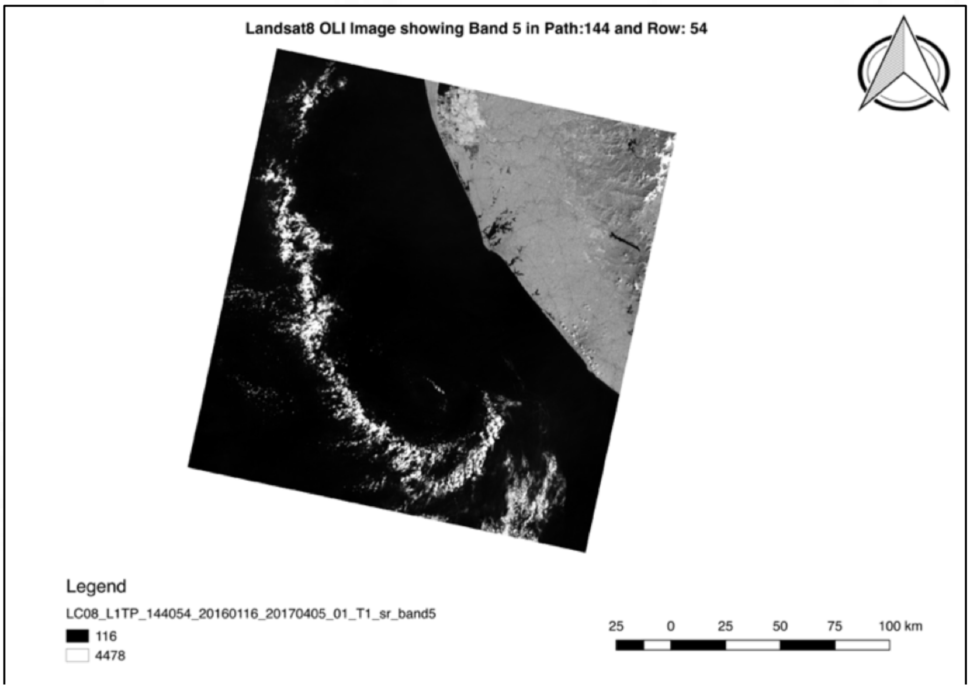


Figure 3.6. Landsat OLI image in path 145 and row 51

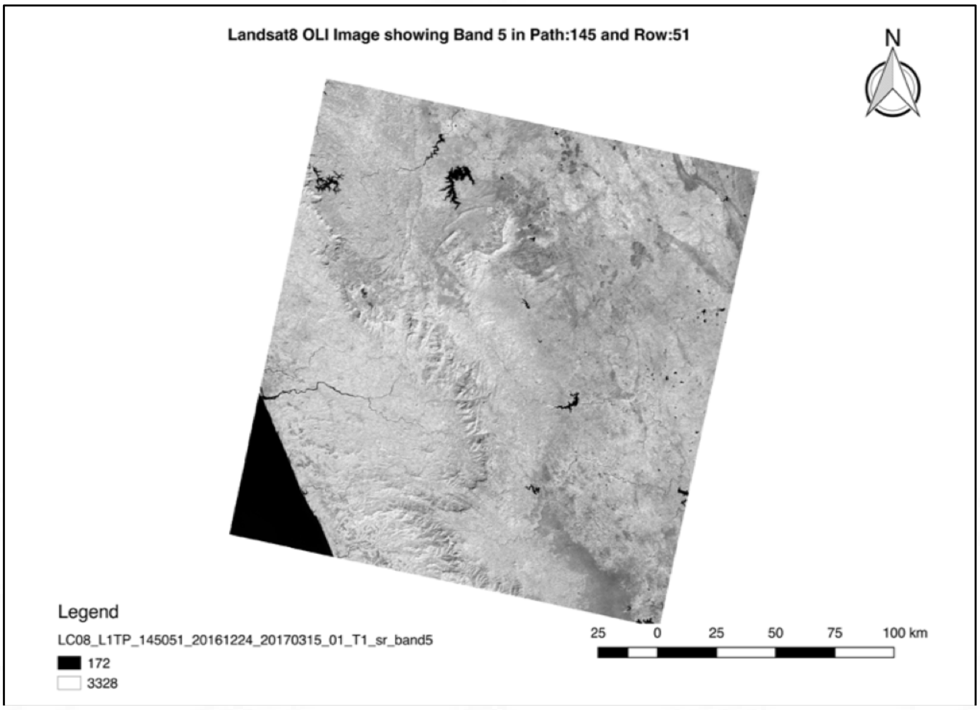
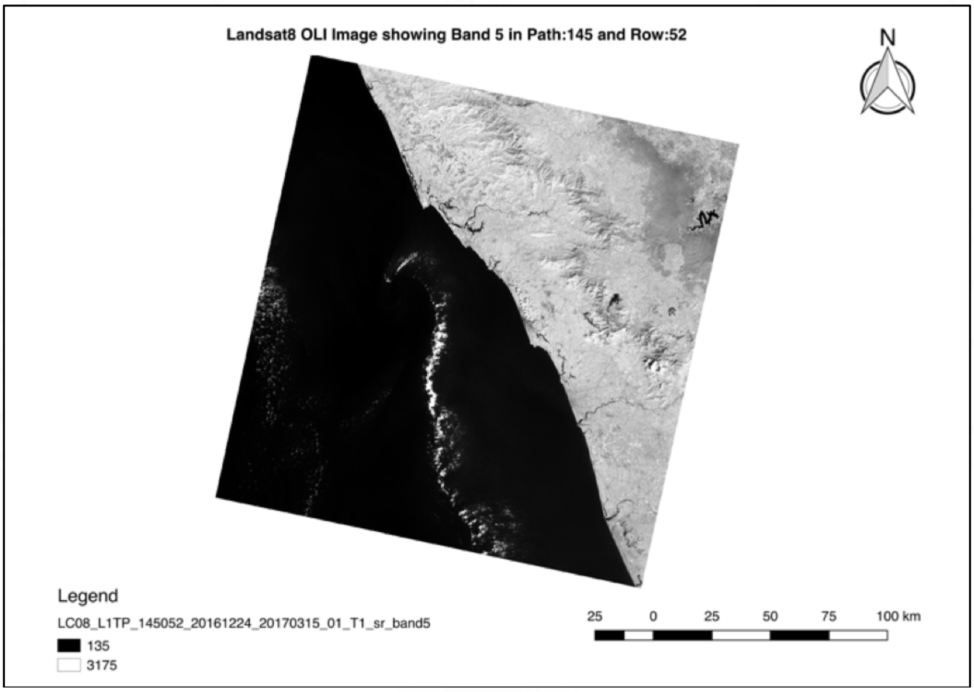


Figure 3.7. Landsat OLI image in path 145 and row 52



The product is packaged as a Geographic tagged image file format (GeoTIFF) (a standard, public-domain image format based on Adobe's TIFF) and is a self-describing format developed to exchange raster images. The GeoTIFF format includes geographic or cartographic information embedded within the imagery that can be used to position the image un a geographic information display

3.5.3.2 Data Download:

The Earth Explorer (EE) is the primary search interface to access aerial mapping, elevation and satellite data held in the USGS archives, including Landsat data products.

1. The website requires a user login with valid credentials of the user.
2. The search criteria tab options allow users to select the geographic area of interest by typing a place name, latitude/ longitude coordinates, path/ row, a shapefile or keyhole markup language (kml) file. The user can also specify the data range and the number of results.
3. The data sets tab lists all categories of data held in the USGS archives. The Landsat Archive section of this tab lists all Landsat datasets from which Level1 data products can be found.
4. After selecting the datasets, the Additional Search Criteria button is active. This section allows the user to search by specific scene ID or Path/ Row and set cloud cover limits.
5. After a successful search, users can view a browse image of the scene. To view the available data products, the Download option icon is present below each scene.

3.5.3.3 NDVI (Normalised Difference Vegetation Index) and NDBI (Normalised Difference Built-up Index)

The Normalised Difference Vegetation Index (NDVI) enables detection of the change in the proportion of vegetated areas (forest, grasslands, sparse grass, etc.) versus non-vegetated areas (exposed ground, built areas, water). NDVI is an indicator of relative biomass and greenness. The value ranges from -1 to +1. Higher positive values indicate denser or healthier vegetation, lower positive values indicate sparsely vegetated areas, and zero or negative values indicate water and impermeable substances such as cement roadways and houses. Variation in vegetation is derived from the standard deviation of NDVI for all green space within each neighbourhood.

The Normalised Difference Built-up Index (NDBI) is a measure of the intensity of imperviousness (Alhawitti & Mitsova 2016). It highlights the urban area distribution in a neighbourhood.

3.5.3.4 NDVI Analysis:

Landsat8 raster images were processed in QGIS software. Atmospheric correction of each raster image was done using Band 4 and Band 5 of each path and row were individually loaded in QGIS for NDVI calculation. Raster calculator tool in QGIS aided in NDVI calculation according to the formula (Alhawitti & Mitsova 2016; Rasul et al. 2018):

$$NDVI = \frac{\mathrm{NIR} - \mathrm{VIS}}{\mathrm{NIR} + \mathrm{VIS}}$$

where NIR is the Non-infrared band (Band 5 in Landsat8), and VIS is the visual band (Band 4 in Landsat8). The NDVI calculated for each image is shown in Figure 3.8 to Figure 3.13.

Following the generation of NDVI tiles for each path and row, all six NDVI tiles were loaded in QGIS. A virtual raster catalogue was prepared using the six tiles (for the extent of Kerala), namely path and row 143054, 144054, 144053, 144052, 145052 and 145051. The virtual layer was then clipped to the extent of state boundaries of the Kerala shapefile.

Zonal statistic tool in QGIS could generate NDVI statistics for each polygon. These statistics included mean, standard deviation, minimum and maximum NDVI values for each polygon. Such statistics were generated district-wise and sub-district-wise. A participant buffer of 1600m was used to generate summary statistics of NDVI at the individual level.

Figure 3.8. NDVI image calculated in Path 145 and Row 51

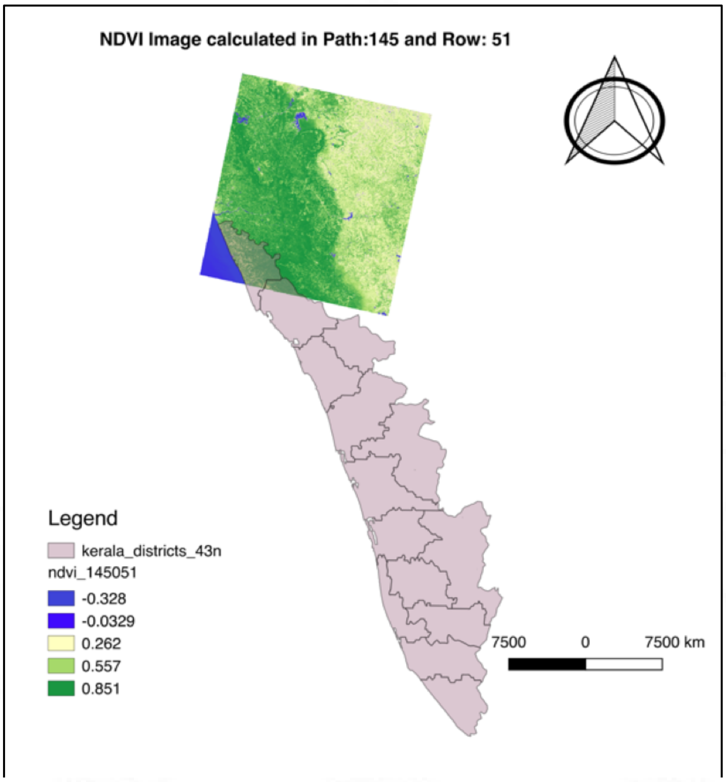


Figure 3.9. NDVI image calculated in Path 145 and Row 52

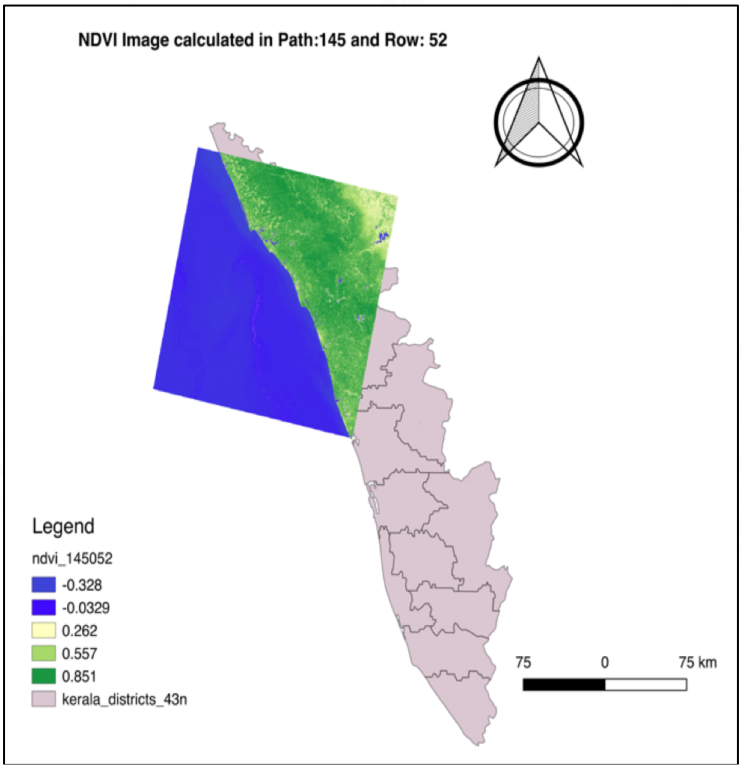


Figure 3.10. NDVI image calculated in Path 144 and Row 52

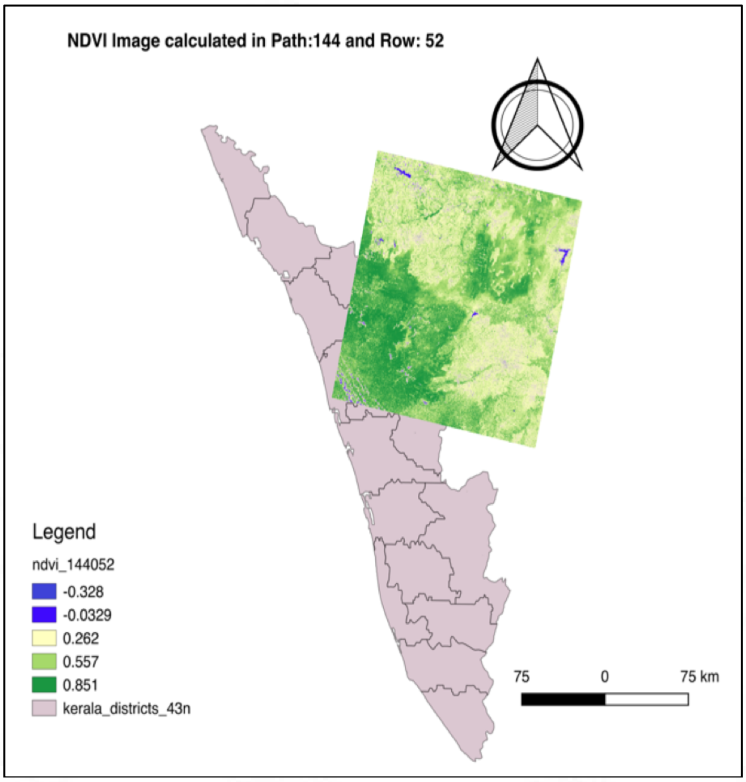


Figure 3.11. NDVI image calculated in Path 144 and Row 53

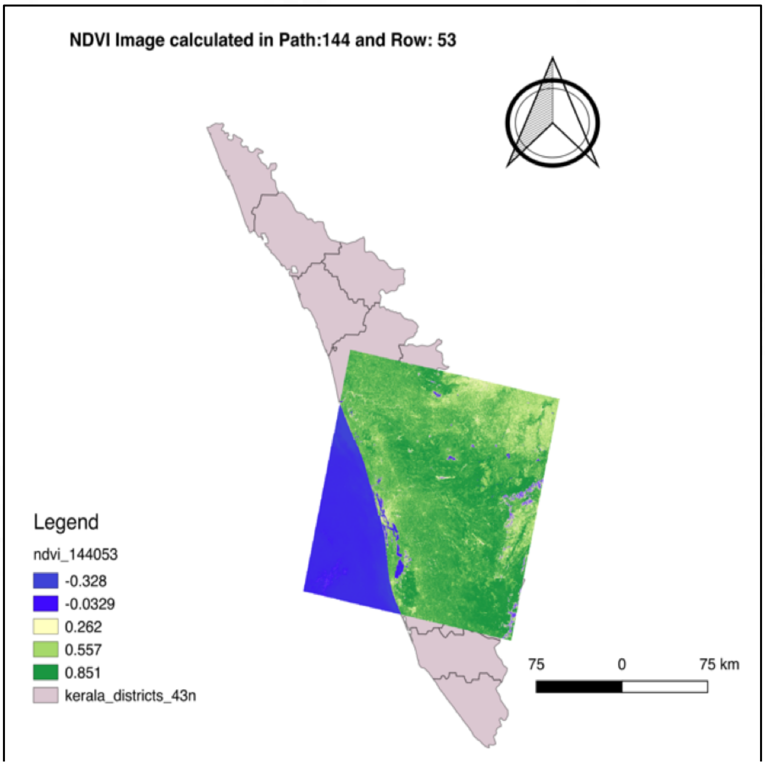


Figure 3.12. NDVI image calculated in Path 144 and Row 54

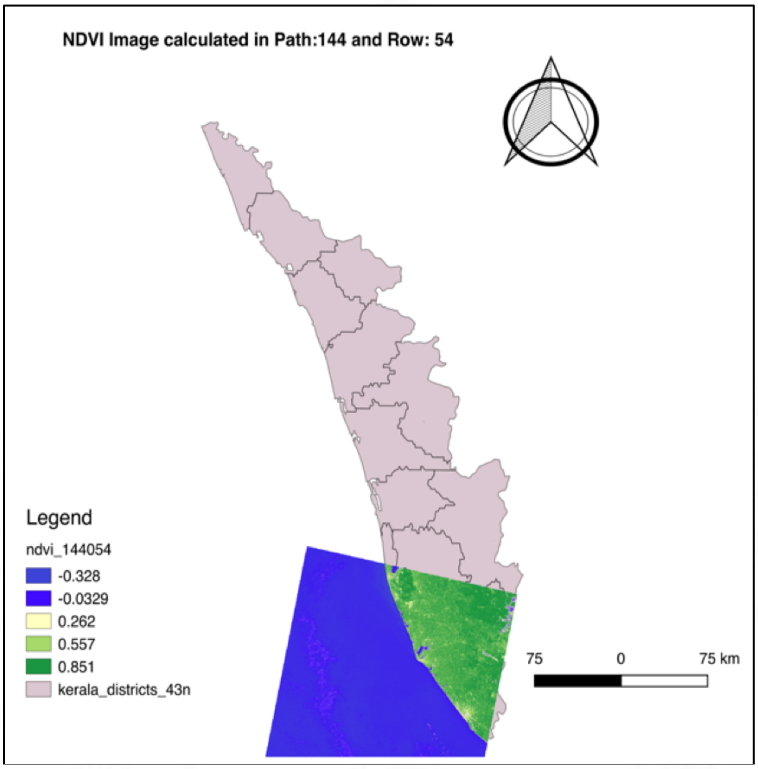
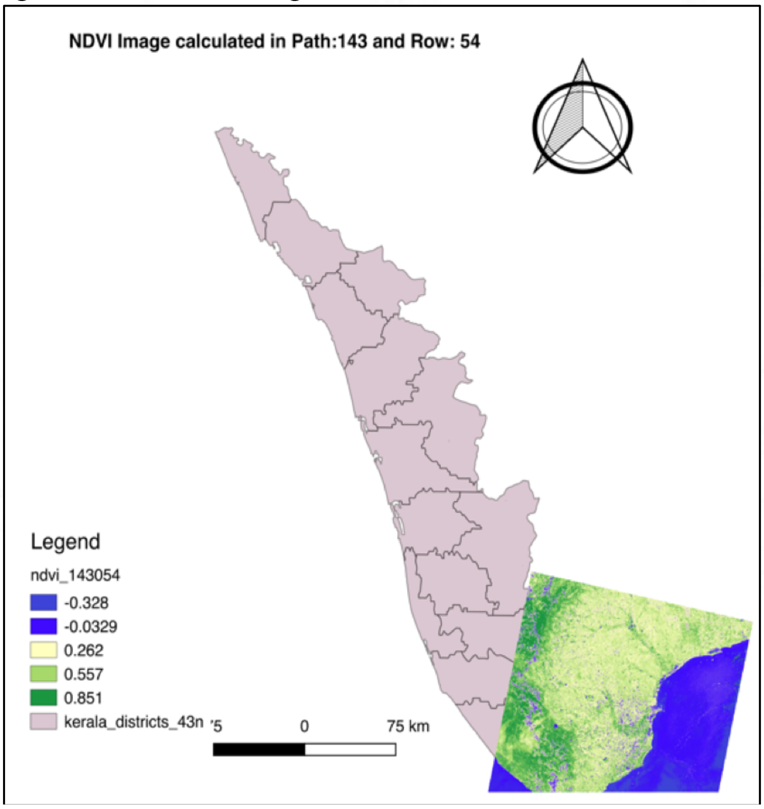


Figure 3.13. NDVI image calculated in Path 143 and Row 54



3.5.3.5 NDBI Analysis:

Landsat8 raster images were processed in QGIS software. Atmospheric correction of each raster image was done using Band 5 and Band 6 of each path and row were individually loaded in QGIS for NDVI calculation. Raster calculator tool in QGIS aided in NDBI calculation according to the formula (Alhawitti & Mitsova 2016; Garg et al. 2016):

$$NDBI = \frac{\text{SWIR} - \text{NIR}}{\text{SWIR} + \text{NIR}}$$

where SWIR is the short-wave infrared band (Band 6 in Landsat8) and NIR is the Non-infrared band (Band 5 in Landsat8). Following the generation of NDBI tiles for each path and row, all six NDBI tiles were loaded in QGIS. All the six tiles (for the extent of Kerala), namely path and row 143054, 144054, 144053, 144052, 145052 and 145051, were merged to create a single tile. This raster layer of NDBI was then clipped to the extent of state boundaries of the Kerala shapefile.

Zonal statistic tool in QGIS could generate NDBI statistics for each polygon. These statistics included mean, standard deviation, minimum and maximum NDBI values for each polygon. Such statistics were generated district-wise and sub-district-wise. A participant buffer of 1600m was used to generate summary statistics of NDBI at the individual level.

3.5.4 Shuttle Radar Topography Mission (SRTM) data

Slope measures the on-ground terrain or topography. Digital Elevation Models (DEM) of 90m x 90m cell size can be used to calculate slope values. The mean of this slope measure will be calculated for all cells that intersected the road network in each participant's 1600m buffer area using zonal statistics in Quantum GIS software. The mean slope will be used as a measure of hilliness or amount of terrain in the buffer area (Villanueva et al. 2013b).

3.5.4.1 Calculation of Land slope:

DEM data were downloaded from http://srtm.csi.cgiar.org. The CGIAR Consortium for Spatial Information (CGIAR- CSI) provides SRTM (Shuttle Radar Topography Mission) 90m resolution Digital Elevation Data. Data search was done for the state of Kerala, and three SRTM raster tiles were downloaded as given in Table 3.3 and shown in Figure 3.14.

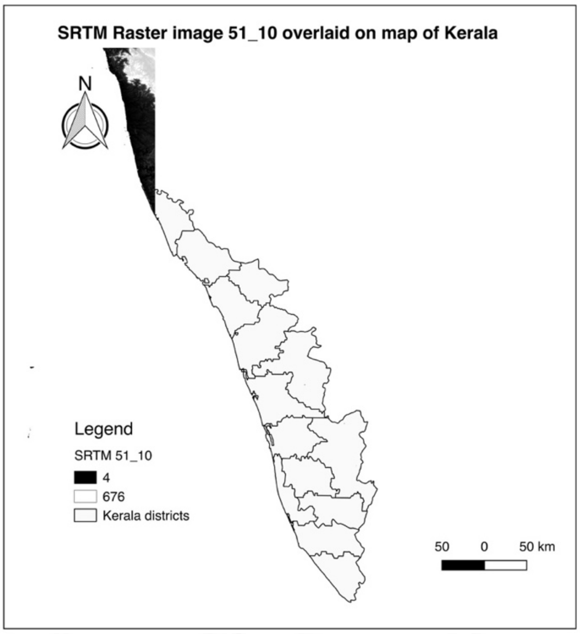
Table 3.3. Steps to access and download DEM data

Step	Criteria	Selection	Results
1	Search criteria	Kerala, India	SRTM 90m DEM Version 4: SRTM 51_10 SRTM 52_10 SRTM 52_11

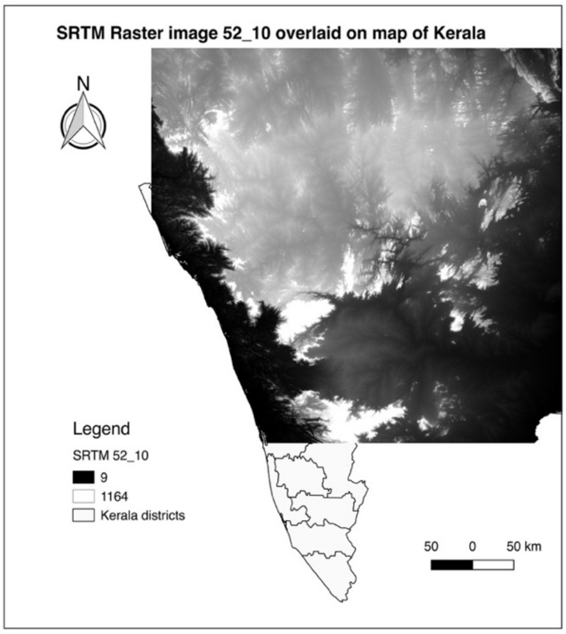
The three tiles were merged and clipped to the extent of Kerala in QGIS. Using DEM (Terrain models) in Raster Analysis of QGIS software, the slope was calculated as shown in Figure 3.15. The mean, standard deviation and range of slope values were calculated district-wise and sub-district-wise using Zonal Statistics

Figure 3.14. SRTM Images across state of Kerala

a. SRTM 51_10



b. SRTM 52_10



c. SRTM 52_11

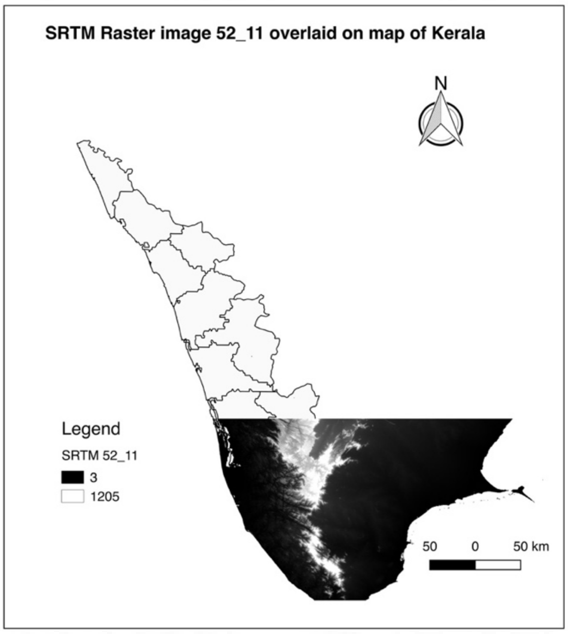
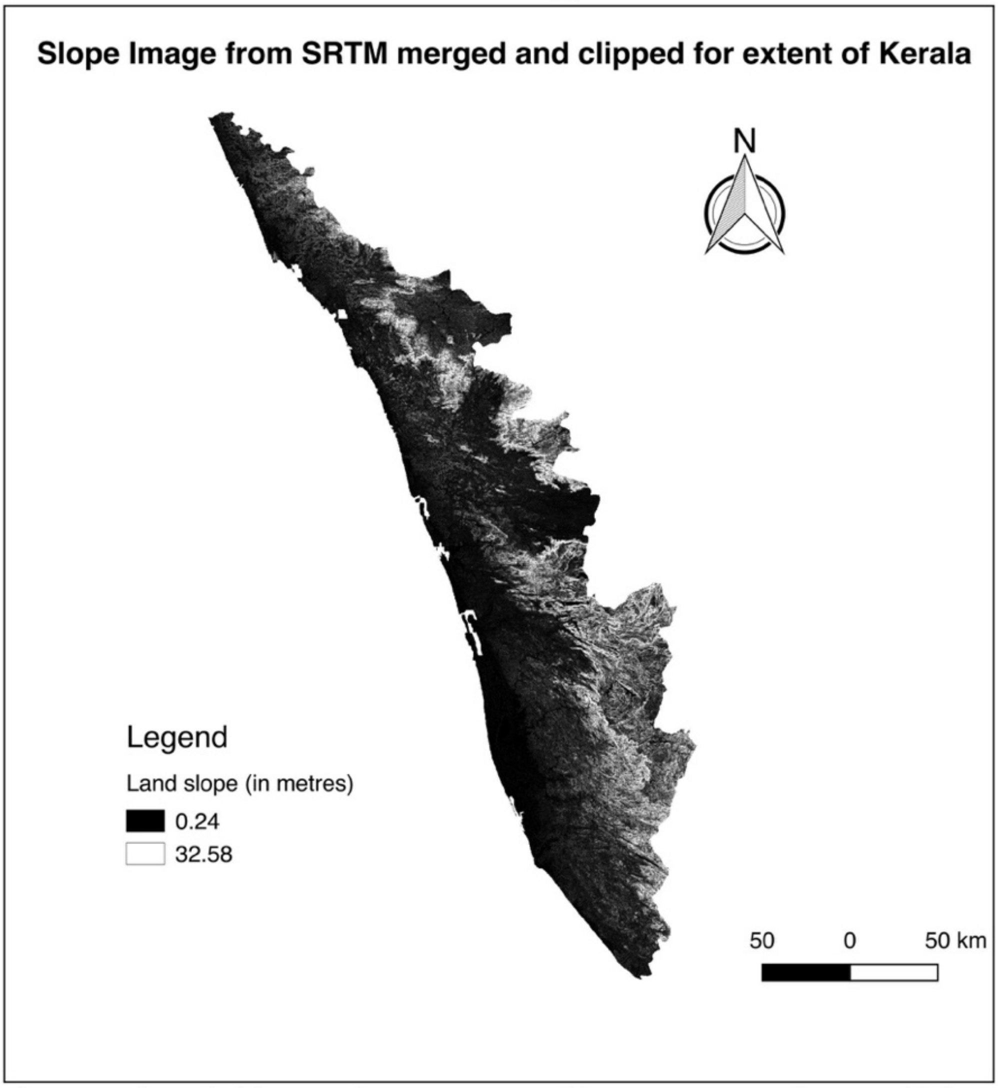


Figure 3.15. Map showing calculated slope from SRTM across state of Kerala



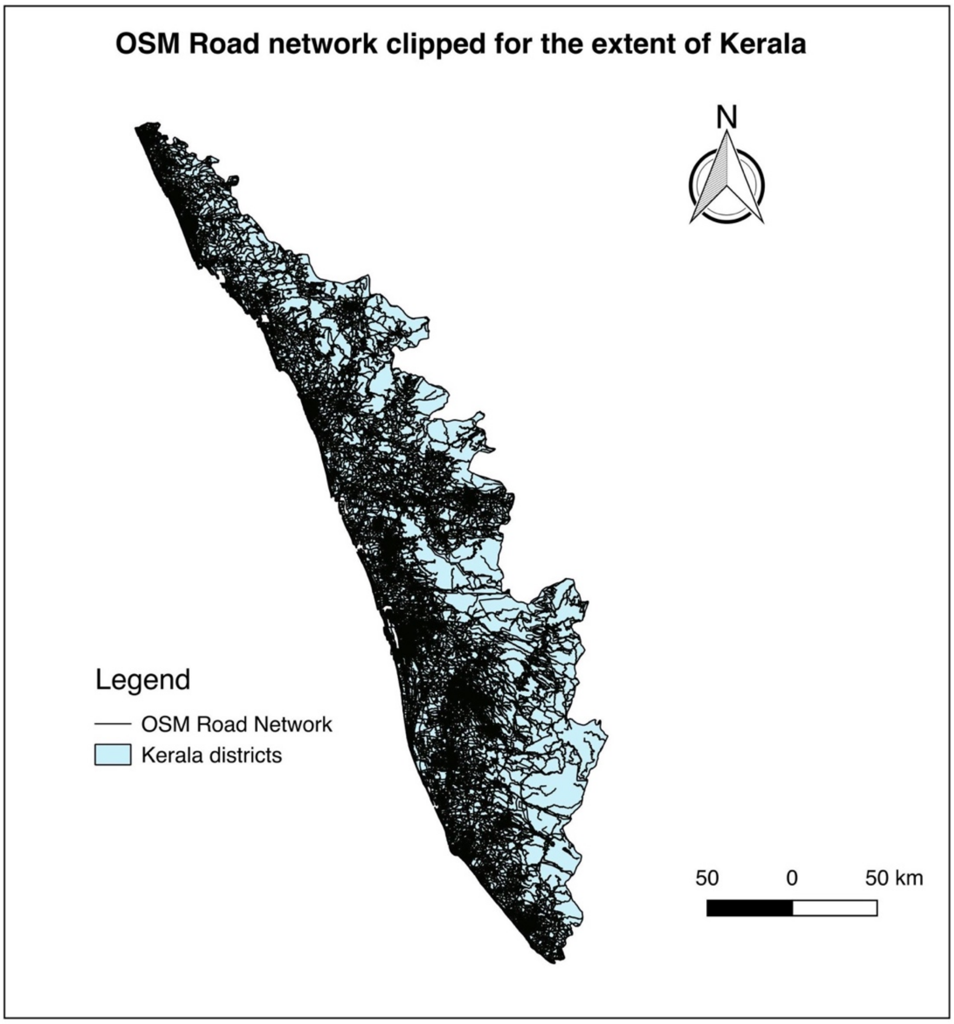
3.5.5 OpenStreetMap (OSM) Data

The road network layer of Kerala was downloaded using OpenStreetMap. OpenStreetMap is a collaborative mapping project and is one of the major contributors for the acquisition of spatial data. The downloaded data included rivers, over-bridges, electricity lines, etc. A subset of roads (where the "highway" identity had a true value) was taken for further analysis. OSM layer of roads was clipped to the extent of Kerala

State, as shown in Figure 3.16. Using the Line intersection tool in Vector analysis, point features were created where the lines intersect each other.

Using Analysis Tools in QGIS, points in each polygon (districts) were calculated for the number of intersections in each district and subdistrict. Points in a buffer area of 1500m around each participant location were also calculated. Intersection density was calculated as the number of intersections per square kilometre for each district and sub-district. This is defined by the number of intersections per square kilometre.

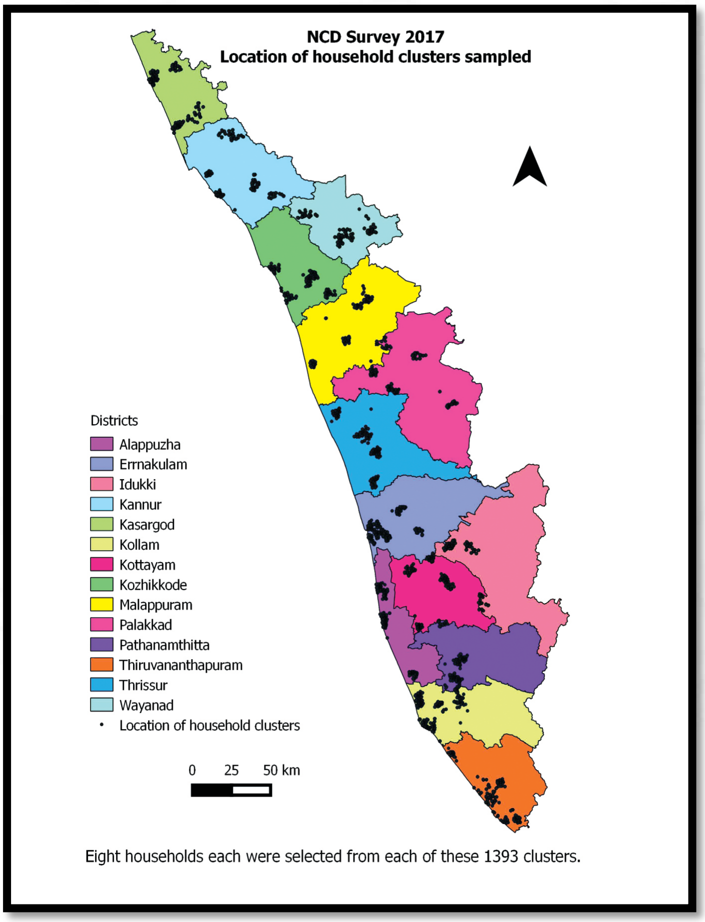
Figure 3.16. Map showing road network for Kerala



3.5.6 Survey data

The outcome dataset was a cross-sectional survey named 'Prevention and Control of Non-communicable diseases (NCDs) in Kerala,' which was conducted in 2016. The survey was aimed at finding state-level estimates of NCD indicators. A total of 12,012 participants selected from urban and rural regions of Kerala were part of the survey using multi-stage cluster sampling from 1393 survey clusters (Figure 3.17). The sample size for this survey was based on national recommendations, with a design effect of 1.5. The scholar accessed this data with special permission from the Principal Investigator of the project at Sree Chitra Tirunal Institute of Medical Sciences and Technology.

Figure 3.17. Location of sampling sites in NCD survey (Courtesy: Project report, NCD survey 2017)



3.5.6.1 Variables obtained from dataset

The data from the NCD Project included sociodemographic variables and those on risk factors of non-communicable diseases. The variables and their value labels are summarised in Table 3.4 below.

Table 3.4. List of variables accessed with value labels

S.No.	Variable	Labels (as in Project data)
1.	Age	In years
2.	Gender	Male, Female, Transgender
3.	Current marital status	Never Married, Cohabiting, currently married, Separated, Divorced, Widowed
4.	Ever attended school	Yes, No
5.	Highest level of education	No formal schooling, Less than primary school, Primary school completed, Secondary school completed, High school, Doing graduation, Graduation completed, Postgraduate degree, Other
6.	Occupation	Professional, Medium to large business, Executive/officer, Agriculture landowner, Sales and marketing executive/ clerical, Self-employed and small business, Skilled manual labourer, Unskilled manual/ agricultural labourer, Student, Homemaker, Retired, Unemployed (able to work), unemployed (unable to work)
7.	Tobacco smoke daily	Yes, No

8.	Smokeless tobacco daily	Yes, No
9.	Consumed alcohol in past 12 month	Yes, No
10.	Routine work involving vigorous-intensity activity	Yes, No
11.	Days of routine work involving vigorous-intensity activity in a typical week	Number of days
12.	Time spent doing vigorous-intensity activity in a typical day	___ minutes ___ hours
13.	Routine work involving moderate-intensity activity	Yes, No
14.	Days of routine work involving moderate-intensity activity in a typical week	Number of days
15.	Time spent doing moderate-intensity activity in a typical day	___ minutes ___ hours
16.	Walk/ bicycle for 10 minutes	Yes, No
17.	Days of walking/ bicycling in a typical week	Number of days
18.	Time spent to walk/bicycle in a typical day	___ minutes ___ hours
19.	Vigorous-intensity sports, fitness / recreational activities for 10 minutes	Yes, No
20.	Days of vigorous-intensity sports, fitness / recreational activities in a typical week	Number of days
21.	Time spent for vigorous-intensity sports, fitness / recreational activities in a typical day	___ minutes ___ hours
22.	Moderate-intensity sports, fitness / recreational activities for 10 minutes	Yes, No

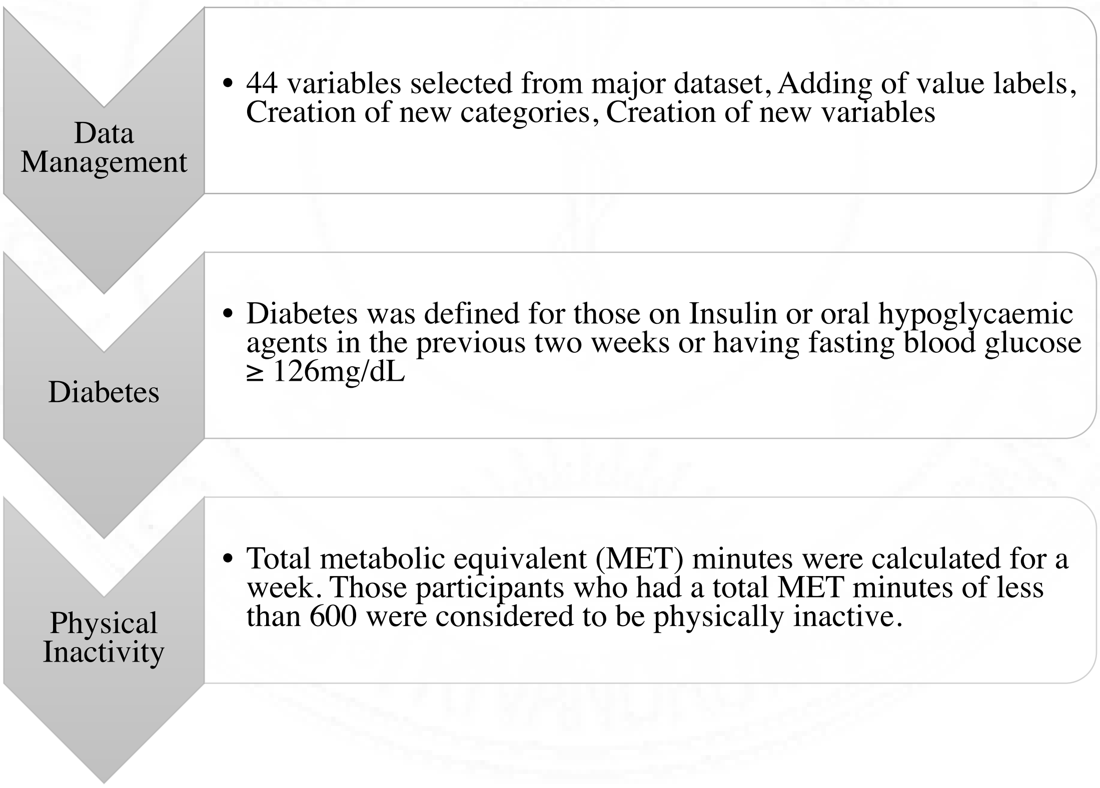
23.	Days of moderate-intensity sports, fitness / recreational activities in a typical week	Number of days
24.	Time spent for moderate-intensity sports, fitness / recreational activities in a typical day	___ minutes ___ hours
25.	Time spent sitting/ reclining on a typical day	___ minutes ___ hours
26.	Medications for raised blood pressure or hypertension in past two weeks	Yes, No
27.	Medications for raised blood sugar or diabetes in past two weeks	Yes, No
28.	Insulin for raised blood sugar or diabetes in past two weeks	Yes, No
29.	Systolic blood pressure reading 1 (mm Hg)	________
30.	Diastolic blood pressure reading 1 (mm Hg)	________
31.	Systolic blood pressure reading 2 (mm Hg)	________
32.	Diastolic blood pressure reading 2 (mm Hg)	________
33.	Systolic blood pressure reading 3 (mm Hg)	________
34.	Diastolic blood pressure reading 3 (mm Hg)	________
35.	Height (in centimetres)	________
36.	Weight (in kilograms)	________
37.	Fasting blood glucose (mg/ dL)	________
38.	State	________

39.	District	_______
40.	Sampling unit	City/ Village
41.	Name of sampling unit	_______
42.	Ward number	_______
43.	Location latitude	_______
44.	Location longitude	_______

3.5.6.2 Defining outcome variables and reclassifying variables

We have defined the outcome variables of diabetes and physical inactivity from the variables obtained from the Project dataset. The operational definitions and the variables thus reclassified are given in Figure 3.18. below.

Figure 3.18. Operational definitions of outcome variables



3.5.7 Boundary dataset

The boundary dataset included spatial data of districts, subdistricts, Panchayats and wards in the state of Kerala. This included geospatial data on location, boundaries and area of the districts and subdistricts. These shapefiles were accessed from the spatial data repository at Achutha Menon Centre for Health Science Studies.

3.6 Data Quality Assessment

3.6.1 Census of India, 2011

The Census Operations in India are carried out in two phases - the House listing and Housing Census followed by the Population Enumeration. All the buildings and houses are numbered for easy identification at the time of actual enumeration. Data on characteristics of the house, information on availability of certain amenities and assets to the households were also collected in this first phase.

The Population Enumeration was undertaken during 9th to 28th February 2011 (both days inclusive). Post enumeration checks were conducted from 1st to 5th March 2011.

A 'Normal household' in Census is defined as a group of persons who normally live together and take their meals from a common kitchen unless the exigencies of work prevents any of them from doing so. The persons in a household may be related or unrelated or a mix of both. However, if a group of unrelated persons live in a Census house but do not take their meals from the common kitchen, they are not considered a part of a common household. Each such person is treated as a separate household.

Metadata & Data Standards (MDDS) Committee provided a new coding pattern for various geographical entities. The Location Code Directory provided unique codes. The coding convention used is as described below:

1. The State code of 2 digits starting from 01 was used like earlier census.
2. All the Districts in India were assigned with 3 digits codes continuously starting from 001.
3. Five digited continuous codes were used for Sub-districts within India.

3.6.2 Prevention and Control of Non-communicable diseases in Kerala

3.6.2.1 Survey objective

The objective of the cross-sectional survey in the project was to generate state level prevalence estimates of key non-communicable diseases (NCD) risk factors. The National guidelines for NCD risk factor survey prepared under the leadership of Indian Council of Medical Research was followed.

3.6.2.2 Sample size

The sample size was determined based on national recommendations to estimate statewide prevalence of NCD risk factors. An equal proportion of sample participants were selected from urban and rural areas. A total of 7200 adults and 4800 adolescents were selected from 12,000 households. These participants reflected a representative sample from the districts of Kerala.

3.6.2.3 Study instruments

The study tool used for the survey was adapted from the national level survey by ICMR and was translated to Malayalam. The behavior survey instrument and the physical and biochemical measurements conformed to recommendations of the WHO STEPwise approach to NCD risk factors surveillance.

- STEP 1: Behavioral factors based on face-to-face interview
- STEP 2: Physical measurements: height, weight, waist circumference, blood pressure and heart rate
- STEP 3: Biochemical measurement including fasting blood glucose.

Fasting blood glucose measurements were determined using glucometers (One-touch ultra easy, Johnson & Johnson).

3.6.2.4 Data collection software and devices

Data was collected using Personal Digital Assistants, to ensure uniformity and efficiency. The templates for the interview schedules were created using Open Data Kit software. These devices were encrypted for the sole purpose of data collection. Geolocations of the households were automatically captured on the devices. The completed data form underwent random checks by the district-level supervisors. Only the investigators or senior project staff had access to download data from the server.

3.6.2.5 Data collection team

The team consisted of BSc. Nursing graduates or General Nurses as data collectors. Also, two District Project Managers were allocated to each district, who had a minimum qualification of Master's degree in Public Health, Epidemiology, Nursing or Social Work. They were trained by the Project Investigators and experts from the ICMR.

3.6.2.6 Data storage and cleaning

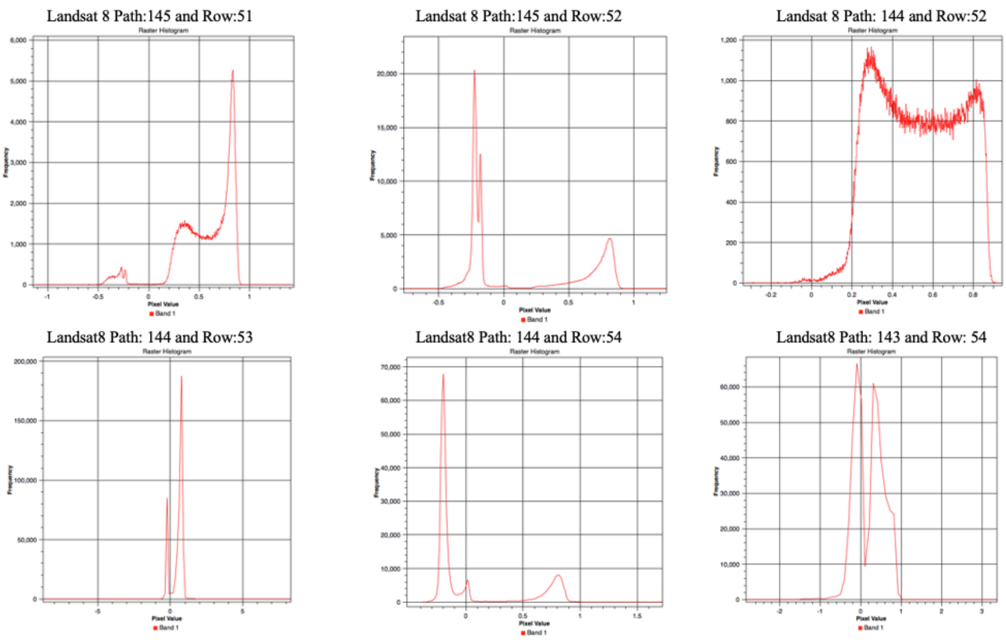
Data was stored in the server at Achutha Menon Centre for Health Science Studies. All missing information were revisited by contacting the data collector/ participant over phone.

3.6.3 Landsat8 data

Landsat8 data were downloaded using quality checks as were mentioned in Section 3.5.3

The raster histograms for each tile were analyzed for null values and extreme values, which is shown in Figure below.

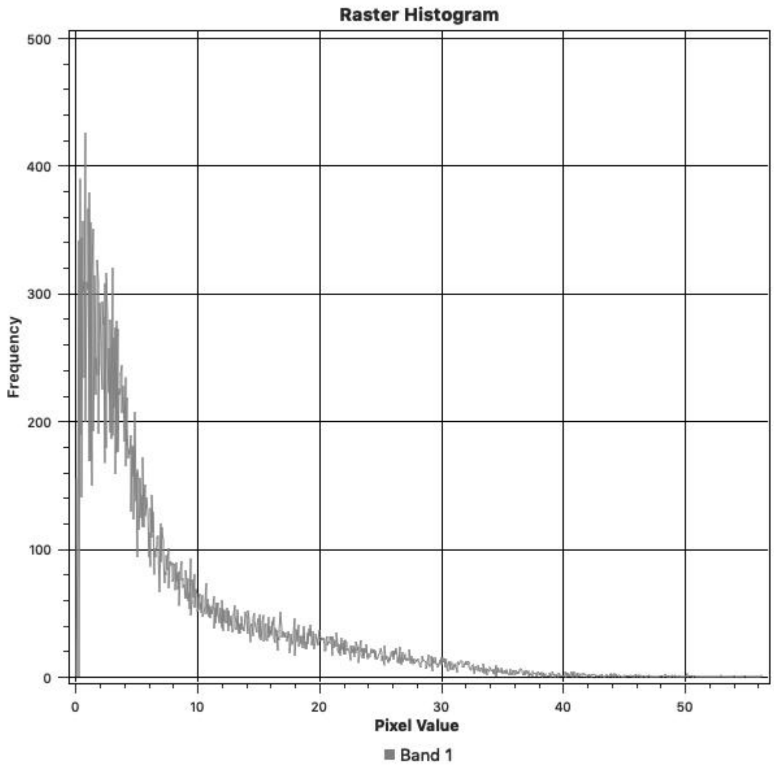
Figure 3.19 Raster histograms of Landsat8 tiles



3.6.4 SRTM Imagery

The slope calculated from SRTM images were also analyzed using the raster histogram as shown below.

Figure 3.20 Raster histogram of slope calculated from SRTM Imagery



3.6.5 OpenStreetMap

OpenStreetMap network layer was validated for true values of the 'highway' identity

3.6.6 State Crime Records Bureau

The datasets shared by the State Crime Records Bureau were Excel workbooks with police station codes and the crime and accident statistics in each police station. The Police station codes mapping was also shared by the SCRB. Each police station website was visited to validate jurisdiction boundaries in each district.

3.7 Data processing

Data processing included the processing of built environment variables at the neighbourhood level.

3.7.1.1 Defining participant neighbourhood

A participant neighbourhood was defined to be a radial buffer of 1600m around a participant's household location. This was defined based on previous studies where 1600m would be the distance attained on walking a return trip at a moderate-to-vigorous intensity pace within 30 minutes, as per the recommendation for daily physical activity among adults (Pereira et al. 2013).

3.7.1.2 Capture of built environment variables in the participant neighbourhood

Data on population density, residential density, crime rates, accident rates were available at the district and subdistrict level and not as raster images. The other variables, greenness, built-up density, land slope, were available as rater images, while road intersections were available as a point layer.

In order to create raster images for variables, Police station locations were obtained using google earth, and 479 police stations were mapped, as in Figure 3.19. Population density and residential density captured from Census 2011, and crime rates and pedestrian accident rates from Crime Records Bureau were matched to the 479 police station points. These 479 locations or police station points were used to create interpolated layers each of population density, residential density, crime rates and accident rates as shown in Figure 3.20.

Figure 3.21. Geocoded locations of police stations in Kerala

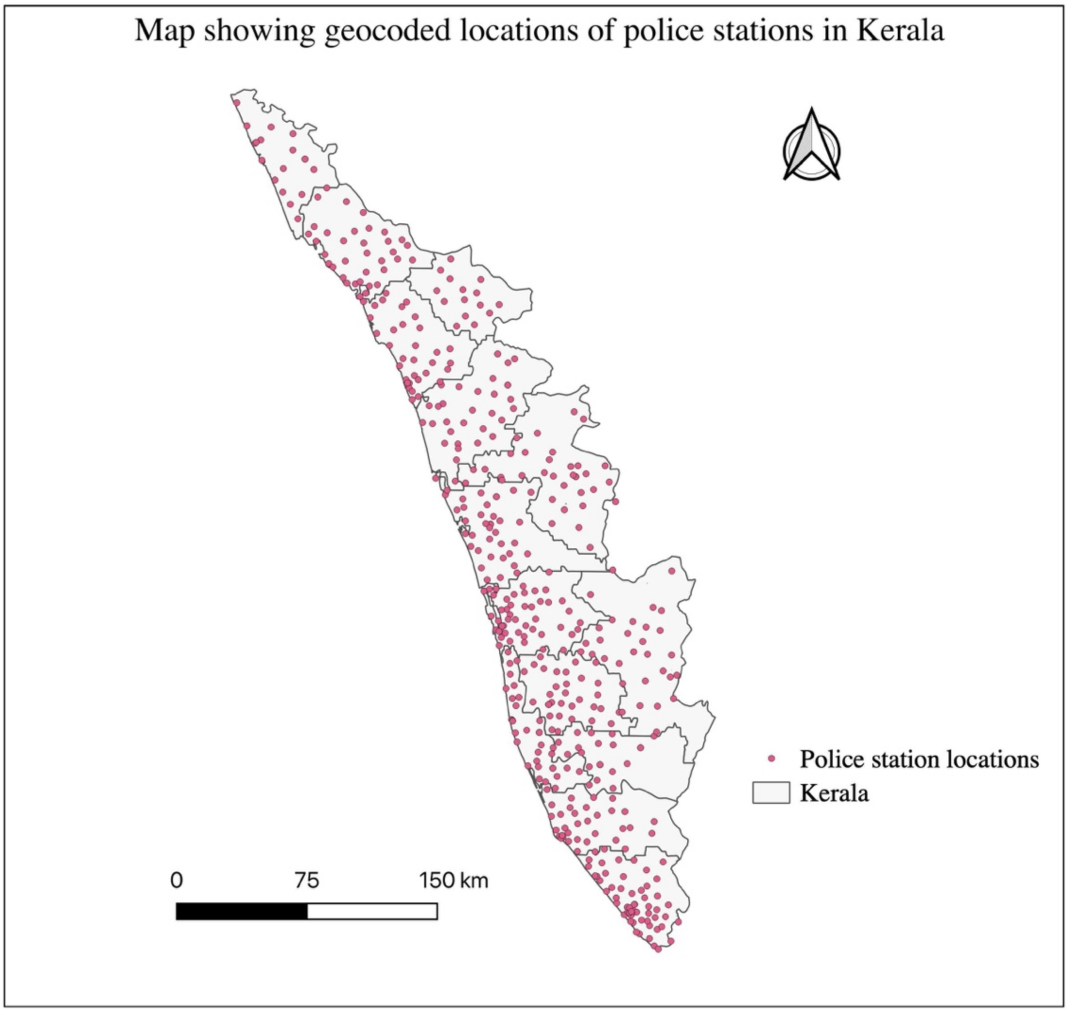
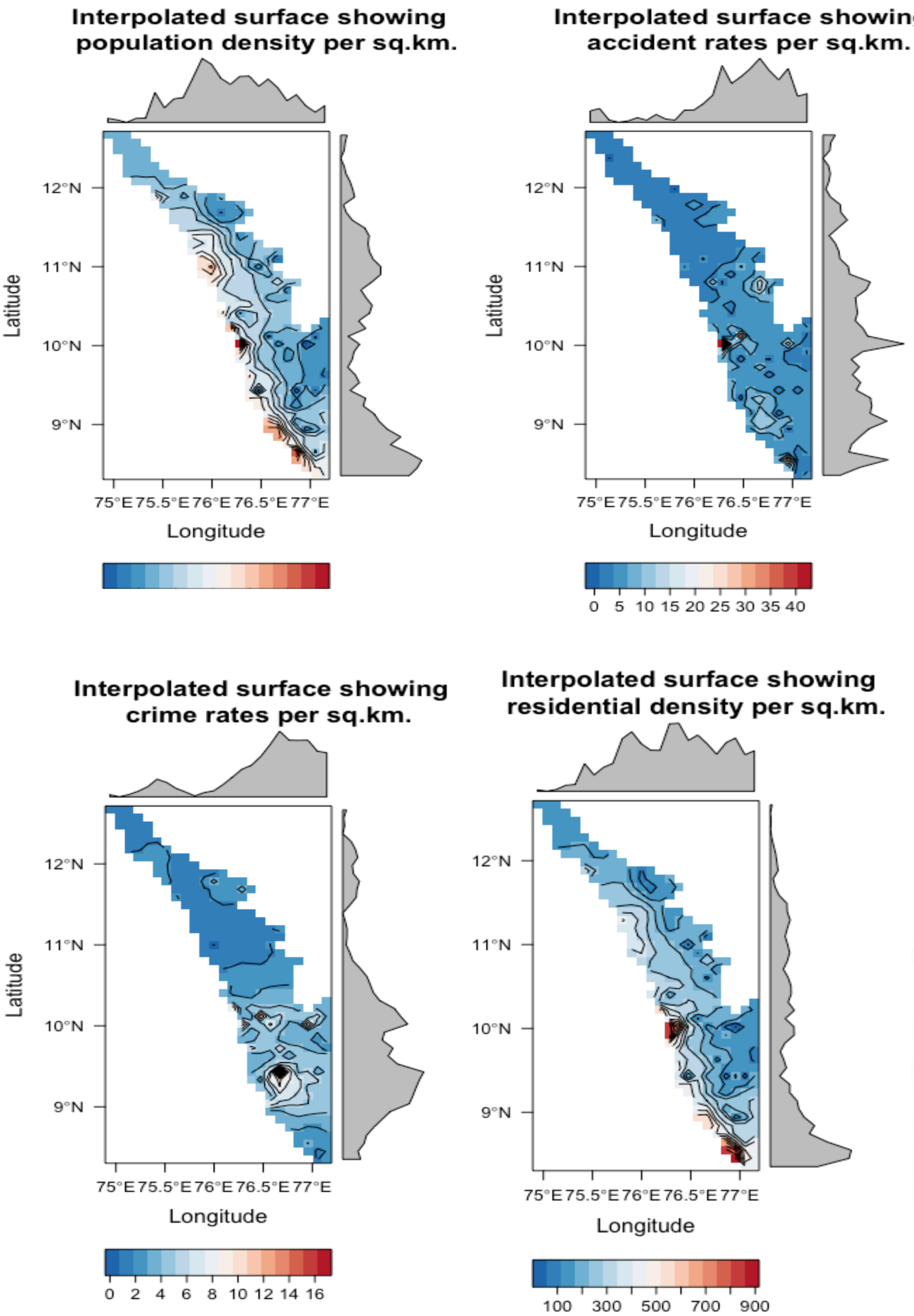


Figure 3.22. Interpolated surfaces of population density, residential density, crime rates and pedestrian accident rates per square kilometre



Following the creation of interpolated surfaces of population density, residential density, crime rates and accident rates, we have estimated the following variables for each participant at the neighbourhood level.

3.7.1.3 Definition of built environment variables in the participant neighbourhood.

The built environment variables captured in the participant neighbourhood were:

i. Population density measured as the total number of persons residing per square kilometre, obtained from Census of India, 2011.
ii. Residential density measured as the number of households per square kilometre, obtained from Census of India, 2011.
iii. Crime rate measured as number of reported crimes per square kilometre, obtained from State Crime Records Bureau, 2016.
iv. Pedestrian accident rate calculated as number of reported pedestrian accidents per square kilometre, collated from State Crime Records Bureau, 2016.
v. Vegetation index measured as mean greenness per square kilometre, estimated from Landsat8 imagery captured for the year 2016.
vi. Built-up index measured as mean built-up density per square kilometre, estimated from Landsat8 imagery captured for the year 2016.
vii. Land slope measured as mean land slope per square kilometre, estimated from SRTM imagery captured for the year 2016.
viii. Intersection density calculated as the number of three-way road intersections per square kilometre, captured from OpenStreetMap

3.8 Data analysis

3.8.1 Objective 1

Distribution of variables were analysed by creation of choropleth maps using QGIS across districts and subdistricts. Correlation between these variables across districts and subdistricts were done using correlation analysis.

3.8.2 Objective 2

Spatial scan statistic was run for each outcome separately. Case files and control files were created for each outcome (diabetes and physical inactivity) separately. The coordinates file had the geographic coordinates for each location ID. Each line of the file represented one geographical location.

A minimum of five participants in a single survey site was selected in the NCD survey. A neighbourhood of 1600m was defined around location of each participant's residence (Neighborhood was defined as informed by previous literature as 1600m would be the distance attained on walking at a moderate-to-vigorous intensity pace within 30 minutes, as per the recommendation for daily physical activity among adults (Smurthwaite & Bagheri 2017). Hence with the assumption of five participants with 1600m buffer would amount to be 8000m/ 8km, radii below and above 8km were studied upon. The analysis was performed at 5km, 7km, 10km and 15km radii to ensure consistency of results.

Cut off rates of 21.3% and 19.1%, respectively, for diabetes in urban and rural sites were set as the cut-off points for detecting high and low spatial clusters of diabetes.

Moreover, 26.1% and 20.1%, respectively for physical inactivity in urban and rural sites, were set as criteria for detecting high and low spatial clusters of physical inactivity in urban and rural areas.

3.8.3 Objective 3

3.8.3.1 Need for discriminant analysis

Capture of the built environment variables were from various sources in order to capture the neighbourhood environment across sample locations in Kerala. All the variables are continuous in nature and occur simultaneously in a neighbourhood. The objective was to figure out whether all of these variables equally contributed to disease status for residents in a neighbourhood and how many of the variables could explain the disease status. Logistic regression analysis would not be sufficient to explain the contributions by each variable or would not be able to determine the most important variable. Moreover, analyzing each variable by quartiles would not capture the actual scenario at the neighbourhood level since all the variables coexist and occur simultaneously. Hence, exploring the contributions of each variable was done using discriminant analysis.

3.8.3.2 Introduction to discriminant analysis

Discriminant analysis (DA) is a multivariate statistical technique used to build a predictive/ descriptive model of group discrimination based on observed predictor variables. It allows the researcher to study differences between two or more groups of objects with respect to several variables simultaneously. The basic purpose of discriminant analysis is to estimate the relationship between a single categorical dependent variable and a set of quantitative independent variables. In DA, one does not define the groups or the discriminating variables as either dependent or independent variables and hence is different from multiple regression. The primary difference in discriminant analysis is that it treats the dependent variable as being measured at the nominal level (which is groups).

It helps in *interpretation* when one needs to examine the ways in which groups differ. Hence, one would be able to 'discriminate' between the groups on the basis of some set of characteristics. This will let us know how well the characteristics discriminate and which of the characteristics are the most powerful discriminators. The set of characteristics used to distinguish among the groups are called *'discriminating variables*. The aim is to derive the linear combination of the independent variables that discriminate best between two or more prior defined groups. The other application of DA is to derive one or more mathematical equations for *classification.* These equations, named *'discriminant functions',* combine the group characteristics in a way that will allow one to identify the group in which a case most closely resembles.

3.8.3.3 Requirements to be fulfilled for Discriminant Analysis.

Discriminant analysis is carried out only when the following requirements are fulfilled:

i. The data cases should be members of two or more mutually exclusive groups. The basic units of analysis should belong to one and only one group.

ii. Sample size: The sample size should be at least two cases per group.

iii. The number of discriminating variables should be less than the total number of cases minus two.

iv. The discriminating variables must be measured at the interval or ratio level of measurement. This will enable the calculation of means and variances and hence be employed legitimately in mathematical equations.

v. Statistical properties of discriminating variables:

   a. No variable may be a linear combination of other discriminating variables. In short, they cannot be the sum of one or more variables that may have been weighted by constant terms. Hence, one cannot use either the sum or the average of several variables along with other discriminating variables.

   b. Two variables that are perfectly correlated cannot be used at the same time.

vi. Homogeneity of variance-covariance matrices: The population covariance matrices must be (approximately) equal for each group. This will allow simplification of the formulas used to calculate discriminant function and certain tests of significance.

vii. Normal distribution: Each group is drawn from a population that has a multivariate normal distribution, which implies each variable has a normal distribution about fixed values on all the others. This would enable the precise computation of tests of significance and probabilities of group membership.

3.8.3.4 Meaning of results in discriminant analysis.

Group Statistics table

This table shows whether are any significant differences between groups on each of the independent variables using group means and ANOVA results data. The Group statistics and Tests of Equality of Group Means provided in tables provide this information. We can proceed with the analysis only if there are significant group differences. The important variables can be identified by inspecting the group means and standard deviation. The highly significant variables will also have a very high value of F statistic.

Group centroids

The absolute magnitude of the group centroid indicates the degree to which a group is differentiated on a function, and the signs of the centroid indicate the direction of the differentiation. It represents the mean discriminant score of members of a group on a given discriminant function. On the other hand, during the classification procedure, the discriminant score of each individual is compared to each group centroid, and the probability of group membership is calculated. The closer a score will be to a group centroid, the greater the probability that the case belongs to that group.

Canonical correlations

The canonical correlation table is another way of indicating the relative importance of the predictors. They are used interchangeably with the Standardized Canonical Discriminant Function Coefficients. This matrix shows the correlations of each variable with each discriminant function. These Pearson coefficients are structure coefficients or discriminant loadings. They are similar to factor loadings in factor analysis. 0.30 is seen as the cut-off between important and less important variables.

Discriminant function coefficients

The interpretation of the discriminant functions is similar to that of multiple linear regression. It provides an index of the importance of each predictor like the standardized regression coefficients (beta) do in regression. The sign indicates the direction of the relationship. The standardized discriminant function coefficients are used to assess the unique contribution of each variable to the discriminant function. The standardized canonical discriminant function coefficients reflect the contribution of one independent variable in the context of other variables in the model. A low standardized coefficient could mean that the groups do not differ much on that variable, or it can mean that a variable's correlation with the grouping variable is redundant with that of another variable in the model. It also means that the larger the standardized coefficient, the greater the contribution of the respective variable to the discrimination between groups.

Classification accuracy

The classification table is also called the confusion table. This table has rows with the observed categories of the dependent and the columns with the predicted categories. When the prediction is perfect, all the cases will lie on the diagonal. The cross-validated set of data provides a more honest presentation of the power of the discriminant function than that by the original classification. Cross-validation is also known as jack-knife classification, wherein it successfully classifies all cases but one to develop a discriminant function and then categorizes the case that was left out. This process is repeated with each case left out in turn and hence brings forth a more reliable function. The overall predictive accuracy of the discriminant function is called the 'hit ratio', and a hit ratio that is 25% larger than that due to chance is accepted.

3.9 Ethical considerations:

The study received approval and clearance from the Institutional Ethics Committee (IEC) of Sree Chitra Tirunal Institute for Medical Sciences and Technology (SCT/IEC/1164/DECEMBER-2017).

The Survey data was obtained from the Project with due permission from the Principal Investigator. The confidentiality and privacy of the respondents were maintained using unique identifiers for each participant. The data was not transferred to any other persons other than the PI and Supervisor.

CHAPTER 4

RESULTS

4 RESULTS

The major objectives of this study were:

4. To determine the geographical distribution of built environment variables across districts and subdistricts of Kerala
5. To evaluate the relationship between built environment variables and the prevalence of non-communicable diseases in Kerala
6. To identify spatial clusters of non-communicable diseases (NCDs) and evaluate built environment characteristics within low and high spatial clusters.

The structure of this chapter is as given below:

1. **Objective 1: Distribution of built environment variables across Kerala**
    a. Geographical distribution of built environment variables across districts and subdistricts in Kerala
    b. Correlation between built environment variables in districts and sub-districts

2. **Objective 2: Relationship between built environment variables and the prevalence of non-communicable diseases in Kerala**
    a. Demographic characteristics of the study participants
    b. Prevalence of outcome variables across districts and panchayats
    c. Descriptive statistics of built environment variables in the neighbourhoods of study participants
    d. Results of discriminant analysis

3. **Objective 3: Identify spatial clusters of non-communicable diseases among a sample population**

    a. Identification of high and low spatial clusters of NCDs among a sample population in Kerala

    b. Sociodemographic and built environment characteristics of participants within high and low spatial clusters

4.1 Objective 1: Distribution of built environment variables across Kerala

4.1.1 Geographical distribution of built environment variables across Kerala

4.1.1.1 Population and residential density

Thiruvananthapuram district had the highest population and residential density, while the Idukki district had the lowest population and residential density. Cochin in Ernakulam ranked top among the subdistricts, and Pirmed in Idukki ranked lowest in population and residential density. The summary table of population and residential density across districts is given in Table 4.1, while the distribution across subdistricts is shown in Supplementary Table S1.

Table 4.1. Table showing population and residential density across districts in Kerala

District	Area (sq.km)	Population	Population density	Number of households	Residential density
Kasaragod	1989	1307375	657.30	273410	137.46
Kannur	2961	2523003	852.08	554298	187.2
Wayanad	2130	817420	383.77	190894	89.62
Kozhikode	2345	3086293	1316.12	697710	297.53
Malappuram	3554	4112920	1157.27	793999	223.41
Palakkad	4482	2809934	626.94	637220	142.17
Thrissur	3027	3121200	1031.12	759210	250.81
Ernakulam	3063	3282388	1071.63	814011	265.76
Idukki	4356	1108974	254.59	279812	64.24
Kottayam	2206	1974551	895.08	487296	220.90
Alappuzha	1415	2127789	1503.74	535958	378.77
Pathanamthitta	2652	1197412	451.51	322684	121.68
Kollam	2483	2635375	1061.37	669375	269.58
Thiruvananthapuram	2189	3301427	1508.19	837877	382.77

4.1.1.2 Crime rates and Pedestrian accident rates

Crime rates were reported to be highest in Ernakulam district and lowest in Malappuram. Among the subdistricts, Cochin and Kanayannur in the Ernakulam district recorded the highest and lowest crime rates. Pedestrian accident rates were highest in Kollam while lowest in Malappuram district. Cochin and Kanayannur subdistricts in Ernakulam reported the highest and lowest pedestrian accident rates, respectively. Summary of distribution of crime and pedestrian accident rates across districts are summarised in Table 4.2, and across subdistricts are given in Supplementary Table S2.

Table 4.2. Crime rates and pedestrian accident rates across districts in Kerala

District	Population	Number of crimes	Crime rate (per 1,000 inhabitants)	Number of pedestrian accidents	Pedestrian accident rates (per 1 lakh inhabitants)
Kasaragod	1307375	12210	9.34	254	19.43
Kannur	2523003	58792	23.30	582	23.07
Wayanad	817420	10492	12.84	182	22.27
Kozhikode	3086293	35576	11.53	808	26.18
Malappuram	4112920	19722	4.80	663	16.12
Palakkad	2809934	29683	10.56	935	33.27
Thrissur	3121200	80289	25.72	927	29.70
Ernakulam	3282388	118168	36.00	1500	45.70
Idukki	1108974	24380	21.98	249	22.45
Kottayam	1974551	58289	29.52	685	34.69
Alappuzha	2127789	47993	22.56	792	37.22
Pathanamthitta	1197412	42397	35.41	393	32.82
Kollam	2635375	90826	34.46	1286	48.80
Thiruvananthapuram	3301427	107721	32.63	1331	40.32

4.1.1.3 Intersection density

The intersection density ranged from 10.94 in Ernakulam district to 1.7 in Wayanad district. Among the subdistricts, Ambalapuzha in Alappuzha ranked lowest (0.01 intersections per sq.km.), and Kanayannur in Ernakulam ranked highest (35.4 intersections per sq.km.). The distribution of intersection density across districts is summarised in Table 4.3. The Supplementary Table S3 gives a summary of intersection density across sub-districts.

Table 4.3. Intersection density across districts in Kerala

District	Area (sq.km)	Intersections	Intersection density (per sq.km)
Kasaragod	1989	9010	4.53
Kannur	2961	6504	2.20
Wayanad	2130	3100	1.46
Kozhikode	2345	8878	3.79
Malappuram	3554	8162	2.30
Palakkad	4482	13842	3.09
Thrissur	3027	20350	6.72
Ernakulam	3063	28240	9.22
Idukki	4356	4298	0.99
Kottayam	2206	13684	6.20
Alappuzha	1415	6264	4.43
Pathanamthitta	2652	3768	1.42
Kollam	2483	10230	4.12
Thiruvananthapuram	2189	14202	6.49

4.1.1.4 Greenness and Built-up density

Ernakulam district had the lowest mean greenness and the highest mean built-up density among the districts. Kasaragod ranked highest for mean greenness, and Kozhikode ranked lowest for mean built-up density among the districts.

Cochin in Ernakulam ranked lowest for greenness and highest for mean built-up density among the subdistricts. In contrast, Nilambur in Malappuram ranked highest for mean greenness, and Kuttanad ranked lowest for mean built-up density. The summary statistics for greenness and built-up density among the districts are summarised in Table 4.4, while the summary for subdistricts is given in Supplementary Table S4.

Table 4.4. Greenness and built-up density statistics across districts in Kerala

District	Greenness			Built-up density		
	Mean	Standard deviation	Range	Mean	Standard deviation	Range
Kasaragod	0.56	0.17	1.19	-0.22	0.13	1.00
Kannur	0.55	0.13	1.31	-0.23	0.10	1.14
Wayanad	0.57	0.11	1.14	-0.22	0.10	1.32
Kozhikode	0.54	0.14	1.30	-0.27	0.09	0.87
Malappuram	0.55	0.13	1.16	-0.25	0.10	1.14
Palakkad	0.49	0.12	1.06	-0.22	0.11	0.94
Thrissur	0.49	0.11	1.02	-0.24	0.09	1.12
Ernakulam	0.44	0.16	0.99	-0.21	0.09	1.06
Idukki	0.51	0.13	1.42	-0.26	0.10	1.01
Kottayam	0.48	0.15	1.25	-0.22	0.08	1.04
Alappuzha	0.45	0.19	0.99	-0.26	0.10	1.07
Pathanamthitta	0.52	0.11	1.16	-0.25	0.07	1.03
Kollam	0.51	0.15	1.26	-0.22	0.08	1.16
Thiruvananthapuram	0.51	0.13	1.23	-0.25	0.08	1.05

4.1.1.5 Land slope

The mean land slope was highest for the Idukki district and lowest for the Alappuzha district. Devikolam in Idukki and Kuttanad in Alappuzha recorded the highest and lowest mean land slope among the subdistricts. The summary of the distribution of mean land slope across districts is given in Table 4.5, and among the subdistricts is provided in Supplementary Table S5.

Table 4.5. Summary statistics of land slope across districts in Kerala

District	Mean slope	Standard deviation	Slope Range
Kasaragod	6.36	6.00	47.68
Kannur	7.23	7.01	50.75
Wayanad	7.87	7.07	56.30
Kozhikode	8.06	8.94	69.18
Malappuram	7.29	8.33	75.69
Palakkad	8.27	9.55	76.14
Thrissur	5.91	7.16	59.31
Ernakulam	3.85	4.95	57.12
Idukki	13.86	9.61	72.72
Kottayam	5.84	6.69	61.67
Alappuzha	1.25	1.52	22.52
Pathanamthitta	11.17	8.74	56.07
Kollam	6.60	7.09	53.47
Thiruvananthapuram	5.91	6.10	56.50

The geographical distribution of all the above mentioned built environment variables are summarised as choropleth maps across districts and subdistricts in Figure 4.1 and 4.2, respectively.

Figure 4.1. Choropleth maps showing the distribution of built environment variables across districts in Kerala

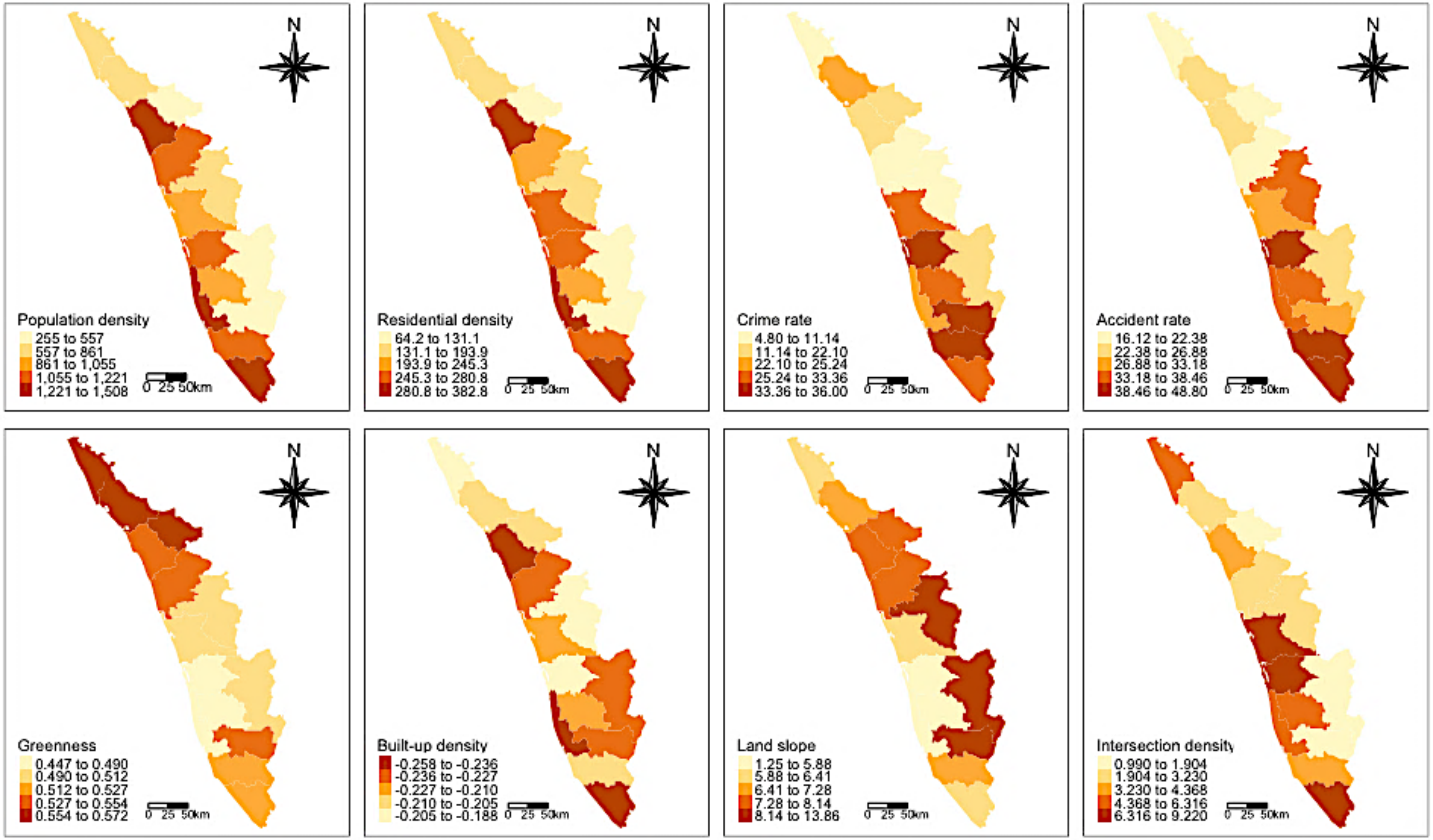
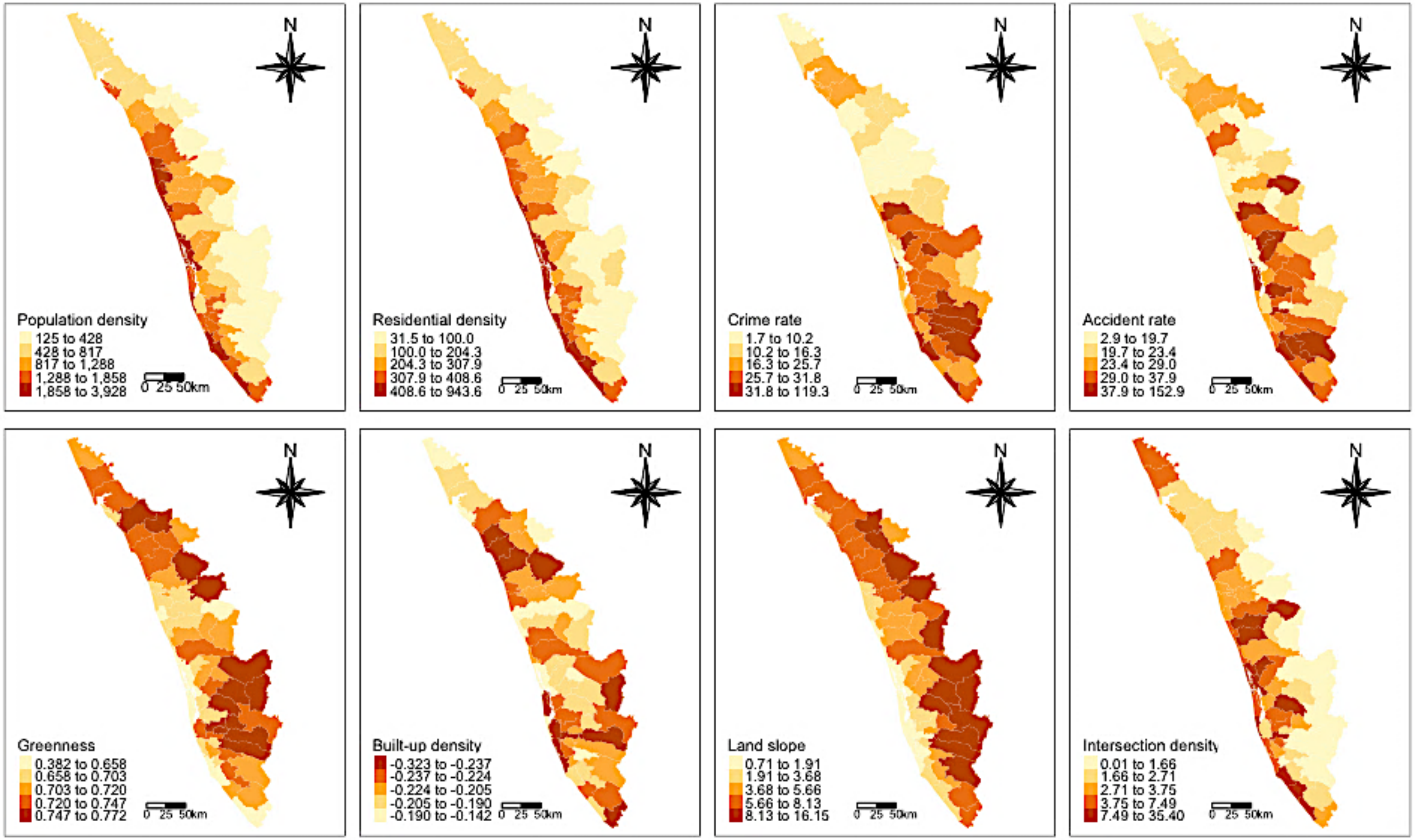


Figure 4.2. Choropleth maps showing the distribution of built environment variables across subdistricts in Kerala



4.1.2 Correlation between built environment variables across districts and subdistricts

The correlation matrix between the captured built environment variables across districts and subdistricts are summarised in Table 4.6.

4.1.2.1 Correlation of built environment variables among districts

There was a high correlation between population density and residential density of the districts ($r = 0.98$, $p<0.01$). Also, as the districts were more densely populated, the intersection density increased ($r = 0.57$, $p<0.05$). Moreover, the more populated districts were congruent with the districts which had lower land slope ($r = -0.74$, $p<0.01$). This relationship was similar to residential density. As the residential units in a district increased, the road intersection density also tended to be greater ($r = 0.62$, $p<0.05$). Also, more residential units were found in districts with lower land slope ($r = -0.72$, $p<0.01$). Furthermore, the three-way road intersection density inclined to be higher in districts with lower land slope ($r = -0.66$, $p<0.01$).

Pedestrian accident rates tended to be higher in districts as the residential units increased ($r = 0.54$, $p<0.05$). The pedestrian accident rates were also higher in conjunction with higher crime rates ($r = 0.78$, $p<0.01$). Also, as the road intersection density in the districts hiked up, the pedestrian accident rates tended to be higher ($r = 0.60$, $p<0.05$). Meanwhile, the pedestrian accident rates were likely to be lower in districts with higher greenness ($r = 0.57$, $p<0.05$).

Table 4.6. Correlation between built environment variables across districts and sub-districts

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Across districts								
Population density (x_1)	1.00							
Residential density (x_2)	***0.98***	1.00						
Crime rate (x_3)	0.14	0.30	1.00					
Accident rate (x_4)	0.40	**0.54**	***0.78***	1.00				
Greenness (x_5)	-0.17	-0.25	-0.47	**-0.57**	1.00			
Built-up density (x_6)	-0.29	-0.27	0.22	0.29	-0.10	1.00		
Intersection density (x_7)	0.57	**0.62**	0.44	**0.60**	-0.45	0.36	1.00	
Land slope (x_8)	***-0.74***	***-0.72***	0.03	-0.36	0.19	-0.26	**-0.66**	1.00
Across Sub-districts								
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Population density (x_1)	1.00							
Residential density (x_2)	***0.99***	1.00						
Crime rate (x_3)	**0.27**	***0.32***	1.00					
Accident rate (x_4)	***0.34***	***0.37***	***0.81***	1.00				
Greenness (x_5)	***-0.83***	***-0.83***	***-0.43***	***-0.54***	1.00			
Built-up density (x_6)	**0.26**	**0.26**	**0.27**	***0.33***	***-0.50***	1.00		
Intersection density (x_7)	***0.69***	***0.73***	**0.29**	0.28	***-0.71***	***0.47***	1.00	
Land slope (x_8)	***-0.67***	***-0.67***	-0.06	**-0.21**	***0.60***	-0.20	***-0.41***	1.00

Bold italic font denotes p<0.01, Bold font denotes p<0.05

4.1.2.2 Correlation of built environment variables among subdistricts

The near-perfect relationship between population density and residential density was manifested by the subdistricts ($r = 0.99$, $p<0.01$). As the subdistricts were more populous and had more residential units, there was a tendency for higher crime rates to be higher ($r = 0.27$, $p<0.05$ and $r = 0.32$, $p<0.01$).

Similarly, the subdistricts with higher population density and residential density showed a tendency to have higher pedestrian accident rates ($r = 0.34$, $p<0.01$ and $r = 0.37$, $p<0.01$). The built – up density ($r = 0.26$, $p<0.05$ and $r = 0.26$, $p<0.05$) and intersection density ($r = 0.69$, $p<0.01$ and $r = 0.73$, $p<0.01$) also showed an inclination to rise with population and residential density of the subdistricts.

However, subdistricts that were more populous and had more residential units displayed lower greenness ($r = -0.83$, $p<0.01$), and those subdistricts were found to be associated with lower land slope ($r = 0.67$, $p<0.01$). Crime rates had an inclination to be higher with higher road intersections ($r = 0.29$, $p<0.05$), urban area distribution ($r = 0.27$, $p<0.05$) and pedestrian accident rates ($r = 0.81$, $p<0.01$). Nevertheless, a declining tendency of crime rates was found in subdistricts with higher greenness ($r = -0.43$, $p<0.01$).

Pedestrian accident rates had a higher disposition in subdistricts with lower greenness ($r = -0.54$, $p<0.01$). Also, the pedestrian accident rates showed a diminishing tendency in subdistricts with higher land slope ($r = -0.21$, $p<0.05$). Moreover, the accident rates in subdistricts had an increasing trend with the rise in built-up density ($r = 0.33$, $p<0.01$).

Subdistricts displayed higher road intersection density with lowering greenness ($r = -0.71$, $p<0.01$) and in subdistricts wherein the land slope was less inclined ($r = -0.41$, $p<0.01$). The greenness within the subdistricts showed an inclination to go higher as the land slope had a greater slope ($r = 0.60$, $p<0.01$). On the contrary, a lower tendency of greenness was witnessed for subdistricts as built-up density increased ($r = -0.50$, $p<0.01$).

4.2 *Objective 2: Relationship between built environment variables and the prevalence of non-communicable diseases in Kerala*

4.2.1 Demographic characteristics of the participants in NCD survey data

The majority (44.2%) of the respondents were from the middle-adults category belonging to 35-64 years, as given in Table 4.7. More than half of the participants were females (62.9%) and were married (83.1%). About half of the respondents had attained a high school education (55.8%). The majority of the participants (64.2%) were unemployed and included students, retired from work and homemakers. Those who were executives or were involved in small and medium businesses constituted about 25.4%.

Table 4.7. Table showing demographic characteristics of the sample population

Category	Subcategory	Distribution (n =11033)	Proportion (%)
Age category (in years)	18 - 34	3590	32.5
	35 - 64	4872	44.2
	> 65	2571	23.3
Gender	Male	4097	37.1
	Female	6936	62.9
Marital status	Unmarried	1862	16.9
	Married	9171	83.1
Education	Primary school or less	2881	26.1
	High school	6158	55.8
	Graduation and above	1994	18.1
Occupation	Unemployed	7079	64.2
	Manual labourers	1151	10.4
	Business/ Executives	2803	25.4

4.2.1.1 *Prevalence of outcome variables across districts and panchayats*

The prevalence of the outcome variables was estimated for the state and each district summarised in Table 4.8. State-level estimates showed 20.2% (2230 participants) of diabetes and 23.1% (2550 participants) of physical inactivity. The prevalence of diabetes and physical inactivity in the urban sample was 21.3% and 26.1%, respectively, while they were 19.1% and 20.1%, respectively, among the rural sample.

Kottayam district showed the highest prevalence of diabetes (34.9%) and physical inactivity (43.6%). The prevalence of diabetes was the lowest (13.4%) in the Wayanad district, while physical inactivity was found to be the least in the Kannur district, with a prevalence of 8.5%.

Table 4.8. Prevalence of outcome variables across districts in Kerala

District	Sample n(%)	Diabetes (%)	Physical Inactivity (%)
Alappuzha	915 (8.3)	13.8	32.0
Kannur	517 (4.7)	27.9	**8.5**
Kozhikode	845 (7.7)	17.4	21.2
Ernakulam	935 (8.5)	31.9	31.9
Idukki	511 (4.6)	27.0	10.2
Kasaragod	916 (8.3)	10.5	25.1
Kottayam	854 (7.7)	**34.9**	**43.6**
Malappuram	738 (6.7)	15.7	34.1
Palakkad	767 (6.9)	17.3	10.7
Pathanamthitta	806 (7.3)	27.5	37.6
Kollam	828 (7.5)	19.3	10.7
Thrissur	907 (8.2)	21.3	14.9
Thiruvananthapuram	846 (7.7)	30.0	12.6
Wayanad	648 (5.9)	**13.4**	17.6
Total	11033	20.2	23.1

4.2.2 Descriptive statistics of built environment variables in the participant neighbourhoods

4.2.2.1 Descriptive statistics of built environment variables in the neighbourhood

The descriptive statistics of all the built environment variables in the participant neighbourhoods are summarised in Table 4.9 below. The density plots of all the built environment variables captured for urban and rural samples are shown in Figure 4.3. The density plots showed a clear divergence between urban and rural samples.

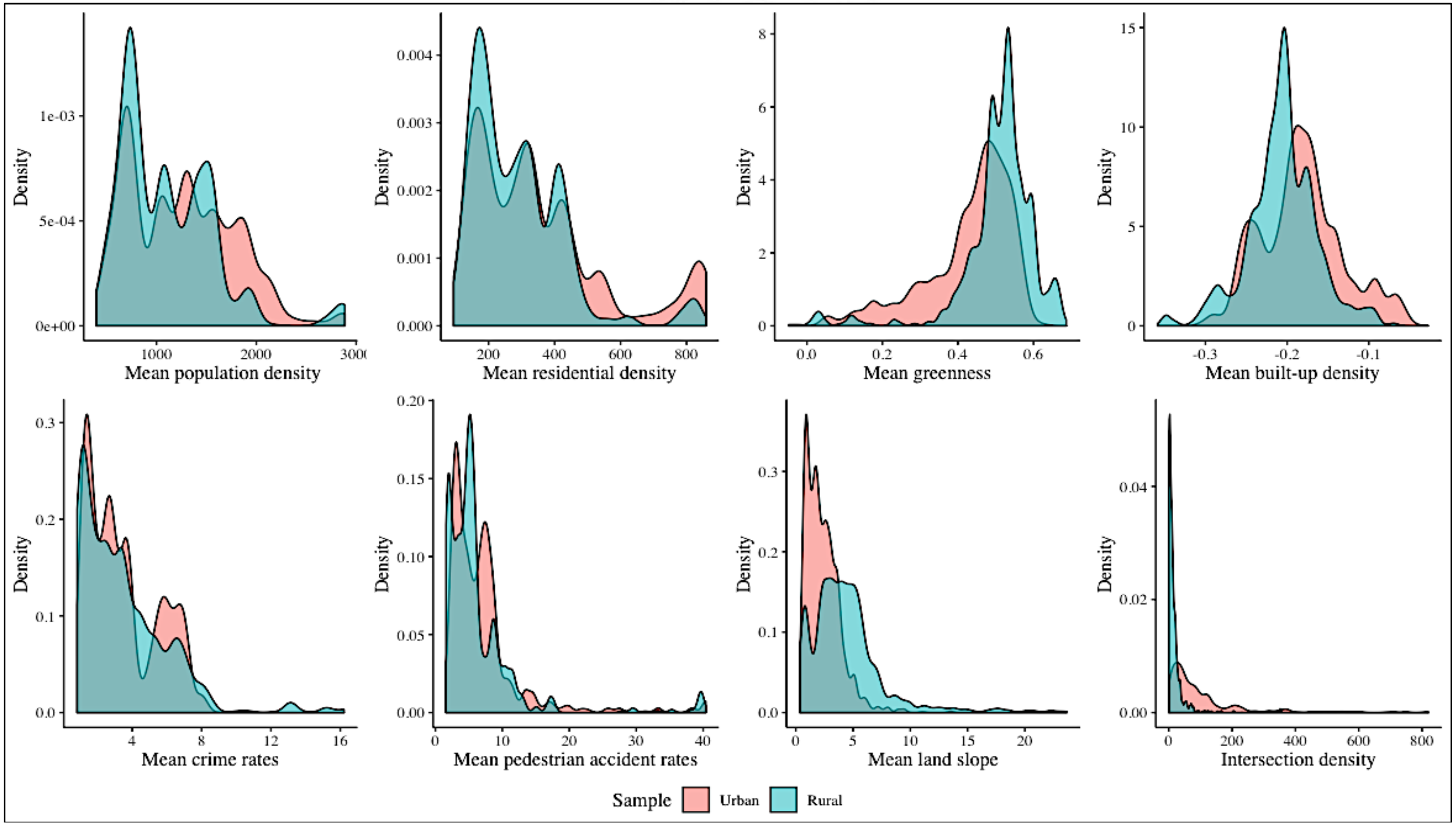
The population and residential density had a tendency to be concentrated towards the left in the rural sample, while the urban sample shows a significant variation. Greenness and built-up density showed a clear difference between urban and rural samples, with the urban sample depicting lower greenness and higher built-up density. Crime rates tended to be higher in the urban sample with low variation than the rural sample. The pedestrian accident rates also showed distinct peaks for urban and rural samples. The land slope was higher with high variation in the rural sample, while the urban sample showed a less dispersed mean slope. As expected, intersection density showed a high peak for the rural sample with less dispersion, meaning the intersection density tended to be lower with minor variation in the rural sample. In comparison, the urban sample showed a higher intersection density with a higher distribution. The stark differences in the urban and rural sample variables persuaded us to analyse them separately because the total sample per se would not show us the right picture.

Hence, further diagnostics and discussions are summarised for the urban and rural sample rather than the total sample.

Table 4.9. Descriptive statistics of built environment variables in the participant neighbourhood

Location	Variable	Min.	1st Qu.	Median	3rd Qu.	Max.
Overall	Population density	395.0	726.5	1079.0	1533.7	2887.8
	Residential density	93.7	183.3	284.8	407.4	859.5
	Crime rate	0.82	1.54	2.84	4.84	16.22
	Pedestrian accident rate	1.59	3.36	5.27	7.85	40.39
	Intersection density	0.0	7.11	21.33	66.67	820.44
	Greenness	-0.048	0.431	0.494	0.539	0.687
	Built-up density	-0.358	-0.223	-0.196	-0.168	-0.027
	Land slope	0.35	1.63	2.86	4.42	23.66
Rural	Population density	395.0	725.2	1049.0	1410.5	2876.6
	Residential density	93.7	173.9	259.6	366.5	832.4
	Crime rate	0.82	1.49	2.65	4.62	16.22
	Pedestrian accident rate	1.59	3.13	4.94	7.22	39.66
	Intersection density	0.00	3.55	8.89	19.55	352.0
	Greenness	0.005	0.482	0.524	0.599	0.686
	Built-up density	-0.358	-0.227	-0.205	-0.180	-0.069
	Land slope	0.35	2.42	3.92	5.53	23.66
Urban	Population density	416.7	731.0	1254.3	1615.5	2887.8
	Residential density	99.2	187.9	316.5	434.3	859.5
	Crime rate	1.07	1.66	2.86	5.28	8.41
	Pedestrian accident rate	1.85	3.40	5.96	8.02	40.39
	Intersection density	0.0	25.7	56.8	120.8	820.4
	Greenness	-0.048	0.379	0.463	0.512	0.636
	Built-up density	-0.306	-0.215	-0.183	-0.154	-0.027
	Land slope	0.40	1.17	2.04	3.12	13.53

Figure 4.3. Density plots of built environment variables in urban and rural participant neighbourhoods



4.2.2.2 *Correlation matrix of built environment variables in the urban and rural participant neighbourhoods*

The correlation matrix with the density plots for the urban and rural samples are summarised in Table 4.10. The population density and residential density are highly correlated (r = 0.89) and the mean greenness is negatively correlated to built-up density (r = -0.73) and intersection density (-0.51). The residential density is also correlated to the pedestrian accident rate (r = 0.65).

The correlation matrix for the rural sample shows a high perfect correlation between population and residential density. Residential density is also highly correlated to pedestrian accident rate (r = 0.69), while negatively correlated to mean greenness (r = -0.071).

Mean greenness is also negatively correlated to built-up density (r = -0.51). Within the rural sample, too, the built-up density shows a near-normal distribution, while the other variables show a skewed distribution. The crime rate distribution shows a slight dip in between, not as distinct as seen for the urban sample.

The scatter plot between population density and crime rate shows a curve after a point in the centre rather than a straight line. This indicates that there could be variation in the rural sample, too, when considering population density and crime rates simultaneously.

Table 4.10. Correlation between built environment variables across urban and rural neighbourhoods of selected participants

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Across urban neighbourhoods								
Mean Population density (x_1)	1.00							
Mean Residential density (x_2)	***0.89***	1.00						
Mean Crime rate (x_3)	***0.32***	***0.28***	1.00					
Mean Accident rate (x_4)	***0.57***	***0.65***	***0.57***	1.00				
Mean Greenness (x_5)	***-0.44***	***-0.51***	**-0.03**	***-0.34***	1.00			
Mean Built-up density (x_6)	***0.29***	***0.38***	**0.03**	**0.33**	***-0.73***	1.00		
Mean Intersection density (x_7)	***-0.55***	***-0.45***	***-0.07***	***-0.24***	***0.48***	***-0.21***	1.00	
Mean Land slope (x_8)	***0.36***	***0.46***	***0.15***	***0.47***	***-0.51***	***0.53***	***-0.29***	1.00
Across rural neighbourhoods								
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Mean Population density (x_1)	1.00							
Mean Residential density (x_2)	***0.95***	1.00						
Mean Crime rate (x_3)	***0.22***	***0.28***	1.00					
Mean Accident rate (x_4)	***0.61***	***0.69***	***0.56***	1.00				
Mean Greenness (x_5)	***-0.65***	***-0.71***	***-0.39***	***-0.81***	1.00			
Mean Built-up density (x_6)	***-0.02***	***0.05***	***0.33***	***0.51***	***-0.51***	1.00		
Mean Intersection density (x_7)	***-0.44***	***-0.41***	***0.20***	***0.29***	***0.43***	***-0.20***	1.00	
Mean Land slope (x_8)	***0.17***	***0.26***	***-0.09***	***-0.30***	***-0.28***	***0.29***	***-0.23***	1.00

Bold italic font denotes $p<0.01$, Bold font denotes $p<0.05$

4.2.3 Relationship of built environment characteristics with diabetes and physical inactivity: Results of Discriminant Analysis

4.2.3.1 Group Statistics

In Table 4.11, we can determine that the mean values of built environment variables are not significantly different in the urban sample and rural sample. These mentioned mean differences stand statistically significant for the Wilk's Lambda test and F statistics given in Table 4.11 and Table 4.12 for diabetes and physical inactivity outcomes.

Table 4.11. Tests of equality of group means of diabetes groups in the urban and rural sample

	Variables	Diabetes		F
		Non-diabetic	Diabetic	
Urban[a]	Prevalence (%)	78.7	21.3	
(N, 5487)	Residential density	352.76 (203.66)	352.45 (196.8)	
	Crime rates	3.33 (1.94)	3.91 (2.01)	82.46
	Pedestrian accident rate	6.98 (6.06)	7.32 (5.27)	50.40
	Greenness	0.43 (0.12)	0.44 (0.10)	
	Built-up density	-0.18 (0.05)	-0.19 (0.05)	25.27
	Land slope	2.34 (1.46)	2.49 (1.55)	36.33
	Intersection density	99.47 (127.16)	104.49 (130.01)	29.12
Rural[b]	Prevalence (%)	80.9	19.1	
(N, 5546)	Residential density	286.56 (145.32)	294.55 (136.42)	23.08
	Crime rates	3.46 (2.52)	3.41 (2.44)	
	Pedestrian accident rate	6.40 (6.42)	5.76 (4.06)	
	Greenness	0.51 (0.10)	0.52 (0.08)	
	Built-up density	-0.20 (0.04)	-0.21 (0.04)	52.11
	Land slope	4.35 (3.28)	4.86 (3.37)	28.41
	Intersection density	15.97 (25.19)	17.85 (42.62)	34.72

[a] Wilks' $\lambda = 0.97$, chi-square = 124.94, $p<0.01$, [b] Wilks' $\lambda = 0.98$, chi-square = 91.59, $p<0.01$

When we consider diabetes as the outcome variable (Table 4.11), built-up density, land slope, and intersection density showed significantly different group means for participants in both urban and rural neighbourhoods. However, for physical inactivity (Table 4.12), crime rates and pedestrian accident rates showed significantly different group means for both urban and rural neighborhoods.

Residential density showed significant group mean differences for both diabetes and physical inactivity in the rural neighbourhoods but was not significant for urban neighbourhoods.

Table 4.12. Tests of equality of group means of physical inactivity groups in the urban and rural sample

	Variables	Physical Inactivity		F
		Physically active	Physically inactive	
Urban[a]	Prevalence (%)	73.9	26.1	
(N, 5487)	Residential density	351.13 (200.06)	357.12 (208.16)	
	Crime rates	3.30 (1.85)	3.88 (2.23)	92.14
	Pedestrian accident rate	6.86 (5.49)	7.60 (6.93)	41.26
	Greenness	0.43 (0.12)	0.44 (0.12)	
	Built-up density	-0.18 (0.05)	-0.19 (0.05)	59.41
	Land slope	2.39 (1.47)	2.29 (1.51)	
	Intersection density	96.33 (119.67)	112.46 (147.75)	53.62
Rural[b]	Prevalence (%)	79.9	20.1	
(N, 5546)	Residential density	285.95 (149.37)	296.61 (118.07)	48.22
	Crime rates	3.33 (2.40)	3.97 (2.82)	74.18
	Pedestrian accident rate	6.24 (6.28)	6.43 (5.00)	63.24
	Greenness	0.51 (0.10)	0.50 (0.09)	
	Built-up density	-0.21 (0.04)	-0.20 (0.04)	55.83
	Land slope	4.69 (3.47)	3.52 (2.24)	114.59
	Intersection density	15.97 (30.03)	17.75 (26.46)	

[a] Wilks' λ = 0.97, chi-square = 162.66, p<0.01, [b] Wilks' λ = 0.96, chi-square = 236.09, p<0.01

4.2.3.2 Group Centroids

The following table, Table 4.13, summarises the group centroids for those with and without diabetes on the discriminant function for both urban and rural sample.

Table 4.13 Group centroids for discriminant function across categories

Outcome groups	Category	Sample	
		Urban	Rural
Diabetes	Diabetic	0.29	0.26
	Non-diabetic	-0.08	-0.06
Physical inactivity	Physically inactive	0.29	0.42
	Physically active	-0.10	-0.11

From the above table, we understand that both among urban and rural participants, the function determined by the built environment variables discriminates those who had diabetes/ were physically inactive from those who were without diabetes/ who were physically active. While those with the outcome scored on the positive end, those without the outcome scored on the opposing end.

4.2.3.3 The relative importance of the discriminatory variables

Table 4.14 reveals that among the urban participants, the crime rate contributes highest to a participant being diabetic or non-diabetic (0.81) or being physically active or inactive (0.75). The pedestrian accident rate is also found as a contributor in differentiating those with diabetes/ physical inactivity. Built-up density and intersection density have also proved to be differentiating participants with diabetes and physical inactivity. The land slope has emerged to be a discriminating variable only for diabetes.

Table 4.14. Canonical correlations of variables in the urban and rural sample

Location		Diabetes	Physical Inactivity
Urban	Residential density		
	Crime rate	0.81	0.75
	Pedestrian accident rate	0.15	0.32
	Greenness		
	Built-up density	-0.29	-0.37
	Land slope	0.28	
	Intersection density	0.11	0.32
Rural	Residential density	0.17	0.14
	Crime rate		0.50
	Pedestrian accident rate		0.06
	Greenness		
	Built-up density	-0.75	0.40
	Land slope	0.47	-0.69
	Intersection density	0.19	

On the other hand, in the rural areas, built-up density proves to be the highest contributor for differentiating outcome groups of diabetes (-0.75) and obesity (0.87) and is also a significant contributor for physical inactivity (0.40). Land slope and residential density contribute to both diabetes and physical inactivity among the rural participants, while crime rates contribute towards physical inactivity. Intersection density has emerged as a discriminating factor for the outcome group of diabetes, while the pedestrian accident rate was significant only for physical inactivity.

4.2.3.4 Discriminant function coefficients

The discriminant function coefficients for the discriminating variables across each category in urban and rural samples are summarised in Table 4.16. This table shows the contributions of each variable to the discriminant function.

Here in Table 4.15, we see crime rates contributing highest towards diabetes and physical inactivity in urban neighbourhoods. However, in rural neighbourhoods, land slope and crime rates contribute highest toward diabetes and physical inactivity, respectively.

Table 4.15. Discriminant function coefficients of variables across outcome groups in both urban and rural sample

Location	Variables	Diabetes	Physical Inactivity
Urban	Residential density		
	Crime rate	1.05	0.81
	Pedestrian accident rate	-0.47	-0.23
	Greenness		
	Built-up density	-0.35	-0.68
	Land slope	0.30	
	Intersection density	0.43	0.67
Rural	Residential density	0.31	0.47
	Crime rate		0.69
	Pedestrian accident rate		-1.15
	Greenness		
	Built-up density	-0.79	0.64
	Land slope	0.55	-0.58
	Intersection density	0.47	

4.2.3.5 Classification accuracy

Table 4.16 below shows how well the discriminant function works and whether it works equally well for each group. We see a high accuracy for diabetes and physical inactivity in both urban and rural sample.

Table 4.16. Classification results for each category in the urban and rural sample

Location	Category	Sensitivity[a]	Specificity[b]	Overall classification accuracy[c]
Urban	Diabetes	0.0 %	100.0 %	78.7 %
	Physical inactivity	0.0 %	100.0 %	73.9 %
Rural	Diabetes	1.3 %	99.9 %	81.0 %
	Physical inactivity	1.2 %	99.3 %	79.6 %

[a] true positive rates, [b] true negative rates, [c] cross-validated results of classification.

The classification table also notes that the accuracy in classifying non-diabetics is higher for all categories in both urban and rural samples.

4.3 Objective 3: Identify spatial clusters of non-communicable diseases among the sample population

4.3.1 Spatial clusters of diabetes

A total of five high spatial clusters and four low spatial clusters were identified both in the urban and rural setting, as shown in Figure 4.4 and Figure 4.5, respectively. The primary clusters of high rates of diabetes (Changanassery in urban setting and Aruvikkara in rural setting) had about 104- and 40-times higher likelihood of being a high-rate spatial cluster of diabetes as compared to other sites both in urban (relative risk [RR] = 3.14, log-likelihood ratio [LLR] = 104.04, $p<0.01$) and rural (RR = 2.68, LLR = 40.48, $p<0.01$) settings, respectively (see Table 4.17).

Similarly, the primary cluster identified for low rates of diabetes had 23 times likelihood (Kasaragod city, RR = 0.30, LLR = 23.45, $p<0.01$) and 16 times likelihood (Vazhakulam, RR = 0.19, LLR = 15.65, $p<0.01$) for being a low-rate spatial cluster of diabetes as compared to other sites in urban and rural settings respectively.

Figure 4.4. Map showing spatial clusters of diabetes among urban sample population in Kerala

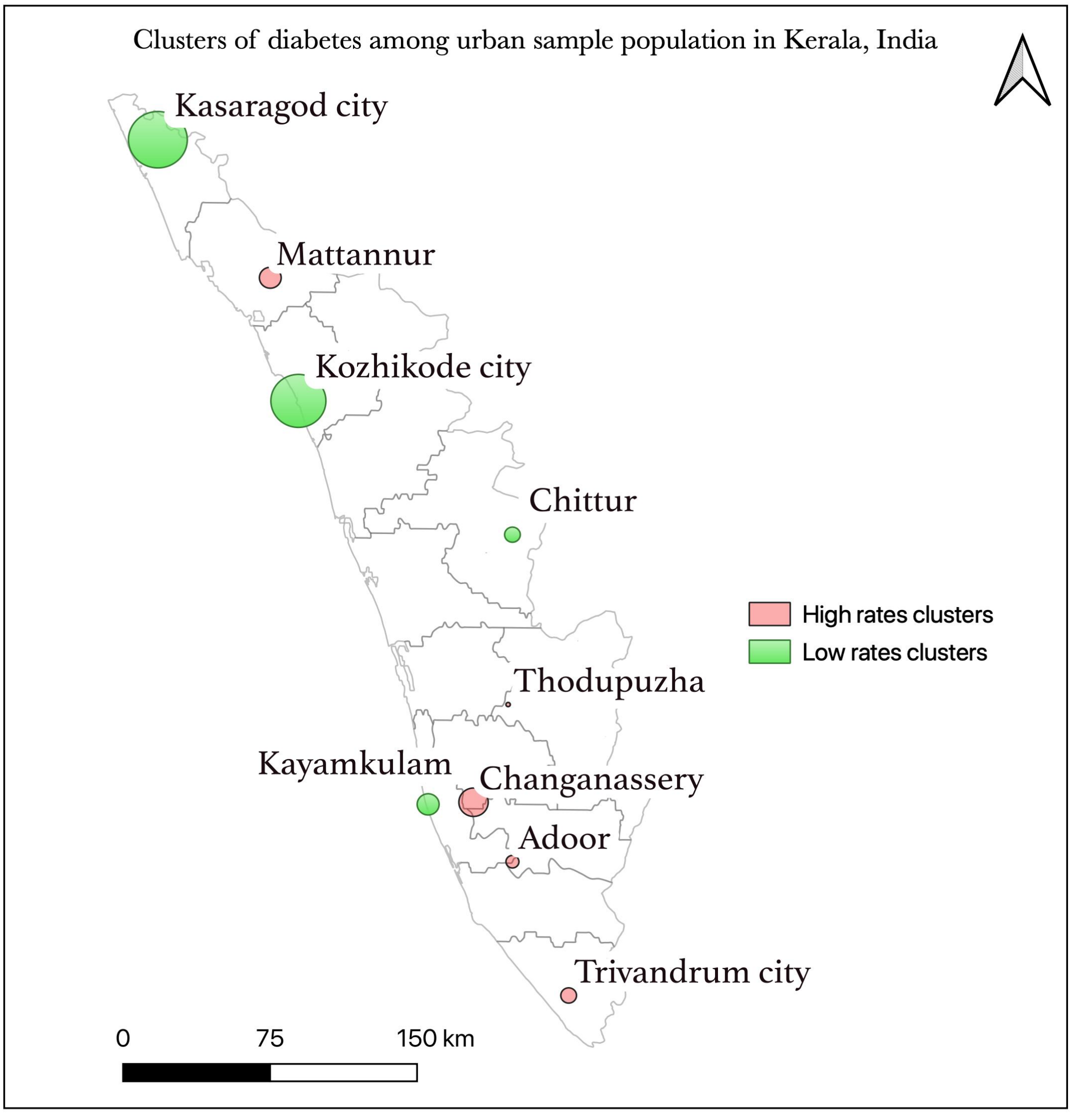


Figure 4.5. Map showing spatial clusters of diabetes among rural sample population in Kerala

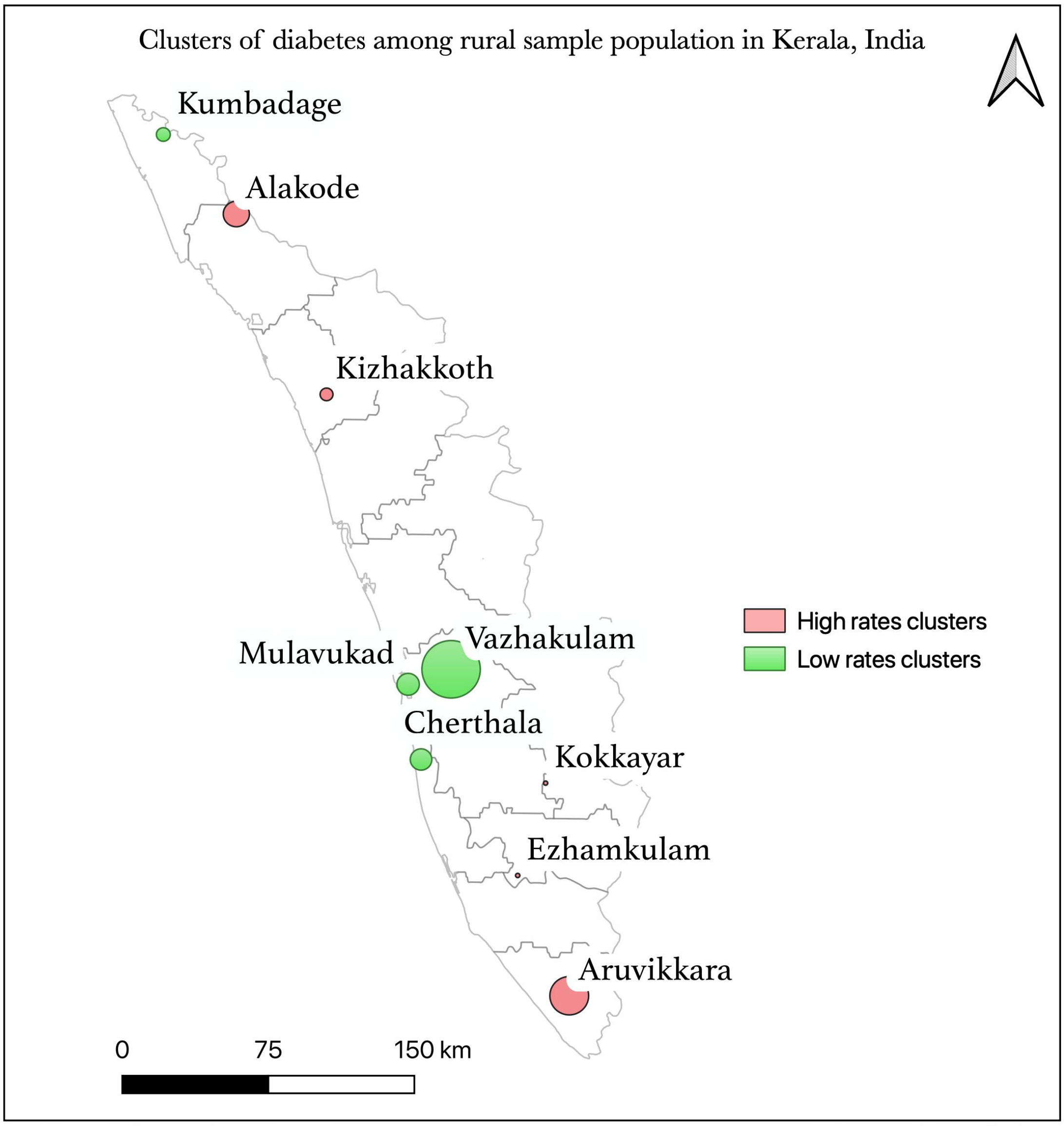


Table 4.17.Table showing the cluster location of diabetes in the sample population

	Location	Radius (km)	Cases Observed/ total participants	LLR
Urban	**Sites of higher rates**			
	1.Changanassery, Kottayam	7.43	167/279	104.04
	2.Adoor, Pathanamthitta.	3.29	70/167	18.62
	3.Trivandrum, city	3.99	17/22	15.78
	4.Mattanoor, Kannur	5.48	50/120	12.94
	5.Thodupuzha, Idukki	1.11	37/79	12.92
	Sites of lower rates			
	1.Kasaragod city	14.7	18/273	23.45
	2.Calicut city	13.9	35/330	13.86
	3.Chittur, Palakkad	3.95	7/133	13.81
	4.Alappuzha city	5.56	3/72	8.76
Rural	**Sites of higher rates**			
	1.Aruvikkara, Trivandrum	9.91	85/174	40.48
	2. Kizhakkoth, Calicut	3.26	43/100	15.19
	3.Kokkayar, Idukki	1.09	13/17	13.11
	4.Alakode, Kannur	6.61	47/128	11.05
	5.Ezhamkulam, Pathanamthitta	1.11	18/33	10.28
	Sites of lower rates			
	1.Vazhakulam, Ernakulam	14.8	17/247	15.65
	2. Mulavukad, Ernakulam	5.66	5/135	14.77
	3.Cherthala, Alappuzha	5.50	11/186	13.96
	4.Kumbadaje, Kasaragod	3.51	0/64	13.69

4.3.2 Spatial clusters of physical inactivity

A total of ten high and seven low spatial clusters of physical inactivity were identified in the urban while there seven high and nine low spatial clusters in the rural, as in Table 4.18.

The primary spatial cluster of physical inactivity (Changanassery in urban setting and Punnapra in rural setting) had thrice the risk of being a spatial cluster of high rates as compared to the sampling sites in both urban (RR = 3.21, LLR = 152.73, $p<0.01$) and rural (RR = 3.87, LLR = 88.9, $p<0.01$) settings.

Meanwhile, the primary clusters of low rates of physical inactivity were found to have about 100% likelihood for being a spatial cluster of low rates of physical inactivity as compared to other sampling sites in both urban (Chittur, RR = 0.05, LLR = 61.37, $p<0.01$) and rural (Kinanoor, RR = 0.0, LLR = 30.20, $p<0.01$) settings.

The location of clusters ranked having the top five highest relative risks for high and low rates for diabetes are shown in Figure 4.6, and for physical inactivity are shown in Figure 4.7.

Table 4.18. Table showing cluster locations of physical inactivity in the selected population

	Cluster Location	Radius (km)	Cases Observed/ total participants	Relative risk
Urban	**Sites of higher rates**			
	1. Changanassery, Kottayam	3.12	203/268	152.73
	2. Adoor, Pathanamthitta	2.19	90/138	47.63
	3. Tirur, Malappuram	1.55	71/102	43.02
	4. Ernakulam city	4.95	106/193	37.33
	5. Kasaragod city (1)	1.08	30/41	19.94
	6. Kasaragod city (2)	1.11	32/52	14.53
	7. Kalpetta, Wayanad	3.33	56/115	13.69
	8. Nileswaram, Kasaragod	4.34	77/179	12.63
	9. Calicut city	4.44	71/162	12.38
	10. Nilambur, Malappuram	1.08	26/48	8.55
	Sites of lower rates			
	1. Chittur, Palakkad	4.90	3/199	61.37
	2. Koyilandi, Calicut	4.89	4/175	38.90
	3. Thrissur city	4.95	15/244	36.81
	4. Ottapalam, Palakkad	4.67	11/193	28.41
	5. Alappuzha city	4.57	18/203	20.03
	6. Thodupuzha, Idukki	3.33	6/123	19.97
	7. Karunagapally, Kollam	2.45	0/64	19.82
	8. Kasaragod city	2.43	3/92	19.50
	9. Kollam city	4.92	19/197	17.96
	10. Kannur city	3.26	5/104	17.95
	11. Mattanur, Kannur	3.94	1/67	16.96
	12. Ottapalam, Palakkad	0.04	0/41	16.86
	13. Trivandrum city	4.93	6/92	10.77
	14. Pathanamthitta city	2.45	10/112	6.67
	15. Trivandrum city	3.99	0/32	6.03
Rural	**Sites of higher rates**			
	1. Punalur, Alappuzha	1.56	97/133	88.91
	2. Ezhamkulam, Pathanamthitta	4.57	103/170	69.51
	3. Thamarassery, Calicut	3.11	55/115	22.68
	4. Cherthala, Alappuzha	4.44	95/272	17.11
	5. Kalady, Kottayam	3.33	35/69	16.21
	6. Vazhakulam, Ernakulam	4.37	67/187	13.00
	7. Anicadu, Pathanamthitta	3.47	44/113	10.79
	Sites of lower rates			
	1.Kinavoor, Kasaragod	4.87	0/92	30.20
	2.Mylapra, Kollam	2.47	1/87	26.61
	3.Kolayad, Kannur	4.88	0/92	20.15
	4.Kizhakkoth, Calicut	3.95	3/146	17.29
	5.Sulthan Bathery, Wayanad	3.98	9/145	15.81
	6.Alagappanagar, Thrissur	3.50	8/155	14.63
	7.Kanjiramkulam, Trivandrum	4.39	3/86	10.95
	8.Udumbanoor, Idukki	4.67	1/61	10.06
	9.Kokkayar, Idukki	10.01	3/83	9.96
	10.East Kallada, Kollam	4.68	3/113	8.91

Figure 4.6. Map showing spatial clusters of physical inactivity among urban sample population in Kerala

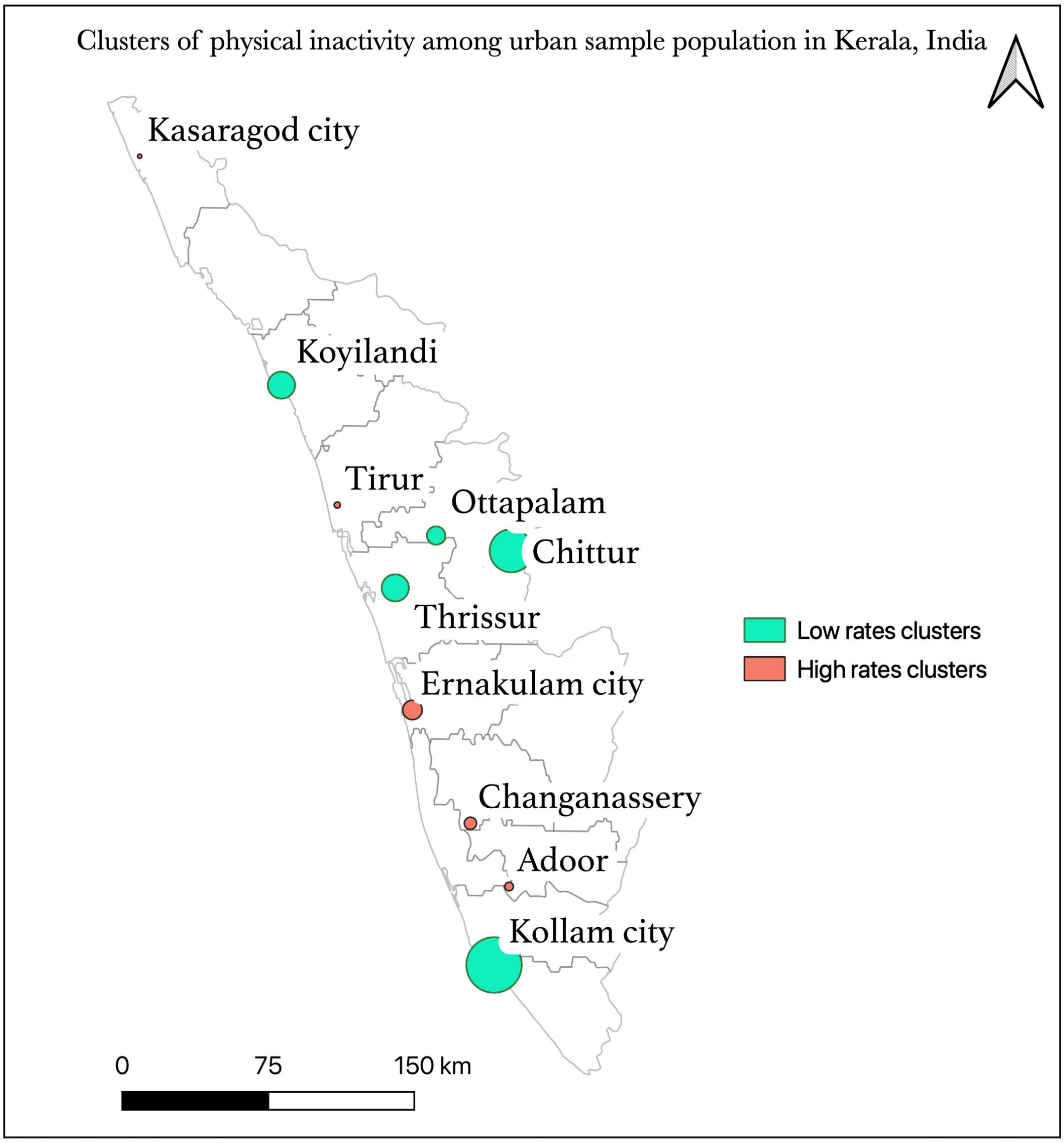
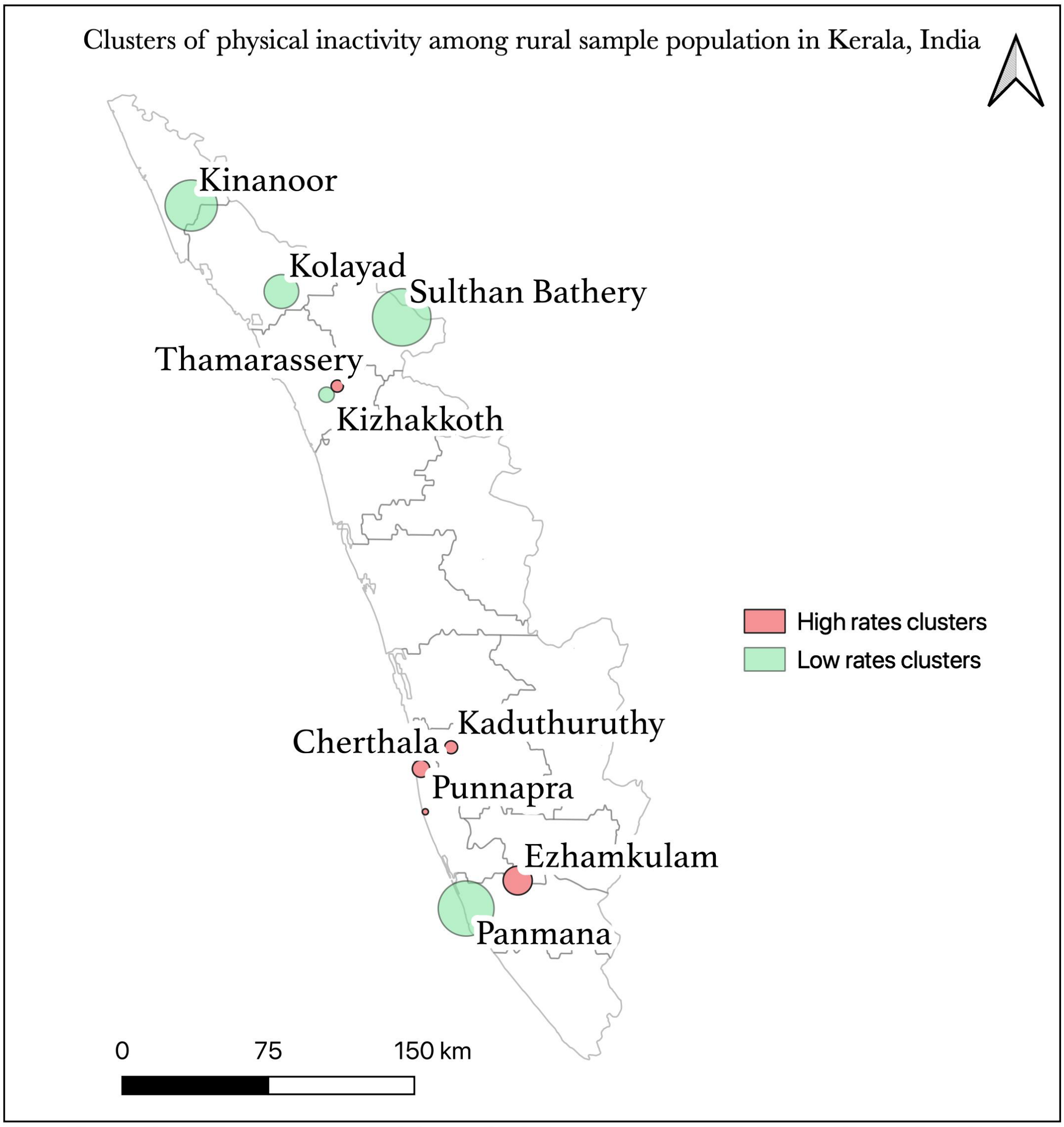


Figure 4.7. Map showing spatial clusters of physical inactivity among rural sample population in Kerala



4.3.3 Comparison of sociodemographic characteristics between high and low clusters

There were significant differences in participants' sociodemographic characteristics ($p<0.01$), except for gender, within high and low clusters of diabetes in the urban setting. On the other hand, among the sociodemographic characteristics, only age (p<0.05) and marital status (p<0.01) showed a significant difference for participants within high and low spatial clusters of diabetes in the rural setting. For participants within high and low spatial clusters of physical inactivity in the urban setting, there were significant differences in gender, educational qualifications and occupational status (p<0.01), while not for age and marital status. In the rural setting, only educational level and occupation showed a statistically significant difference among participants belonging to high and low spatial clusters of physical inactivity (p<0.01) (see Table 4.19).

Table 4.19. Sociodemographic characteristics of participants in spatial clusters of diabetes and physical inactivity

Outcome	Diabetes				Physical Inactivity			
Location	Urban		Rural		Urban		Rural	
Type of cluster	High	Low	High	Low	High	Low	High	Low
Demographic factors								
Age of participants								
18 – 34	***37.0***	***24.9***	**27.8**	**36.5**	29.6	30.5	32.0	32.2
35 – 55	***43.2***	***45.6***	**50.3**	**45.5**	45.6	45.7	43.1	43.9
>55	***19.8***	***29.5***	**21.9**	**18.0**	24.8	23.8	24.9	23.9
Gender								
Female	67.0	63.4	58.7	62.0	***58.5***	***67.3***	63.5	59.4
Male	33.0	36.6	41.3	38.0	***41.5***	***32.7***	36.5	40.6
Marital status								
Single	**12.2**	**16.9**	***15.1***	***23.5***	15.6	15.6	18.1	16.3
Married	**87.8**	**83.1**	***84.9***	***76.5***	84.4	84.4	81.9	83.7
Educational status								
Primary school/Less	***22.8***	***30.5***	28.1	21.9	***22.7***	***26.4***	***20.1***	***31.6***
Higher secondary school	***56.3***	***53.3***	57.7	62.2	***58.2***	***51.0***	***62.3***	***52.7***
Graduation and above	***20.9***	***16.1***	14.3	15.9	***19.2***	***22.7***	***17.6***	***15.7***
Occupational status								
Unemployed	***68.2***	***66.0***	66.3	62.8	***60.6***	***66.9***	***65.3***	***60.4***
Manual labourer	***4.4***	***10.9***	12.2	10.2	***5.3***	***8.8***	***11.0***	***15.8***
Executives/ Businesses	***27.4***	***23.1***	21.4	26.9	***34.1***	***24.3***	***23.7***	***23.8***
Behavioural factors								
>2 servings of Fruits	***80.3***	***33.4***	44.4	49.7	***55.8***	***41.0***	***44.0***	***37.3***
>3 servings of Vegetables	***65.1***	***47.5***	74.5	25.5	***72.8***	***57.4***	60.6	60.8
Tobacco use	4.4	4.1	***7.9***	***2.4***	4.2	5.1	***5.1***	***9.0***

All cell values are in proportions, Bold italic font denotes p<0.01, Bold font denotes p<0.05

4.3.4 Comparison of built environment variables between high and low clusters

Diabetes clusters

In the urban setting, as given in Table 4.20, participants belonging to low clusters had statistically significant higher population density (3366 versus [vs] 2307 persons/square kilometer (sq.km.), residential density (714.87 vs 572 households/sq.km.), built-up density (-0.18 vs -0.20) and intersection density (99 vs 80 per sq.km.). Also, they had lower crime rates (15.17 vs 76.85 per 1,000 persons), pedestrian accident rates (72.84 vs 114.34 per 100,000 persons), greenness (0.44 vs 0.50) and land slope (1.89 vs 2.51), when compared to those belonging to high clusters.

Table 4.20. Neighbourhood characteristics of participants in spatial clusters of diabetes and physical inactivity in the urban sample

Location	Urban	
Type of cluster	High (n = 667)	Low (n = 808)
Diabetes clusters		
Population density	**1065.91 ± 244.52**	**951.07 ± 327.24**
Residential density	**280.36 ± 99.29**	**254.08 ± 119.33**
Crime rate	**5.06 ± 1.96**	**1.59 ± 0.79**
Pedestrian accident rate	**6.92 ± 3.15**	**4.24 ± 1.88**
Greenness	**0.48 ± 0.06**	**0.39 ± 0.13**
Built-up density	-0.19 ± 0.03	-0.18 ± 0.05
Land slope	**2.81 ± 1.33**	**2.25 ± 0.97**
Intersection density	**79.32 ± 72.07**	**90.05 ± 76.50**
Physical inactivity clusters		
Population density	**1194.43 ± 549.51**	**1245.04 ± 487.38**
Residential density	342.84 ± 222.67	331.59 ± 165.29
Crime rate	**3.70 ± 2.44**	**2.92 ± 1.42**
Pedestrian accident rate	**7.98 ± 8.19**	**6.18 ± 3.38**
Greenness	**0.43 ± 0.13**	**0.41 ± 0.11**
Built Index	**-0.18 ± 0.06**	**-0.17 ± 0.07***
Land slope	**2.30 ± 1.59**	**2.41 ± 1.53**
Intersection density	**144.09 ± 175.15**	**103.33 ± 111.18**

All cell values are given as mean ± standard deviation, Bold font depicts significant relationship (p<0.05).

However, in the rural setting, as given in Table 4.21, participants belonging to low clusters had statistically significant higher population density (1674 vs 1333 persons/sq.km.), residential density (404.72 vs 329.78 households/sq.km), crime rates (107.89 vs 51.54), pedestrian accident rates (395.67 vs 386.73), built-up density (-0.16 vs -0.25). In contrast, they had lower greenness (0.39 vs 0.53) and land slope (1.63 vs 5.54) when compared to those belonging to high clusters.

Table 4.21. Neighbourhood characteristics of participants in spatial clusters of diabetes and physical inactivity in the rural sample

Location	Rural	
Type of cluster	High (n = 452)	Low (n = 632)
Diabetes clusters		
Population density	**1211.74 ± 372.28**	**1546.84 ± 722.36**
Residential density	**368.31 ± 179.45**	**441.03 ± 213.31**
Crime rate	**2.39 ± 1.56**	**5.25 ± 2.31**
Pedestrian accident rate	**5.49 ± 4.60**	**14.82 ± 12.69**
Greenness	**0.53 ± 0.10**	**0.38 ± 0.17**
Built-up density	**-0.24 ± 0.04**	**-0.16 ± 0.06**
Land slope	**6.96 ± 3.39**	**1.89 ± 1.32**
Intersection density	22.57 ± 71.32	25.81 ± 33.42
Physical inactivity clusters		
Population density	**1075.05 ± 499.79**	**1075.06 ± 499.79**
Residential density	**335.63 ± 63.64**	**270.16 ± 123.55**
Crime rate	**5.56 ± 3.47**	**3.27 ± 1.85**
Pedestrian accident rate	**7.42 ± 3.69**	**5.43 ± 3.35**
Greenness	**0.48 ± 0.08**	**0.54 ± 0.06**
Built-up density	**-0.19 ± 0.04**	**-0.22 ± 0.06**
Land slope	**2.50 ± 1.75**	**5.28 ± 4.19**
Intersection density	**17.47 ± 19.13**	**12.95 ± 18.21**

All cell values are given as mean ± standard deviation, Bold font depicts significant relationship (p<0.05).

Physical inactivity clusters

Both population and residential density were not found to be significantly different in high and low physical inactivity clusters located in the urban and rural setting. Among the urban participants, those belonging to low clusters had statistically significant lower crime rates (31.34 vs 43.46 per 1,000), pedestrian accident rates (71.90 vs 95.62 per 100,000), greenness (0.42 vs 0.46) and intersection density (109.95 vs 146.01); and higher built-up density (-0.17 vs -0.18).

Among the rural participants, those belonging to lower physical inactivity clusters had lower crime rates (76.17 vs 117.23 per 1,000), pedestrian accident rates (104.55 vs 175.04 per 100,000), built-up density (-0.24 vs -0.21), land slope (2.22 vs 4.12) and intersection density (14.34 vs 17.48 per sq.km.). In contrast, they had higher greenness (0.56 vs 0.51) when compared to those belonging to high physical inactivity clusters.

CHAPTER 5

DISCUSSION

5 DISCUSSION

5.1 Introduction

This thesis was formulated to capture built environment variables using available open-source solutions and understand the relationship between the neighbourhood's built environment characteristics and non-communicable diseases in the Indian setting. This research was conceptualized based on gaps in research literature from India. It depicted the relationship between the selected built environment characteristics in the neighbourhood and the prevalence of diabetes and physical inactivity in the previous chapter. This relationship was established through two methodological considerations: by comparing spatial clusters of high and low rates of diabetes and physical inactivity and depicting the most significant contributors to diabetes and physical inactivity. This chapter purposes of providing the interpretation of the results, explain potential implications for public health and suggest recommendations for future research.

This chapter is organized in the following manner:

1. Summary of findings from this research
2. Distribution and relationship between built environment variables across Kerala
3. Relationship between built environment variables and the prevalence of diabetes and physical inactivity
4. Constraints in the capture of data in low-and-middle-income countries
5. Importance of policy initiatives

6. Strengths and limitations of this research
7. Future recommendations

5.2 Summary of findings from this research

5.2.1 Summary of objective 1

This objective depicted distinct patterns in the distribution of the variables of interest, namely, population density, residental density, crime rates, pedestrian accident rates, built-up density, greenness, intersection density and land slope, across the districts and subdistricts of Kerala. Moreover, strong correlations were found between certain built environment variables, across both districts and subdistricts.

5.2.2 Summary of objective 2

The discriminant analysis results have given us evidence of the varied influence of built environment variables on each outcome for both urban and rural neighbourhoods.

Urban scenario:

Crime rates and the pedestrian accident rate has proved to be a significant discriminator for diabetes and physical inactivity. This finding provides evidence that crime rates and pedestrian accident rates in the neighbourhood have a profound effect on individuals' ability to walk or engage in physical activity and hence contribute to being obese or having diabetes.

Intersection density has been found to contribute to diabetes and physical inactivity. This finding could point towards the importance of road intersections in the urban neighbourhoods to engage in physical activity and contribute to inhabitants being diagnosed with diabetes. Similarly, built-up density in urban neighbourhoods has contributed to physical inactivity and diabetes. This implies that the urbanicity in the urban neighbourhoods accounting for the residential, commercial and recreational spaces within the neighbourhoods are significant for inhabitants to engage in physical activity and having diabetes.

Rural scenario:

Residential density proves to be a significant contributor to diabetes and physical inactivity. This finding implies the importance of higher residential density in rural neighbourhoods to engage in physical activity to be non-diabetic. Built-up density and land slope in the rural neighbourhoods have shown contribution towards diabetes and physical inactivity. Crime rates and pedestrian accident rates have emerged to be inconspicuous for physical inactivity. Intersection density seemed to contribute to diabetes, though not emerging as a significant one for physical inactivity or obesity.

5.2.3 Concordance of results from discriminant analysis and spatial cluster analysis

Urban scenario

All the discriminating variables found to be significant contributors towards diabetes and physical inactivity were significantly different in high and low spatial clusters of diabetes. The discriminating variables were crime rates, pedestrian accident rates, intersection density, built-up density and land slope for diabetes. Simultaneously, they were crime rates, pedestrian accident rates, intersection density and built-up density for physical inactivity.

Rural scenario

Discriminators such as residential density, built-up density and land slope proved significantly different for high and low spatial clusters of diabetes except for intersection density. While for the spatial clusters of physical inactivity, all the discriminating variables showed significant differences among high and low clusters.

5.3 Distribution and relationship between built environment variables across Kerala

Distribution across districts and subdistricts showed that population density and residential density were highly correlated and related to accident rates, intersection density and land slope. The higher population density and residential density reflected higher built-up density within the subdistricts. Higher residential density was related to higher intersection density, crime rates and pedestrian accidents. But higher population and residential densities were related to lower land slope and greenness. These could determine the urbanicity of the districts and sub-districts.

Population density is closely linked with the built-up area, and they are imminent to depict urbanization (Ehrlich et al. 2018). The detailed study of population and built-up land among districts for 30 years from Yemen, a south-west Asian country, showed population density and its relationship to built-up growth. They concluded that an increase in population is primarily followed by growth in the built-up area, though not immediately following the population trend (Zeug & Eckert 2010).

A recent study from Istanbul, which tried to depict the spatial distribution of crime rates across districts, showed higher crime rates due to population and migration (Ergun & Yirmibeşoğlu 2007). In Columbus, Ohio, urban neighbourhoods showed a curvilinear association between residential density and crime rates. They have also found evidence that dense urban settings increase pedestrian traffic (Browning et al. 2010). Meanwhile, findings among 142 municipalities in the United States depict that population density had a significant negative relationship with property crimes (Battin & Crowl 2017). The relationship between population densities and vegetation was analyzed within suburban and urban areas in the United States, using satellite sensors to capture vegetated areas. The authors found the vegetation fraction (a measure of greenness) diminishing with the rise in population densities in urban and suburban areas (Pozzi & Small 2002). Furthermore, higher pedestrian accident rates in dense regions and high-density urban neighbourhoods have been documented previously from Los Angeles (Loukaitou-Sideris et al. 2007).

Our study could also demonstrate the inverse relationship of greenness with crime and pedestrian accident rates. Authors from Portland reported similar findings when they tried to identify the effect of green infrastructure on violent crimes in the neighbourhood. The findings indicated a strong negative correlation between violent crimes and the greenness following planting trees in the neighbourhoods (Burley

2018). Fan and colleagues mirrored these results in a systematic review in the United States based on ten studies on urban green space and crime rates. This review has summarised that urban green space dramatically influences the lowering of crime rates in the neighbourhoods (Fan et al. 2011). Moreover, neighbourhood vegetation was also found to directly influence the decrease in Chicago crime rates (Bogar & Beyer 2016).

5.4 Relationship between built environment variables and the prevalence of diabetes and physical inactivity

5.4.1 Neighbourhood walkability

Walkable neighbourhoods are characterized by higher population density, residential density and street connectivity. Hence, we discuss findings related to population density, residential density in this section.

Population and residential density were conducive for diabetes in both urban and rural settings. These findings are synchronous with a recent systematic review that population density and residential density are positively associated with diabetes mellitus and metabolic syndrome (Malambo et al. 2016). On similar lines, a cross-sectional study from 78,023 adults in Canada demonstrated lower glycated haemoglobin (hbA1c) to be significantly associated with walkability (Loo et al. 2017). Moreover, longitudinal follow-up of 1079 participants in the CARDIA (Coronary Artery Risk Development in Young Adults) study from Alabama showed a lowering of cardiometabolic risk factors with increased neighbourhood walkability(Braun et al.

2016). Previous cross-sectional studies have also correlated the prevalence of diabetes with walkability in the neighbourhoods (Glazier et al. 2014; Müller-Riemenschneider et al. 2013), though these findings cannot be taken as causal relationships, they can be suggestive evidence for future planning of neighbourhoods.

Many studies have identified similar trends for physical activity and obesity clusters and meeting physical activity recommendations (Tamura et al. 2014; Troped et al. 2017). Evidence from 14 cities across ten countries has also shown residential density to be positively associated with physical activity (Sallis et al. 2016). However, a recent systematic review on evidence from LMICs has rightly pointed out the stark difference in density in developing countries. The highly dense neighbourhoods might reflect unplanned urbanization and are not substantially comparable to density in developed countries (Elshahat et al. 2020). Kerala has also exhibited a similar pattern of rapid urbanization, and more importantly, the dense neighbourhoods in Kerala are closely linked to the residents' socioeconomic status (SES). The neighbourhood SES also determines the physical environment, access to services, social connections, and culture within the neighbourhoods (Devassy et al. 2020). This analogy on neighbourhood SES and its linkages on diabetes and physical activity are still lacking from LMICs.

Moreover, highly dense neighbourhoods within LMICs portray the social status of the residents. There can also be social prejudice towards those who own cars and those who engage in walking (Shoham et al. 2015). Also, a dense neighbourhood may not be ideal to reside in LMICs due to inadequate safety related to lack of bicycling infrastructure and high-speed motorized transport (Bener 2005). Hence, the findings of this study favour the argument for context specificity of the relationship between dense physical environments on diabetes or physical activity.

5.4.2 Road inter-connectedness

The body of evidence on road inter-connectedness has interchangeably used street connectivity and intersection density to find linkages with diabetes and physical inactivity. Therefore, we discuss our findings on intersection density with studies that have captured both street connectivity and intersection density.

Higher intersection density was found in low clusters of diabetes in the urban setting. This finding portrays the importance of street connectivity in urban neighbourhoods. Street connectivity has been positively associated with a lower sedentary time in about 17 urban areas, selected across 12 countries (Wendel-Vos et al. 2007). The intersection density is closely associated with walkability, which has lower the incidence of diabetes in Ontario, Canada (Mena et al. 2017). A recent cross-sectional study among New Zealand adolescents showed an increase in diabetes-related metabolic factors with an increase in street connectivity in the neighbourhood (Smith et al. 2019).

On the contrary, in our study, the road intersection density was not related to the prevalence of physical inactivity in both urban and rural settings. This contrast could be due to the difference in the capture of diabetes using objective methods and estimation of physical activity using subjective measures.

Higher intersection density has been previously found to favour physical activity and walking behaviours in developed nations (Adlakha et al. 2016c). Also, walkable neighbourhoods were positively related to physical activity in the London Cohort Study (Clary et al. 2020). Recent findings from China showed a positive association of the number of intersections with physical activity and attributed reduced shopping distance and higher neighbourhood commerce with higher road network connections (Sun et al. 2019). Evidence from Missouri, United States, showed higher engagement in parks by residents living in higher quartiles of street connectivity (Kaczynski et al. 2014). However, other evidence from LMICs showed no association of physical activity with self-reported or objective street connectivity (Elshahat et al. 2020). The reasons for insignificant relationships with physical activity can be attributed to the stark differences in road infrastructure, lack of pedestrian pathways and weak road-traffic policy enforcement in LMICs (World Health Organization et al. 2009). Beyond these infrastructural deficiencies, developing countries face gendered norms or societal pressure that hinder walking in the day/night or cause uncomfortable scenes within neighbourhoods (Kaplan et al. 2015). The other contrasting feature in LMICs is the overdependence on taxis or autorickshaws, which might deem street connectivity or access to various facilities within the neighbourhood as unimportant (Finn & Mulley 2011).

5.4.3 Built-up density and urbanicity

Our findings showed that higher built-up density or greater urbanicity were related to lower prevalence of diabetes and physical inactivity in the urban areas. The inverse relationship portrays that a higher number of buildings and a higher ratio of marketplaces in urban settings are opportunistic for urban residents. This relationship could also mean that the urban residents found urbanized neighbourhoods safe for engaging in physical activity or walking for leisure.

The urbanicity advantage is congruent with other studies from the US, where land-use was associated with meeting physical activity recommendations. In contradiction, the Philippines' findings indicated urban areas to be obesogenic (Li et al. 2008; Dahly et al. 2013). Urbanicity and rurality have been linked to socioeconomic conditions in the United States, where rural areas showed a very high burden of diabetes (Stewart et al. 2011). The probable pathways were delineated to lack of safe places or sidewalks, lack of parks near neighbourhoods and lower access to primary care (Eberhardt & Pamuk 2004; Krishna et al. 2010).

Similarly, the built environment's quality was closely linked to discrimination and poverty, which were associated with a higher risk of diabetes. This relationship was demonstrated in North Carolina using a spatial modelling approach beyond the food environment and physical activity pathways (Bravo et al. 2019). Moreover, low-income households are likely to be located near unhealthy stores rather than healthy food outlets, as demonstrated in the United States. Findings from China and Sweden showed a similar pattern of diabetes and its relationship with socioeconomic characteristics (Sundquist et al. 2015; Zhang 2017). The density of fast-food restaurants has been associated with diabetes prevalence in the United States. Salois and colleagues demonstrated the importance of the local food economy on diabetes prevalence (Salois 2012). They have argued that the presence of fast-food restaurants has a more significant impact on the prevalence of diabetes than supermarkets or grocery stores in the neighbourhood. A coherent finding was demonstrated in Braver and colleagues' systematic review, where both convenience stores and fast-food restaurants were associated with higher diabetes prevalence (den Braver et al. 2018).

5.4.4 Land slope

Low lying areas or more downward land slope were related to a lower prevalence of diabetes in urban areas in this study. This finding is contrary to results from Perth, Australia. Villaneuva and colleagues found hilly neighbourhoods to be protective of diabetes (Villanueva et al. 2013a). Fujiwara and colleagues used data from the Japan Gerontological Evaluation Study and determined no association of diabetes with the hilliness in the neighbourhood. However, they found a protective effect against poorly controlled diabetes (Fujiwara et al. 2017). Also, evidence from China could not demonstrate a relationship between land terrain and physical activity but could show that residents in areas with steeper slopes had lower body mass indices (Sun et al. 2019).

5.4.5 Crime rates in the neighbourhood

Crime rates were significantly lower in neighbourhoods with low rates of both diabetes and physical inactivity in the urban environment. This relationship was earlier documented for perceived crime rates, where a very low incidence of diabetes mellitus was associated with perceived neighbourhood crime (Dendup et al. 2021). The urban scenario was similar to previous studies from Canada, where a higher prevalence of diabetes was related to higher crime rates. A similar trend is reflected in Chennai, India, where walkability was related to low crime rates. From Ghana, adults engaged in more elevated amounts of physical activity in neighbourhoods with low crime rates (Green et al. 2003; Dake 2012; Adlakha et al. 2016d).

Counties with high crime rates in the United States had been found to have a higher prevalence of diabetes, and about 60% of this relationship was mediated by physical activity (Hanigan et al. 2020). Area-level influences demonstrated similar trends in the United States by violent crime rates on diabetes (Dewulf et al. 2016) and physical activity (Foster & Giles-Corti 2008). Crime rates were also significantly found to play a mediating role between being physically active and the risk of developing diabetes (fish.2010). Other studies from LMICs, from Mexico and Brazil showed that perceived safety was linked to meeting recommended levels of total physical activity (Parra et al. 2010; Jáuregui et al. 2016a). Some findings indicate that East-Asian countries are less likely to consider safety an influential factor within the built environment (Lee et al. 2017). Moreover, perceived safety from crime have also been related to physical activity, weight status and walking (Troped et al. 2011).

However, the crime rates did not depict a significant relationship with diabetes or physical inactivity in the rural environment. Evidence form African adults showed a non-significant relationship between the crime rates and meeting physical activity recommendations (Oyeyemi et al. 2011). However, Stewart and colleagues found that rural areas have an elevated rate of diabetes prevalence due to a lack of safe places and inaccessible parks (Stewart et al. 2011). Ding and colleagues have also recommended further investigations on domain-specific physical activity and crime rates (Ding et al. 2013). On the contrary, findings from underserved neighbourhoods in the United States showed that crime rates aided in amplifying barriers to meet physical activity recommendations (Park et al. 2020). Moreover, those with diabetes residing in high-crime neighbourhoods were associated with decreased odds of diabetes control. These results were mirrored for treatment adherence (Tung et al. 2018) and glycemic control (Lê-Scherban et al. 2019) among adults living in unsafe neighbourhoods.

5.4.6 Pedestrian traffic in the neighbourhood

Low pedestrian traffic rates were significantly related to a lower prevalence of diabetes and physical inactivity in urban settings. Lower traffic rates have been earlier related to lower insulin resistance and lower prevalence of obesity (Thiering et al. 2016b). Perceived safety from traffic has also contributed to meet physical activity recommendations (Zhou et al. 2013). In Kansas City, participants in neighbourhoods with low traffic routes were more likely to use parks and engage in physical activity (Kaczynski et al. 2014). Conversely, an inverse relationship, was documented among Nigerian adults, where perceived traffic safety was related to decreased amounts of physical activity (Oyeyemi et al. 2012). In contrast, non-significant relationships were found in Mexico and Brazil (Parra et al. 2010; Jáuregui et al. 2016b).

Transportation is different in LMICs since physical activity is more significantly associated with public transport services (Elshahat et al. 2020). Also, the suburban roads enable vehicular traffic but unsafe for pedestrians, hence proving a barrier for physical activity (Loukaitou-Sideris et al. 2007). Moreover, traffic congestion is closely linked to the residential density with thin neighbourhood clary. Hence, urban neighbourhoods are innately prone to higher pedestrian accident rates.

5.4.7 Greenness in the neighbourhood

Lower greenness was significantly associated with a lower prevalence of diabetes and physical inactivity in the urban areas. However, an increase in physical activity was seen with greenness in the neighbourhood among late middle-aged adults from Belgium, adolescents from Germany and adult women in the United States (Markevych et al. 2016; Dewulf et al. 2016; James et al. 2017). Also, cross-sectional studies from Canada showed that those participants residing in the highest quartile of greenness were more likely to participate in walking (McMorris et al. 2015), and those who had higher greenness around their homes or along the path of commute had been more involved in walking and cycling (van Heeswijck et al. 2015). Results from the United Kingdom Biobank among 3,33,183 participants tend to show a similar trend of increased odds of walking and cycling with increased greenness in the neighbourhood (Sarkar 2017). Also, lessons from China prove that a 0.1 unit increase in greenness showed 0.88 lower odds of insulin resistance. Evidence from rural Chinese Uyghur adults also showed a declining prevalence of diabetes with higher greenness (Fan et al. 2019). Dalton and colleagues have demonstrated that greenness in the neighbourhood proved to be protective for incident diabetes among older adults (Dalton et al. 2016). However, physical activity failed to be a significant mediator in the relationship between greenness and diabetes in many studies (Astell-Burt et al. 2014; Thiering et al. 2016a; Dalton et al. 2016). Hence, there was no sufficient evidence from LMICs to substantiate the role of greenness in the risk of diabetes or in meeting physical activity recommendations.

5.5 Constraints in the capture of data in low-and-middle-income countries

Researchers in low-and-middle-income countries face challenges in data collection, storage, sharing, and ensuring data quality across sites and sources (Nori-Sarma et al. 2017). The Central Government's institutions have more tight and stringent rules for non-spatial data sharing, which can be stumbling blocks for young researchers in LMICs. Similar hurdles are in place for access to spatial data; for example, the Bhuvan website run by the National Remote Sensing Centre includes long procedural delays, processing fee, etc. These hurdles can potentially impact the research flow and pose a burden for young researchers in public health. One recent change in the GIS data policy in India to ease access to geospatial data will be largely beneficial for upcoming researchers (Ministry of Science and Technology 2021).

Moreover, the compilation of data from various sources raises concerns about compatibility and standardization. Institutions (E.g. Crime Records Bureau) and databases (E.g. Census) have data in multiple data formats (Microsoft Excel/ Microsoft Word/ PDF) and different jurisdictional boundaries (A police station boundary could include two census blocks).

Physical activity research among the developed nations has a widely captured walkability index, which includes data characteristics on land use and accessible destinations (e.g., bus stops, restaurants, hotels, gyms, parks, etc.). The data that was require for computing the walkability index was found lacking and, in some instances, were not shared for research. Land use data described by the Census of India provides a description of agricultural land, barren land, and cropland which are not sufficient to compute the walkability index. Moreover, data on land spaces of residential/ institutional/commercial use are easily accessible in the high-income countries, while not for the low-and-middle-income countries. Nevertheless, the coming decade can witness advanced spatial techniques and expertise to generate these data.

5.6 Importance of policy initiatives

The Government of India has implemented the National Programme for Prevention and Control of Cancer, Diabetes, Cardiovascular Diseases and Stroke (NPCDCS) across all States (Government of India 2016b). India was among the first nations to implement the Global Action Plan recommended by the World Health Organization in 2013 (World Health Organization 2013b). The main objectives of this programme are focussed on increasing awareness, setting up NCD clinics and initiating screening. However, the policies seem to be lagging on the creation of active societies, active environments, active people and active systems as recommended by the Global Action plan on physical activity by the WHO. Several initiatives in the past body of literature substantiate successful results by policy changes and regulations.

Strategies to improve bicycling and pedestrian transportation have paid dividends to raise physical activity levels, as Omura and colleagues elaborated in their advisory from the American Heart Association (Omura et al. 2020). They have based their recommendations on a systematic review of 90 studies focussed on interventions and population-based approaches that enabled physical activity. Based on microscale interventions that are best suited for the residents in a neighbourhood, community designs will be highly recommended in developing countries (Elshahat et al. 2020). The LMICs have an additional burden of lack of walking paths, hurdles in maintaining cleanliness and enforcement of road regulations (World Health Organization et al. 2009).

Few previous attempts in enforcing safety within cities and neighbourhoods were to regulate traffic by using traffic control devices – traffic signals, the lighting of streets and pavement markings (Loukaitou-Sideris 2006). Traffic calming measures in Europe, Canada and the United States, including road narrowing, creating medians and traffic circles, brought down traffic crashes by about 77%. The basic physical infrastructure for pedestrians to walk is necessary and should be incorporated in the city designs, which is lacking in suburban residential streets (Perdue et al. 2003). Lack of attention on pedestrians in modern city planning techniques has made the roads less safe to walk. Therefore traffic regulations beginning with the lowering of vehicular speeds and creating safe zones around schools and homes are recommended with high priority to enable safe environments for physical activity and walking. Also, reasonable measures to encourage active transport include a combination of road pricing, improving bike and pedestrian infrastructure, and densification of cities (Ahmad et al. 2020).

Beyond traffic safety, upstream level interventions are most necessary to tackle crimes and fear of crime. Each neighbourhood may have different characteristics depending on the location and the socioeconomic position of the residents. Understanding each neighbourhood's intricacies and catering to individual needs would be the right way forward (Park et al. 2020). In urban poor or rural neighbourhoods, both the social and physical environment may be disadvantageous for residents, such as housing, poverty, lack of education or inadequate food access. In such scenarios, considerations of local contexts and geographic conditions are unavoidable (Boulware et al. 2020). Prior policy initiatives on reducing crimes encompassed improved lighting on the streets and creating safe hang-out places (Loukaitou-Sideris 2006). Moreover, neighbourhoods with good socioeconomic positions could initiate programs within their boundaries by recruiting volunteers to escort the vulnerable citizens, including women and children.

Design interventions within neighbourhoods that are collaborative and democratized within the communities concerned is recommended. Especially in the present pandemic of coronavirus disease (COVID -19), having time and activity zones and activity from home-door to home door within the neighbourhood may help residents maintain physical activity (Jurak et al. 2020). Few reports have evidence that children and adults had a unique trend to engage in physical activity on the sidewalks and roadways during the pandemic (Dunton et al. 2020). Also, in some instances, traffic calming signs were installed on the streets for the drivers to slow down and allow pedestrians to engage in walking with social-distancing measures. Empowering local communities to make decisions and maintain safety within the neighbourhoods will be crucial.

Not all interventions reflect substantial changes in behaviour. Recent evidence from the Netherlands showed the introduction of activity spaces in Dutch cities to encourage physical activity among children. However, longitudinal follow-up of 1841 children indicated that the physical activity levels only in socially disadvantaged families (Mölenberg et al. 2019).

5.7 Strengths and limitations of this research

This thesis has multiple strengths which have contributed significantly to public health research in LMICs. One of the most significant strengths was the possibility to capture available built environment variables using open-source solutions and their reproducibility. The other important strength was the inclusion of a large dataset of sample population selected across the expanse of a whole state in India. This sample has dealt with the possible bias of choosing a uniform kind of neighbourhood and has brought the diversity of neighbourhood characteristics of participants across Kerala.

The cost-effectiveness of such an exploration will help researchers to use available resources to the maximum. Also, such an investigation can be reproduced as time-series studies or comparative studies among diverse settings. The present study was a first-of-its-kind attempt to answer the neighbourhood influences on diabetes and physical inactivity. The stark differences in the built environment characteristics among the urban and rural areas were brought forth by this research, which seems to be a significant step towards further study.

Another important revelation from this study is not to neglect spatial analysis in public health research. Spatial epidemiology can expand the horizons of unchartered territories in public health. Such an enquiry could also provide resolutions to scores of unanswered questions in LMICs. Available resources with accurate spatial analysis approaches could enrich and equip public health researchers in this fast-advancing digital world.

This study could also emphasise the opportunities and importance of an inter-disciplinary approach to disease occurrence and prevalence. The strong influence of spatial parameters on the disease prevalence underscores the need to bring in elements of geography in the realm of public health research. This can be best designed using collaborative approach with varied disciplines including geography experts, cartography designers and health experts.

There are a few weaknesses in this research that may have directly or indirectly impacted the findings. Firstly, though significant differences in the built environment characteristics were found in the spatial clusters of high and low diabetes and physical inactivity rates, the findings cannot demonstrate causality. To state the causal relationship, there is a need to depict that the exposure of the built environment characteristics had been in place before the participants were diabetic or physically inactive. Since it was not possible to display time in this research, one cannot affirm that the exposure caused the outcome.

Secondly, another shortcoming of this thesis is concerning the exposure to the built environment characteristics in the neighbourhood. The length of exposure to these characteristics was not captured since there was no data on the length of stay at the present residence. This can affect the exposure of the participants in terms of time or temporality. Hence, the exposure cannot be standardized and could compromise the statistical inferences.

Thirdly, there was a shortcoming in the discordance between the manner of capturing diabetes and physical inactivity. Diabetes was measured as an objective measurement of blood glucose levels in the blood samples, while physical inactivity was defined through subjective assessment using a questionnaire. This might be why specific built environment characteristics were unmatched for those with diabetes and physical inactivity. There are also previous pieces of evidence pointing towards self-reports of physical inactivity overestimating the findings when compared to that which is captured objectively using an accelerometer. Again, this thesis dealt only with the total metabolic equivalent minutes and not specific to any of the domains of physical inactivity, namely transport, or recreational, or walking, Fourthly, there was also a limitation to develop models concerning the built environment characteristics, as the available variables were insufficient to measure the walkability index. A walkability index is considered the standard measurement in built environment research related to physical inactivity. This index is estimated from street connectivity, residential density and land-use mix. Calculating the walkability index was not possible in this thesis since we had no access to data on the land-use mix. Moreover, the multi-level nature of data capture, both at the participant residence level and Panchayat level, requires further exploration and capture of built environment characteristics to truly create an explanatory model.

Fifthly, limitations due to assimilating data from various sources exist, such as the difference in categories across datasets and differing jurisdiction boundaries. For example, one police station jurisdiction may include limits of two census boundaries. Differing boundaries were dealt with to an extent after manifold references to police stations' jurisdiction details and census boundaries. Furthermore, some of the data captured were not initially captured for research purposes, especially crime and pedestrian accident statistics. Hence, one cannot assure the quality of such data. Though this research has the luxury of using the available open-source data in public health research, there are uncertainties about those compiled through crowdsourcing, especially that with OpenStreetMap. More importantly, they are not complete and reliable compared to the data available in developed countries.

5.8 Future recommendations

This thesis could demonstrate relationships between built environment characteristics within the neighbourhood and diabetes and physical inactivity in India. Yet, there is a large void of how and why this relationship is significant in low-and-middle-income countries. There are also no answers to how much influence the neighbourhood contributes to an individual being physically inactive or having diabetes.

Additionally, a lack of clarity exists on which neighbourhood characteristics primarily influence sociodemographic groups. Studies focussing on older adults or working adults or those who travel to work or those who are unemployed need to be undertaken to throw light on specific influences for these groups. Further research should also elucidate the differences in particular occupation groups, for example, the groups involved in fishing, who are engaged in strenuous physical activity in the occupations but reside in low-lying or coastal areas.

Besides, there is an enormous cavity in governmental policies for safe and walkable neighbourhoods in LMICs, especially India. This research's findings are indeed a wake-up call for research on policies drafted and implemented. The onus of the citizens being physically active or walking needs to be shifted to the policymakers too. Therefore, an in-depth investigation of policies implemented within neighbourhoods could be undertaken in the future. However, it is worthy of adulation that the Government of India has initiated the Fit India Movement under the Ministry of Youth

Affairs and Sports. The objectives of this movement are aligned to the findings of this research, which encourages citizens to participate in indeigenous sports, and make fitness reach every school/ college/ university/ panchayat/ village.

Another arena of further examination is the perception of built environment characteristics within the neighbourhood across different cultures. Being a multi-cultural country and having diverse norms and values, India has a high scope of bringing out differences in perception of safety or walkability within neighbourhoods. Even within Kerala, the northern and southern residents have stark differences in their norms and values. Therefore, there can be a study within the state across various cultural backgrounds to elucidate how residents perceive their neighbourhood safety and walkability.

Moreover, a monumental task is to detect the unnoticed characteristics of neighbourhoods within LMICs: cleanliness, stray dogs, etc. The list can include many, which this research cannot summarise. There needs to be a qualitative exploration to bring to light such characteristics that profoundly influence residents' choices to walk or be active in their neighbourhoods. This particular research area is crucial for LMICs because these unnoticed characteristics are not components of settings in developed countries.

The discovery of a walkability index standardized for a neighbourhood seems to be a long-lasting goal. Such an attempt could be possible in future with advanced statistical techniques and spatial analytical modelling. After that, an unbiased index could genuinely determine how much walkable or safe a neighbourhood is for a resident. Moreover, this exploration also needs to be undertaken for a cohort with a specific duration of stay within the specified community, which can help delineate the neighbourhood's actual effects on physical inactivity.

CHAPTER 6

SUMMARY AND CONCLUSION

6 SUMMARY AND CONCLUSION

In the backdrop of a global epidemic of non-communicable diseases, the LMICs need to shoulder greater responsibilities in tackling the same. The findings of this study reiterated the need for evidence on the objective built environment from LMICs. Also, the results of this research enlighten the importance of engaging spatial analyses in public health investigations.

This thesis found evidence on the pattern of distribution of built environment characteristics across a state in India. Moreover, contributing factors in the neighbourhood for diabetes and physical inactivity showed urban-rural differences, requiring further exploration. The findings have confirmed similarities to the results from high-income countries on the relationship between the built environment and physical activity/ diabetes. Also, this dissertation has provided compelling evidence on harnessing available open-source solutions to understand linkages to the high burden of non-communicable diseases.

Further enlightenment on the pathways in which the built environment relates to lifestyle behaviours and physical activity in LMICs is imperative. Several recommendations have been proposed on advancing the direction of NCD research toward urbanicity, access and safety within neighbourhoods in LMICs.

Additionally, the findings advocate for a whole-of government approach to public health, rather than a focussed approach by the health sector on its own. The results therefore, call for a stratagem of interdisciplinary research involving collaborative efforts and amalgamated decision-making processes by technical experts in fields apart from public health.

In conclusion, the role of 'place' and the necessity of 'spatial data' should be considered with utmost importance in further research on the epidemiology of non-communicable diseases in LMICs.

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ANNEXURES

LIST OF PUBLICATIONS FROM THESIS

1. **Using open-source data to explore distribution of built environment characteristics across Kerala, India (Indian Journal of Public Health, June 2020)**
   Available at: https://www.ijph.in/text.asp?2020/64/2/191/286818
   This paper intended to delineate methods to capture available and accessible built environment variables for the state of Kerala, India. All the built environment variables for districts and subdistricts were captured using open-source solutions and were collated from Census of India, State Crime Records Bureau, OpenStreetMap and satellite Imagery.

2. **Spatial clusters of diabetes and physical inactivity: do neighborhood characteristics in high and low clusters differ? (Asia Pacific Journal of Public Health, Dec 2019)**
   Available at: https://journals.sagepub.com/doi/10.1177/1010539519879322
   This paper was based on PhD thesis and attempted to find spatial clusters of diabetes and physical inactivity among a sample population in Kerala using SaTScan. and to evaluate built environment characteristics within high and low spatial clusters

3. **Gender differences in the relationship between built environment and non-communicable diseases: A systematic review (Journal of Public Health Research, April 2018)**
   Available at : https://www.jphres.org/index.php/jphres/article/view/1239
   This paper summarizes the current evidence on influence of gender in the relationship between built environment and non-communicable diseases.

CURRICULUM VITAE

Education

Sree Chitra Tirunal Institute for Medical Sciences and Technology
Doctor of Philosophy - PhD, Public Health

2015 – 2020

This doctoral program was granted Institute Fellowship from SCTIMST for five years. The research was on the built environment and non-communicable diseases in Kerala using a dataset of 12000 participants. Distribution of built environment characteristics among districts and sub-districts of Kerala were attempted using QGIS. Spatial clusters of diabetes and physical inactivity were identified using SaTScan. Got trained in Epidemiology, Biostatistics, Quantitative and Qualitative research methods. Software handled included R program, IBM SPSS, QGIS, SaTScan, Zotero and Mendeley.

Sree Chitra Tirunal Institute for Medical Sciences and Technology
Master of Public Health (M.P.H.)

2013 – 2014

This program was funded and granted a fellowship from SCTIMST for two years. Courses included Basic Biostatistics, Introduction to Epidemiology, Health and Development, Public Health Technology, Database management, Health Policy, Health Systems, Health Economics, Social determinants of health, Gender Issues in health, Chronic disease epidemiology, Infectious Disease Epidemiology, and Ethics in Health Research. The dissertation for this program involved geocoding of 8279 cases of dengue fever in Thiruvananthapuram district, Kerala. Spatial clusters were identified, and the relationship to climatic variables was identified. Temperature, humidity and rainfall were accessed from the Indian Meteorological Department. Association to Breteau indices were also analyzed.

Sikkim Manipal University - Distance Education
Master of Business Administration (MBA), Health/ Healthcare Administration/ Management

2011 – 2013

This program included training in Management Process and Organization Behavior, Human Resource Management, Production and Operation Management, Marketing Management, Research Methodology, Health Administration, Financial Management, Legal aspects in Healthcare services, Quality management in Healthcare services and Public relations for Healthcare organizations. A study on stress among ICU nurses was conducted as part of the Project.

National Institute of Mental Health and Neuroscience
Bachelor of Science (B.Sc.), Registered Nursing, Nursing Administration, Nursing Research and Clinical Nursing

2007 – 2011

Honors & Awards

Best Outgoing Student Award from NIMHANS

Jul 2011

Awarded for overall performance in BSc. Nursing course at National Institute of Mental Health and Neurosciences.

Award for Academic Excellence in BSc. Nursing course

Feb 2012

Awarded for the highest marks obtained in the final examinations of the BSc. Nursing course from 2008 – 2011 in NIMHANS, Bangalore

Dr. Richard Cash Scholarship Holder for MPH Programme in SCTIMST

Jan 2013

Funding and fellowship granted for the Master of Public Health course in Achutha Menon Centre for Health Science Studies, SCTIMST.

DAAD Fellowship holder for German Student-Exchange Programme in MPH

Oct 2014

Scholarship granted in Germany, as part of the Student Exchange Programme between Achutha Menon Centre for Health Science Studies and School of Public Health, University of Bielefeld, Germany.

Dr.R.N.Roy Award for best paper in 2017

Awarded by the Indian Public Health Association for the best paper published in Indian Journal of Public Health in 2017. The paper was titled 'Spatio-temporal clustering of dengue cases in Thiruvananthapuram district, Kerala'

Publications

1. **Using open-source data to explore the distribution of built environment characteristics across Kerala, India (Indian Journal of Public Health, June 2020)**
   Available at: https://www.ijph.in/text.asp?2020/64/2/191/286818

2. **Spatial clusters of diabetes and physical inactivity: do neighbourhood characteristics in high and low clusters differ? (Asia Pacific Journal of Public Health, Dec 2019)**
   Available at: https://journals.sagepub.com/doi/10.1177/1010539519879322

3. **Gender differences in the relationship between the built environment and non-communicable diseases: A systematic review (Journal of Public Health Research, April 2018)**
   Available at: https://www.jphres.org/index.php/jphres/article/view/1239

4. **Spatio-temporal clustering of dengue cases in Thiruvananthapuram district, Kerala (Indian Journal of Public Health, June 2017)**
   Available at: https://www.ijph.in/text.asp?2017/61/2/74/207409

5. **Surgery in Spontaneous Intracerebral Hemorrhage- A series analysis (Journal of Neurology and Stroke, July 2015)**
   Available at: https://doi.org/10.15406/jnsk.2015.02.00060

Training and Conferences

- 'Training on Introduction to SPSS Statistics v.25.0' by SPSS South Asia Private Ltd. (20th July 2019)
- 'Workshop on Critical Appraisal of literature, Systematic Review and Meta-analysis' by Achutha Menon Centre for Health Science Studies (25 – 27 July 2018)
- 'Advances in GIS" by National Remote Sensing Centre, Hyderabad (August 7 – 18, 2017)
- Workshop on 'Approaches to Qualitative Research' by Achutha Menon Centre for Health Science Studies (27 June – 1st July 2017)
- 'Workshop on R for descriptive studies' by CR Soman School of Health Research (26 – 27 May 2017)
- Presented paper for 'Peri-Doctoral Workshop' (20 – 22 March 2017)
- 'Workshop on Geospatial technologies in Public Health' by Achutha Menon Centre for Health Science Studies (9 -11 March 2016)
- Presented paper on 'Gender differences in the relationship between built environment and non-communicable diseases' for 'Achutha Menon Centre Public Health Conference (AMCCON) 2015
- Workshop on 'Protocol development' by CR Soman School of Health Research (5-6 September 2015)
- Fellowship on Health Technology Assessment by Amrita Institute of Medical Sciences and Research Centre (16 – 20 September 2014)
- Workshop on 'Analyzing Medical and Health Data using R' by Achutha Menon Centre for Health Science Studies (29 -30 September 2014)
- Workshop on 'Research Methodology' by Department of Epidemiology, NIMHANS, Bangalore (18 – 21 December 2013)
- Short course on 'Ethics in Health Research' by Achutha Menon Centre for Health Science Studies (26 -31 August 2013)
- Workshop on 'Scientific writing' by Sree Chitra Tirunal Institute of Medical Sciences and Technology (12 -13 June 2013

APPENDICES

APPENDIX A – ETHICS COMMITTEE APPROVAL

श्री चित्रा तिरुनाल आयुर्विज्ञान और प्रौद्योगिकी संस्थान, त्रिवेन्द्रम
तिरुवनन्तपुरम - ६९५०११, केरल, इंडिया

SREE CHITRA TIRUNAL INSTITUTE FOR MEDICAL SCIENCES AND TECHNOLOGY, TRIVANDRUM
Thiruvananthapuram - 695 011, Kerala, India
(An Institute of National Importance under Govt. of India)

Grams : Chitramet, Phone : +91-471-2443152, Fax : +91-471-2550728 / 2446433, E-mail : sct@sctimst.ac.in, Website : www.sctimst.ac.in

Institutional Ethics Committee
(IEC Regn No. ECR/189/Inst/KL/2013)

SCT/IEC/1164/DECEMBER-2017 15.01.2018

Ms. Joanna Sara Valson
PhD Student, AMCHSS
SCTIMST, Thiruvananthapuram

Dear Ms. Joanna Sara Valson,

The Institutional Ethics Committee reviewed your application to conduct the study entitled "RELATIONSHIP BETWEEN BUILT ENVIRONMENT AND NON-COMMUNICABLE DISEASES IN KERALA (IEC/1164)" on 15th January, 2018.

The following documents were reviewed:
Original submission

1. Covering letter addressed to the Chairperson, IEC, SCTIMST dated 29.11.2017 with check list
2. TAC Approval Letter 3. IEC Application Form 4. Project Proposal 5. Information sheet and Consent Form
6. Questionnaire 7. Permission from concerned departments

Revised submission

1. Covering letter addressed to the Chairperson, IEC, SCTIMST dated 20.12.2017 with check list
2. TAC Approval Letter 3. IEC Application Form 4. Project Proposal 5. Information sheet and Consent Form
6. Questionnaire 7. Permission from concerned departments

The IEC Review Criteria
The study fulfils the expedited criteria from ethics review criteria vide section 9.1 of the Standard Operating Procedures (April 2017) of the SCTIMST-IEC.

IEC Decision
The IEC approved the conduct of the study in the present form.
Remarks:
The Institutional Ethics Committee expects to be informed about the progress of the study, any SAE occurring in the course of the study, any changes in the protocol and patient information/informed consent and asks to be provided a copy of the final report.
There was no member of the study team who participated in voting / decision making process. The ethics committee is organized and operated according to the requirements of Good Clinical Practice and the requirements of the Indian Council of Medical Research (ICMR).

Sincerely,
MRamanathan

Mala Ramanathan
Member Secretary, IEC

APPENDIX B – SUPPLEMENTARY TABLES

Supplementary Table S1. Distribution of population and residential density across sub-districts of Kerala

Sl. No.	Sub-district	Area (in sq.km.)	Population	Population density	No. of houses	Residential density
1	Kasaragod	972.59	681734	701	132057	135.78
2	Hosdurg	988.91	625641	633	141353	142.94
3	Taliparamba	1330.66	764888	575	175372	131.79
4	Kannur	430.56	784984	1823	165323	383.97
5	Thalassery	1206.06	973131	807	213603	177.11
6	Mananthavadi	740.43	258140	349	58911	79.56
7	Sulthan Bathery	774.86	297863	384	72206	93.19
8	Vythiri	611.18	261417	428	59777	97.81
9	Vadakara	575.57	687265	1194	152553	265.05
10	Quilandy	731.11	728168	996	172883	236.47
11	Kozhikode	1032.08	1670860	1619	372274	360.7
12	Ernad	703.85	910978	1294	178209	253.19
13	Nilambur	1343.29	574059	427	120552	89.74
14	Perinthalmanna	505.91	606396	1199	118792	234.81
15	Tirur	447.68	928672	2074	170514	380.88
16	Tirurangadi	322.04	713017	2214	131272	407.63
17	Ponnani	200.35	379798	1896	74660	372.65
18	Ottapalam	845.98	930692	1100	201045	237.65
19	Manarkkad	1209.39	384393	318	83238	68.83
20	Palakkad	713.13	612116	858	144585	202.75
21	Chittur	1136.23	437738	385	104996	92.41
22	Alathur	571.07	444995	779	103356	180.99
23	Talappilly	679.36	632086	930	148429	218.48
24	Chavakkad	234.73	470898	2006	108151	460.75
25	Thrissur	630.12	874615	1388	215213	341.54
26	Kodungallur	145.39	312238	2148	76926	529.1
27	Mukundapuram	1329.15	831363	625	210491	158.37
28	Kunnathunad	464.3	469164	1010	115490	248.74
29	Aluva	531.59	468408	881	115905	218.03
30	Paravur	173.36	410571	2368	102472	591.09
31	Kochi	129.38	508212	3928	122084	943.61
32	Kanayannur	303.06	851406	2809	216544	714.53
33	Muvattupuzha	521.89	336224	644	82746	158.55
34	Kothamangalam	927.91	238403	257	58770	63.34
35	Devikulam	1052.09	177621	169	45480	43.23
36	Udumbanchola	1077.13	429780	399	109322	101.49
37	Thodupuzha	884.93	325951	368	80784	91.29
38	Peerumade	1402.62	175622	125	44226	31.53
39	Meenachil	692.86	406471	587	97873	141.26
40	Vaikom	319.3	310414	972	76876	240.76
41	Kottayam	499.89	631885	1264	157693	315.46
42	Changanassery	261.91	355736	1358	88683	338.6
43	Kanjirappally	421.47	270045	641	66171	157
44	Cherthala	323.87	542657	1676	132772	409.95

45	Alappuzha	112.9	347701		83532	
46	Ambalappuzha	189.07	454864	2406	109411	578.68
47	Kuttanad	289.39	193007	667	47416	163.85
48	Karthikappally	221.87	406524	1832	104723	472
49	Chengannur	141.87	197419	1392	53005	373.62
50	Mavelikkara	236.84	333318	1407	88631	374.22
51	Thiruvalla	151.95	223503	1471	59551	391.91
52	Mallappally	168.83	134219	795	35532	210.46
53	Ranni	1049.91	198194	189	53172	50.64
54	Kozhenchery	1015.37	338560	333	92825	91.42
55	Adoor	308.57	302936	982	81604	264.46
56	Karunagappally	180.42	428802	2377	106937	592.71
57	Kunnathur	138.08	199456	1444	50624	366.63
58	Pathanapuram	1235.51	432904	350	115661	93.61
59	Kottarakkara	550.57	586434	1065	152944	277.79
60	Kollam	380.21	987779	2598	243209	639.67
61	Chirayinkeezhu	380.68	634270	1666	158980	417.62
62	Nedumangad	926.77	645326	696	169220	182.59
63	Thiruvananthapuram	307.55	1140845	3709	286141	930.39
64	Neyyattinkara	570.91	880986	1543	223536	391.54

Supplementary Table S2. Distribution of crime and pedestrian accident rates across subdistricts of Kerala

No.	Sub-district	Number of crimes	Crime rate (per 1,000 inhabitants)	Pedestrian accidents	Pedestrian accident rate (per 1,00,000)
1	Kasaragod	5670	8.32	126	18.48
2	Hosdurg	6540	10.45	128	20.46
3	Taliparamba	19237	25.15	163	21.31
4	Kannur	16737	21.32	158	20.13
5	Thalassery	22818	23.45	261	26.82
6	Mananthavady	3727	14.44	61	23.63
7	Sulthanbathery	4074	13.68	71	23.84
8	Vythiri	2691	10.29	50	19.13
9	Vadakara	6090	8.86	162	23.57
10	Quilandy	6511	8.94	161	22.11
11	Kozhikode	22975	13.75	485	29.03
12	Ernad	4525	4.97	194	21.30
13	Nilambur	3871	6.74	84	14.63
14	Perinthalmanna	2120	3.50	84	13.85
15	Tirur	4240	4.57	132	14.21
16	Tirurangadi	2996	4.20	104	14.59
17	Ponnani	1970	5.19	65	17.11
18	Ottappalam	5700	6.12	225	24.18
19	Mannarkad	3514	9.14	77	20.03
20	Palakkad	8806	14.39	449	73.35
21	Chittur	5481	12.52	93	21.25
22	Alathur	6182	13.89	83	18.65
23	Talappilly	9411	14.89	136	21.52

24	Chavakkad	7717	16.39	99	21.02
25	Thrissur	36645	41.90	353	40.36
26	Kodungallur	3278	10.50	34	10.89
27	Mukundapuram	23238	27.95	305	36.69
28	Kunnathunad	14419	30.73	235	50.09
29	Aluva	16809	35.89	216	46.11
30	Paravur	6333	15.42	64	15.59
31	Kochi	60628	119.30	777	152.89
32	Kanayannur	1415	1.66	25	2.94
33	Muvattupuzha	10678	31.76	123	36.58
34	Kothamangalam	7886	33.08	60	25.17
35	Devikulam	4760	26.80	38	21.39
36	Udumbanchola	7002	16.29	61	14.19
37	Thodupuzha	8312	25.50	109	33.44
38	Peerumade	4306	24.52	41	23.35
39	Meenachil	12661	31.15	147	36.16
40	Vaikom	8929	28.76	90	28.99
41	Kottayam	18219	28.83	240	37.98
42	Changanassery	9341	26.26	106	29.80
43	Kanjirappally	9139	33.84	102	37.77
44	Cherthala	12283	22.63	278	51.23
45	Alappuzha	5096	14.66	98	28.19
46	Ambalappuzha	4603	10.12	117	25.72
47	Kuttanad	3872	20.06	39	20.21
48	Karthikappally	10443	25.69	115	28.29
49	Chengannur	5567	28.20	64	32.42
50	Mavelikkara	6129	18.39	81	24.30
51	Thiruvalla	8073	36.12	104	46.53
52	Mallappally	3540	26.37	14	10.43
53	Ranni	7519	37.94	40	20.18
54	Kozhenchery	10759	31.78	125	36.92
55	Adoor	12506	41.28	110	36.31
56	Karunagappally	14124	32.94	142	33.12
57	Kunnathur	4904	24.59	128	64.17
58	Pathanapuram	14767	34.11	165	38.11
59	Kottarakkara	15071	25.70	405	69.06
60	Kollam	41960	42.48	446	45.15
61	Chirayinkeezhu	15927	25.11	217	34.21
62	Nedumangad	14831	22.98	177	27.43
63	Thiruvananthapuram	53831	47.19	619	54.26
64	Neyyattinkara	23132	26.26	318	36.10

Supplementary Table S3. Distribution of intersection density across sub-districts of Kerala

Sl. No.	Sub-district	Area (in sq.km.)	Intersections	Intersection density

1	Kasaragod	972.59	3680	3.78
2	Hosdurg	988.91	4144	4.19
3	Taliparamba	1330.66	2562	1.93
4	Kannur	430.56	1366	3.17
5	Thalassery	1206.06	3008	2.49
6	Mananthavadi	740.43	1298	1.75
7	Sulthan Bathery	774.86	790	1.02
8	Vythiri	611.18	1016	1.66
9	Vadakara	575.57	1554	2.70
10	Quilandy	731.11	1392	1.90
11	Kozhikode	1032.08	6110	5.92
12	Ernad	703.85	2318	3.29
13	Nilambur	1343.29	1198	0.89
14	Perinthalmanna	505.91	1564	3.09
15	Tirur	447.68	1326	2.96
16	Tirurangadi	322.04	1026	3.19
17	Ponnani	200.35	560	2.80
18	Ottapalam	845.98	3482	4.12
19	Manarkkad	1209.39	1268	1.05
20	Palakkad	713.13	6430	9.02
21	Chittur	1136.23	1722	1.52
22	Alathur	571.07	1278	2.24
23	Talappilly	679.36	6936	10.21
24	Chavakkad	234.73	966	4.12
25	Thrissur	630.12	6778	10.76
26	Kodungallur	145.39	830	5.71
27	Mukundapuram	1329.15	4760	3.58
28	Kunnathunad	464.3	2758	5.94
29	Aluva	531.59	4200	7.90
30	Paravur	173.36	5130	29.59
31	Kochi	129.38	3124	24.15
32	Kanayannur	303.06	10728	35.40
33	Muvattupuzha	521.89	1424	2.73
34	Kothamangalam	927.91	730	0.79
35	Devikulam	1052.09	940	0.89
36	Udumbanchola	1077.13	1078	1.00
37	Thodupuzha	884.93	1854	2.10
38	Peerumade	1402.62	568	0.41
39	Meenachil	692.86	5652	8.16
40	Vaikom	319.3	1106	3.46
41	Kottayam	499.89	3744	7.49
42	Changanassery	261.91	1240	4.73
43	Kanjirappally	421.47	1524	3.62
44	Cherthala	323.87	1232	3.80
45	Alappuzha	112.9	1770	15.68
46	Ambalappuzha	189.07	2	0.01
47	Kuttanad	289.39	518	1.79
48	Karthikappally	221.87	1166	5.26
49	Chengannur	141.87	908	6.40
50	Mavelikkara	236.84	714	3.02
51	Thiruvalla	151.95	1526	10.04

52	Mallappally	168.83	440	2.61
53	Ranni	1049.91	636	0.61
54	Kozhenchery	1015.37	876	0.86
55	Adoor	308.57	734	2.38
56	Karunagappally	180.42	1096	6.08
57	Kunnathur	138.08	228	1.65
58	Pathanapuram	1235.51	1798	1.46
59	Kottarakkara	550.57	1290	2.34
60	Kollam	380.21	5354	14.08
61	Chirayinkeezhu	380.68	2854	7.50
62	Nedumangad	926.77	2216	2.39
63	Thiruvananthapuram	307.55	7300	23.74
64	Neyyattinkara	570.91	1868	3.27

Supplementary Table S4. Distribution of greenness and built-up density across sub-districts of Kerala

		Greenness			Built-up density		
No.	Sub-district	Mean	Standard deviation	Range	Mean	Standard deviation	Range
1	Kasaragod	0.5799	0.1339	1.1818	-0.171	0.153	1.005
2	Hosdurg	0.5965	0.1237	1.0904	-0.192	0.133	0.894
3	Taliparamba	0.5671	0.1228	1.0862	-0.227	0.100	0.909
4	Kannur	0.4931	0.1511	1.2486	-0.190	0.114	1.017
5	Thalassery	0.5695	0.0924	1.2594	-0.179	0.125	1.091
6	Mananthavady	0.5520	0.0805	1.0881	-0.213	0.097	0.762
7	Sulthanbathery	0.6046	0.1150	1.0345	-0.186	0.111	1.020
8	Vythiri	0.5542	0.1462	1.1297	-0.219	0.100	1.143
9	Vadakara	0.5451	0.1126	1.2402	-0.267	0.090	0.758
10	Quilandy	0.5553	0.1292	1.0915	-0.276	0.092	0.879
11	Kozhikode	0.5621	0.1200	1.1409	-0.246	0.095	0.842
12	Ernad	0.5407	0.1104	1.0061	-0.213	0.104	0.827
13	Nilambur	0.6354	0.1208	0.9267	-0.243	0.104	0.918
14	Perinthalmanna	0.5006	0.0745	0.8118	-0.207	0.095	0.745
15	Tirur	0.4936	0.1234	0.9705	-0.233	0.116	1.070
16	Tirurangadi	0.5050	0.1091	0.8823	-0.232	0.108	0.957
17	Ponnani	0.4275	0.1705	0.9797	-0.173	0.131	0.874
18	Ottappalam	0.4785	0.0955	0.8964	-0.184	0.105	0.840
19	Mannarkad	0.5513	0.1203	0.9223	-0.215	0.114	0.821
20	Palakkad	0.4429	0.1348	0.9612	-0.178	0.123	0.942
21	Chittur	0.4771	0.1218	0.9944	-0.201	0.121	0.874
22	Alathur	0.5069	0.0895	0.8367	-0.215	0.105	0.745
23	Talappilly	0.4914	0.0984	1.0103	-0.200	0.106	0.867
24	Chavakkad	0.4651	0.1087	0.9559	-0.186	0.123	1.121
25	Thrissur	0.4967	0.1159	0.8950	-0.227	0.098	0.969
26	Kodungallur	0.4408	0.1447	0.8446	-0.217	0.102	0.675
27	Mukundapuram	0.4994	0.1149	0.9953	-0.225	0.090	1.004
28	Kunnathunad	0.4977	0.0969	0.9059	-0.197	0.092	0.953
29	Aluva	0.4627	0.1138	0.8641	-0.192	0.097	0.973
30	Paravur	0.3833	0.1672	0.9322	-0.181	0.107	0.814

31	Kochi	0.2220	0.1667	0.9019	-0.142	0.117	0.777
32	Kanayannur	0.3734	0.1451	0.9317	-0.150	0.112	0.934
33	Muvattupuzha	0.5095	0.0853	1.0758	-0.203	0.087	0.915
34	Kothamangalam	0.4979	0.0790	0.8506	-0.190	0.091	1.015
35	Devikulam	0.5085	0.1278	1.2547	-0.227	0.119	1.015
36	Udumbanchola	0.5221	0.1317	1.0564	-0.265	0.106	0.854
37	Thodupuzha	0.4974	0.1341	1.3772	-0.201	0.104	0.888
38	Peerumade	0.5085	0.1523	1.1821	-0.225	0.097	0.836
39	Meenachil	0.5237	0.0743	1.1675	-0.200	0.080	1.030
40	Vaikom	0.4585	0.1402	0.9867	-0.231	0.091	0.804
41	Kottayam	0.4772	0.1372	1.2332	-0.230	0.099	0.883
42	Changanassery	0.5317	0.0864	1.1199	-0.228	0.102	0.880
43	Kanjirappally	0.5304	0.0635	0.7753	-0.197	0.080	0.909
44	Cherthala	0.4396	0.1590	0.9423	-0.242	0.084	0.864
45	Alappuzha	0.4185	0.1186	0.8765	-0.178	0.116	0.845
46	Ambalappuzha	0.4266	0.1194	0.8297	-0.246	0.063	0.559
47	Kuttanad	0.5187	0.1619	0.9191	-0.323	0.099	0.850
48	Karthikappally	0.4937	0.1242	0.9630	-0.242	0.101	0.886
49	Chengannur	0.4865	0.1045	0.7885	-0.222	0.085	1.070
50	Mavelikkara	0.5225	0.1039	0.8716	-0.228	0.085	0.997
51	Thiruvalla	0.5131	0.0930	0.7198	-0.248	0.089	0.847
52	Mallappally	0.5279	0.0702	0.7699	-0.210	0.074	0.954
53	Ranni	0.5312	0.1305	1.1442	-0.243	0.078	0.979
54	Kozhenchery	0.5296	0.0931	0.9442	-0.221	0.081	1.068
55	Adoor	0.5477	0.0737	0.8250	-0.190	0.076	1.046
56	Karunagappally	0.4699	0.1603	0.9485	-0.237	0.083	0.817
57	Kunnathur	0.5037	0.1337	0.8570	-0.221	0.082	0.828
58	Pathanapuram	0.5437	0.1385	0.9168	-0.215	0.083	1.170
59	Kottarakkara	0.5560	0.0750	0.9096	-0.196	0.072	0.912
60	Kollam	0.3975	0.2297	0.9903	-0.198	0.088	0.940
61	Chirayinkeezhu	0.5361	0.1118	0.9686	-0.225	0.076	0.970
62	Nedumangad	0.5557	0.1137	1.0417	-0.237	0.078	0.881
63	Thiruvananthapuram	0.4339	0.1538	1.1878	-0.204	0.119	0.951
64	Neyyattinkara	0.4939	0.1205	0.8954	-0.251	0.098	0.797

Supplementary Table S5. Distribution of slope across sub-districts of Kerala

No.	Sub-district	Mean slope	Standard deviation	Slope Range
1	Kasaragod	5.63	4.63	37.14
2	Hosdurg	7.65	7.02	47.68
3	Taliparamba	7.57	6.85	50.19
4	Kannur	2.75	1.90	15.69
5	Thalassery	7.99	7.72	50.75
6	Mananthavady	8.92	7.64	57.34
7	Sulthanbathery	5.30	3.46	44.83
8	Vythiri	11.22	9.62	66.19
9	Vadakara	7.13	8.27	54.76
10	Quilandy	7.60	8.62	69.18
11	Kozhikode	7.67	8.25	68.86

12	Ernad	6.87	6.40	60.57
13	Nilambur	11.34	11.08	71.92
14	Perinthalmanna	5.67	5.08	43.36
15	Tirur	3.18	2.75	22.54
16	Tirurangadi	3.11	2.56	35.87
17	Ponnani	2.06	1.52	9.63
18	Ottappalam	4.11	3.63	46.65
19	Mannarkad	13.33	10.68	70.23
20	Palakkad	6.48	9.56	76.14
21	Chittur	8.38	9.64	69.69
22	Alathur	5.48	7.22	53.50
23	Talappilly	4.91	4.76	45.54
24	Chavakkad	1.09	0.95	8.82
25	Thrissur	4.68	5.89	46.45
26	Kodungallur	1.03	1.02	7.87
27	Mukundapuram	7.69	8.46	59.31
28	Kunnathunad	5.23	6.10	57.12
29	Aluva	2.48	2.57	39.86
30	Paravur	1.14	0.86	6.40
31	Kochi	1.05	0.85	5.14
32	Kanayannur	1.84	1.68	12.08
33	Muvattupuzha	4.49	3.43	30.49
34	Kothamangalam	4.34	4.96	45.63
35	Devikulam	16.15	10.67	72.72
36	Udumbanchola	11.29	7.81	57.07
37	Thodupuzha	11.37	9.42	55.86
38	Peerumade	14.16	8.76	62.81
39	Meenachil	8.35	7.91	53.39
40	Vaikom	2.28	2.27	20.44
41	Kottayam	2.90	2.55	24.20
42	Changanassery	3.38	2.69	22.32
43	Kanjirappally	7.96	6.27	44.95
44	Cherthala	0.86	0.62	5.24
45	Alappuzha	0.72	0.56	6.24
46	Ambalappuzha	1.28	1.06	5.09
47	Kuttanad	0.71	0.50	5.20
48	Karthikappally	0.76	0.50	3.72
49	Chengannur	1.95	1.83	15.34
50	Mavelikkara	1.56	1.29	15.65
51	Thiruvalla	1.76	1.82	21.48
52	Mallappally	4.54	3.11	28.89
53	Ranni	13.59	8.84	63.83
54	Kozhenchery	11.70	8.61	56.07
55	Adoor	4.83	3.78	32.55
56	Karunagappally	1.01	0.82	6.35
57	Kunnathur	2.23	1.66	11.24
58	Pathanapuram	10.13	8.31	53.47
59	Kottarakkara	4.45	2.84	28.36
60	Kollam	2.16	1.78	12.68
61	Chirayinkeezhu	3.57	2.51	24.77
62	Nedumangad	7.64	6.99	56.50

63	Thiruvananthapuram	2.53	1.89	14.64
64	Neyyattinkara	5.67	5.84	50.25

APPENDIX C - PUBLICATIONS

Systematic reviews and meta-analysis

Gender differences in the relationship between built environment and non-communicable diseases: A systematic review

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Significance for public health

Tackling non-communicable diseases is a major hurdle for majority of the countries worldwide. Varied built environmental conditions and facilities bear differing influences on both men and women. Women in particular face difficulties more than men in access and control over resources to deal with non-communicable disease conditions. This paper tries to bring out the differences from published literature. Moreover, this paper has attempted to review articles which have delved beyond sex differences and included other axes. The Gender Analysis Matrix developed by WHO was incorporated in this paper to aid in categorising and delineating these differences. These results would be fundamental in further primary research and help in policy and planning of non-communicable diseases.

Abstract

Non-communicable diseases are on the rise globally. Risk factors of non-communicable diseases continue to be a growing concern in both developed and developing countries. With significant rise in population and establishment of buildings, rapid changes have taken place in the built environment. Relationship between health and place, particularly with non-communicable diseases has been established in previous literature. This systematic review assesses the current evidence on influence of gender in the relationship between built environment and non-communicable diseases. A systematic literature search using PubMed was done to identify all studies that reported relationship between gender and built environment. All titles and abstracts were scrutinised to include only articles based on risk factors, prevention, treatment and outcome of non-communicable diseases. The Gender Analysis Matrix developed by the World Health Organization was used to describe the findings of gender differences. Sex differences, biological susceptibility, gender norms/ values, roles and activities related to gender and access to/control over resources were themes for the differences in the relationship. A total of 15 out of 214 articles met the inclusion criteria. Majority of the studies were on risk factors of non-communicable diseases, particularly cardiovascular diseases. Gender differences in physical access to recreational facilities, neighbourhood perceptions of safety and walkability have been documented. Men and women showed differential preferences to walking, engaging in physical activity and in perceiving safety of the neighbourhood. Girls and boys showed differences in play activities at school and in their own neighbourhood environment. Safety from crime and safety from traffic were also perceived important to engage in physical activity. Gender norms and gender roles and activities have shown basis for the differences in the prevalence of non-communicable diseases. Sparse evidence was found on how built environment affects health seeking behaviour, preventive options or experience with health providers. Though yet unexplored in the developing or low/middle income countries, there seems to be a major role in the gendered perception of how men and women are affected by non-communicable diseases. Large gaps still exist in the research evidence on gender-based differences in non-communicable diseases and built environment relationship. Future research directions could bring out underpinnings of how perceived and objective built environment could largely affect the health behaviour of men and women across the globe.

Introduction

Non-communicable diseases (NCDs) have emerged to be the growing concern worldwide. NCDs were responsible for 68% (38 million) deaths globally in 2012.[1] Prevalence rates of risk factors of non-communicable diseases are also increasing. Inactivity levels varies among World Regions, with the highest value in the United States (43%) and lowest in Southeast Asia (17%).[2] The present era has also witnessed a large explosion of population, growing urbanisation and establishment of high-rise buildings. The infrastructure of the environment where people live largely affects the health of the population. Hippocrates had recognised the importance of this relationship in the fifth century B.C. *If you want to learn about the health of a population, look at the air they breathe, the water they drink, and the places where they live.* Built environment has been closely related to physical activity, travel behaviour and sedentary behaviour of individuals.[3] *Built environment* refers to the man-made structures and surroundings and includes roads, neighbourhoods, recreational facilities such as parks and playgrounds, food sources, building and houses in which people live and perform activities of eating, playing educating and working.[4] Various research studies have evidenced that built environment affects lifestyle, obesity levels, activity levels, walking behaviour and dietary behaviour of individuals. Results have shown differences for men, women, boys and girls.[5-8] There are differences in walking behaviour, physical activity levels and health outcomes based on sex. The question *why are the results different for men and women living in similar built environment?* has not been researched in particular. This paper attempts to gather evidence from published studies on how and why the results have been different for men and women or for boys and girls across the globe, with a view to exploring research gaps. This article is based on a systematic review and the author attempts to describe the search strategy to identify articles, the inclusion and exclusion criteria for selection of articles, process of data analysis and results of the review.

Search strategy

A systematic review was done in February 2017 (13th to 28th) on PubMed database using the MeSH terms: *gender* AND *built environment*, *built environment variables*, built *environment measures*, *built environment analysis*, *healthy living*, *built environment design*, *built environment effects*, *built environment features*. All the articles till 2016 were selected. A summary of the search strategy is shown in Figure 1.

Inclusion criteria

The articles should have mentioned measurement of built environment and its features as an exposure; risk factors/ prevalence/ recovery of non-communicable diseases should have been measured as an outcome. Community-based studies were included. Full text articles available in English were selected.

Exclusion criteria

Those articles which did not measure built environment either objectively or subjectively, where there were no clear description of how built environment was captured and those which did not have measurement of non-communicable diseases or its risk factors being addressed as an outcome, were excluded from the review. Also, articles that have looked into reliability of measurement tools, those which are describing only the methodology, those which are dealing with policy analysis and pilot studies were excluded. The shortlisted articles were finally screened based on whether the articles have dealt beyond sex differences. Either how biological differences exist, or how roles and activities, or norms or values, or access to and control over resources have influenced the outcome should have been studied.

Data analyses

Country-wise distribution was mapped for the selected articles. Sample population and type of study were also examined. Mapping of studies was done onto the Gender Analysis Matrix (GAM) Framework of World Health Organization (WHO)[9,10] as shown in Table 1. The GAM framework helps us to analyse whether gender-based division of labour, gender roles and norms, access to and control over resources, and power make a difference to risks and vulnerability to a health problem, health seeking behaviour, ability to access health services, preventive and treatment options, experiences with health services and health providers, health outcomes, and social and economic consequences of illness. Though the matrix has been initially used to identify gaps in policies or interventions (previously attempted for tobacco,[11] HIV/AIDS, blindness), it is also helpful in identifying information gaps for further research. A meta-analysis was not attempted due to differences in measurements across studies.

Results

A total of 15 articles met the inclusion criteria and were selected for analysis. Majority (40%) of the studies were from United States. Cross-sectional study type was incorporated by all the studies. A summary of the articles is given in Table 2.[12-26] Mapping of studies onto GAM Framework showed that all articles addressed issues in the vulnerability axis and rest of the axes had not been researched regarding relationship between gender differences and built environment factors in non-communicable diseases (Table 1).

Though the search criterion was for non-communicable diseases, the articles found were related to depressive symptoms,

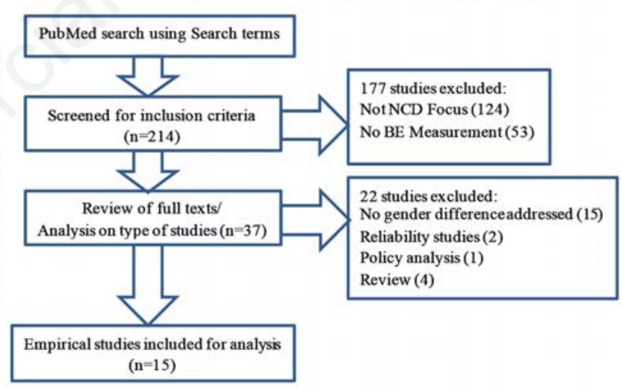

Figure 1. Flowchart showing the method used for systematic review.

Table 1. Studies mapped onto the GAM framework.

Relation between built environment and NCDs	Are there sex differences in...	How do biological differences between women/men influence their...	How do the different roles and activities of men/women affect their...	How do gender norms/values affect men and women's...	How do access to and control over resources affect men and women's...
Vulnerability: incidence, prevalence	✓	✓	✓	✓	✓
Health seeking behaviour					
Ability to access health services					
Preventive and treatment options, responses to treatment of rehabilitation					
Experiences with health services and health providers					
Outcome of health problem: *e.g.* recovery, disability, death					
Consequences (economic and social, including attitudinal)					

stress, physical activity and obesity. Since the number of studies in each category was insufficient to be summarised per se, the results are therefore discussed under the broad categories of mental health (depressive symptoms and stress)[12-14] and Risk factors of NCDs (Physical activity/Obesity). The built environment features captured in the studies are summarised in Table 3.[12-16,18-26]

Mental health (depressive symptoms/stress)

Sex differences

Women who lived in neighbourhoods with low green space had higher perceived levels of stress than compared to men.[14] The Jamaican study revealed that depressive symptoms were also more common among women (25.6%) than among men (14.8%). It was found that women living in informal communities (communities which were unplanned and those which evolved without adequate housing, water supply, sewerage treatment, modern waste disposal services and affordable electricity supply) were depressive in greater proportions, while the main factor that affected men was the low physical conditions (dilapidated housing, deteriorating infrastructure and high noise levels) in the urban neighbourhood in Jamaica.[12]

Biological differences

Roe *et al.* describes that there exists a differential neuroendocrine response to the environment between men and women. Urban neighbourhoods with high green space has been directly associated with low stress levels as shown by cortisol levels in salivary samples studied among adults in Scotland. Stress in men is associated with higher cortisol levels and *high and flat* pattern of diurnal cortisol decline, while stress in women initiate low cortisol concentration and *low and flat* diurnal cortisol decline. In comparison to men, this less steep decline of diurnal cortisol levels exhibited among women depicts the chronicity of stress levels among women.[14]

Table 2. Summary of the studies selected for analysis.

Authors	Study setting	Objective	Outcome	Age group	Sample size	Exposure measure	Outcome measure
Burgi *et al.*, 2015[15]	Winterthur, Switzerland	Locations where children engaged in PA	Physical Activity	11-14 years	119	Objective	Objective
Hillsdon *et al.*, 2015[24]	North-west region of England, UK	Distance from home where PA took place	Physical Activity	18-91 years	195	Objective	Objective
Oyeyemi *et al.*, 2014[26]	Maiduguri, Nigeria	Effect of neighbourhood-level income on PA	Physical Activity	12-19 years	1006	Perceived	Subjective
Klinker *et al.*, 2014[17]	Denmark	Context-specific outdoor behaviour	Physical Activity	11-16 years	170	Objective	Objective
Mullings *et al.*, 2013[12]	Jamaica	Mental health effects of urban neighbourhood	Depressive symptoms	15-74 years	2848	Subjective	Objective
Klinker *et al.*, 2014[16]	Copenhagen, Denmark	Domains and sub-domains for week day PA	Physical Activity	11-16 years	367	Subjective	Objective
Li *et al.*, 2014[20]	Portland, US	Neighbourhood racial concentration and obesity risks	Obesity	>18 years	17,020	Objective	Self-report
Stone *et al.*, 2014[18]	Toronto, Canada	Whether CIM and PA differ by place of residence	Physical Activity	10-12 years	856	Objective	Objective
Pelclova *et al.*, 2014[22]	All 14 regions in Czech Republic	Relation between walking recommendations with perceived neighbourhood attributes	Physical Activity	>50 years	2839	Subjective	Self-report
Roe *et al.*, 2013[14]	Dundee, UK	Link between perceived green space and stress levels	Stress	33-55 years	104	Subjective	Objective
Duncan *et al.*, 2013[13]	US	Relation between built environment features and youth depressive symptoms	Depressive symptoms	9-12th grade	1170	Objective	Self-report
Kowaleski *et al.*, 2013[19]	NHANES data, US	Influence of neighbourhood characteristics on child obesity risks	Obesity	2-11 years	1753	Objective	Objective
Hobin *et al.*, 2013[23]	Ontario, Canada	Relation between school environment and PA	Physical Activity	9-12th grade	21,754	Objective	Self-report
Page *et al.*, 2010[25]	UK	Relation between Perception of BE and PA at outdoor play, active commuting and structured exercise	Physical Activity	10-11 years	1307	Subjective	Self-report
Grafova *et al.*, 2008[21]	US	Influence of neighbourhood environment on weight status	Obesity	>55 years	15,221	Subjective	Self-report

Different roles and activities

The Jamaican study states that women tend to focus more on survival of children and not on their own mental health status.[12] The authors from UK explained that greater hypocortisolemia among women in neighbourhoods with low green space was a result of chronic stress and exhaustion due to roles at home and work.[14]

Gender norms/values

In Jamaica, men define manhood with their own socioeconomic circumstances. When poor, they have less control over their environment and social circumstances. Hence, males were found to have a greater risk for depression when living in a poor neighbourhood with lack of personal socioeconomic resources.[12] Furthermore, informal communities with male-dominated social networks within the community were found advantageous only to the men, while women were threatened. Such neighbourhoods provided less opportunity for social interaction for women, hence social participation was low. Also, in Jamaican results, there was evidence that women had to ask men for financial assistance and further use their sexuality as part of their survival mechanism.[12] A cross-link between walkable neighbourhoods and depression was that even if the neighbourhoods were walkable, girls in US had depression due to high crime rates and busy intersections, indicating the importance of safety and privacy for the girls.[13]

Access to and control over resources

Jamaican women living in poor neighbourhoods had higher risk of depression. Their limited social resources, low flexibility for social interaction and low social participation caused a greater risk for depressive symptoms in an urban informal community. Living in a scary environment with the threat of violence and trying to protect themselves and their children might perhaps be a triggering factor for depressive symptoms among women. On the other hand, men tend to demonstrate power and influence through their economic status. Thus, low physical conditions and lack of freedom could predispose men for depression. [12] Higher green space or park space in the immediate neighbourhood helped women to engage in physical activity and hence could lower their depressive symptoms.[14]

Risk factors of NCDs (physical activity/obesity)

Sex differences

Looking at locations where children engaged in PA, the Winterthur authors found that boys achieve more moderate-to-vigorous physical activity (MVPA) than girls at school playgrounds, sports facilities, at recess and during the day.[15] The Denmark study pointed out that boys spend more time outdoor for MVPA than the time spent by girls. Also, half of the girls who participated in the study did not accumulate any MVPA in sports clubs and sports facilities.[16,17] Girls had greater levels of activity on the streets as compared to the boys. Also, girls in the suburban areas had more MVPA when going to school.[15] However, girls were less likely to travel to and from school or take part in outdoor activities. The Canadian study pointed out that parents permitted independent mobility for 70% of the boys as compared to 54% of girls.[18] Girls in US were more at risk for obesity in neighbourhoods with poverty than boys.[19-21]

Men in Czech Republic were more likely to meet physical activity recommendations than women.[22] Women had 43% higher risk of being obese than men while living in neighbourhoods with higher concentration of non-Hispanic African American population in the US. This was probably because African American women had the tendency to interact with women from the similar ethnic background and hence were able to maintain social cohesion among them.[20] On the contrary, men of American origin living in neighbourhoods with higher African-American concentration tend to have lower risk for obesity. Possible reasons were in such an environment with greater African concentration, Caucasian men were socioeconomically backward than the African-Americans and hence had a tendency to engage in heavy work-related occupa-

Table 3. Built environment features captured across studies according to outcome.

Outcome measure	Infrastructure-related	Access to services	Physical conditions	Socio-economic condition	Community variables
Depression/ Stress levels	Paved roads, side-walks, clean streets,[12] Greenspace,[14] Community design, access to walking destinations[13]	Social, commercial and Public services,[12] Shopping centres, transport[13]	Condition of house, noise level, condition of streets[12]	Poverty index[12]	Informal or formal[12]
Physical Activity/ Obesity	Home setting, own and other school setting, recreational facility, streets[15] School grounds, sports facilities, clubs, playgrounds.[16,23] Land-use mix,[22] Street connectivity, park accessibility.[20] Tree canopy cover, neighbourhood greenery, access to parks.[19] Neighbourhood including pedestrian network[24]	Service destinations[23,26]	Aesthetics[22] nuisance,[25] air pollution[21]	Socio-economic status.[18,20] Economic advantage and disadvantage[21]	Immigrant concentration, residential stability[21] traffic and crime safety.[22] Perceived safety, social norm, constraint,[25] Social cohesion[20]

tions or take public transport. Also, street connectivity had a protective effect for Caucasian men in Portland, which aided greater transportation and walking.[20]

Biological differences

The authors from Switzerland claim that there is a plausible explanation that stage of maturation has an influence on the amount of physical activity; more mature children appear to be less active. Early maturation in girls might cause them to be less active at school, or during play.[15]

Different roles and activities

Boys are more comfortable in taking part in activities which demand more flexibility and strength or in vigorous ball games, while girls prefer activities like skipping, sedentary play or social conversation.[15,23] Also, boys have a tendency to take part in sports and TV watching while girls tend to spend time studying, doing housework and take part in leisure activities at home.[19] Men in deprived neighbourhoods in United States tend to engage in manual labour and walk for transportation since they do not own cars.[20] In areas with high concentration of migrants, men were found to be at greater risk of being obese. This was probably because men tend to socialise with newer immigrants, go out for social parties, taste newer foods and hence have poor diet control or time to engage in physical activities. On the other hand, women were found to be less obese in areas with high street connectivity (High street connectivity is closely linked to population density in the neighbourhood). Possible reasons indicate that women have a basic instinct to maintain relations and hence tend to socialise better when they live in neighbourhoods with denser populations.[21]

Gender norms/values

Girls in Switzerland actively commute to school (walk/cycle) when the streets are considered safe.[15] Parental concerns for safety, security and traffic density were also high for girl children in Toronto and hence girls had low independence to move around in the neighbourhoods.[18] Girls in US were more at risk of being overweight when they lived at areas where greater number of residents in the neighbourhood commuted long hours to work. When the parents had to travel long hours to work, they had less time to demonstrate model healthy behaviours or to accompany girls for recreation activities. Also, a low risk of being overweight among girls was found when there was higher proportion of residents in the neighbourhood who were overweight; there is a cautionary effect among parents in such an environment to be over-protective of their daughters and hence encourage healthy diet and physical activity.[19] High street connectivity, low traffic and crime rates were important for Japanese men to take part in physical activity, while Japanese women preferred aesthetics and proximity to different destinations for exercise or walking. This probably denotes that men and women value different properties in the neighbourhoods to engage in walking or exercise.[22] Social cohesion and socio-economic status acted as mediators for white women in Portland to take part in physical activity.[20] Furthermore, it has been found in UK that men tend to move away from their homes more than women in relation to being involved in low, moderate and physical activity; women might be more restricted to nearby resources or destinations due to safety issues.[24]

Access to and control over resources

School environment plays a crucial role in encouraging girl children to take part in physical activity. They take part in physical activity more than three days per week only when a separate room for physical activity was available at schools. Also, when facilities were accessible, girls take part in structured activities. Those schools which cater to physical needs of the girls encouraged the girls to take part in physical activity at school.[15,23,25] Furthermore, poor neighbourhoods in US which have low physical amenities for recreation or exercise, cause lack of trust among parents to leave their daughters outside their home for physical activity and hence girls tend to stay at home and engage in household chores.[19] Access to destinations, residential density and availability of infrastructures were significantly associated with physical activity or active transportation to school for boys in Nigeria, while this was not true for girls. Even if the boys had greater perceived safety, those living in high-income neighbourhoods had low leisure-time physical activity than those in low-income neighbourhoods. However, this was not true for girls.[26] Furthermore, boys had only the risk of being overweight when they lived in rural areas; perhaps depicting that rural neighbourhoods have less access to physical activity resources and therefore the boys engage majority of their time in watching TV or playing computer games.[19] Higher air pollution levels (probably in areas with higher number of recreational facilities) were linked to reduced risk of obesity among women.[21] Rural neighbourhoods and car ownership have also demonstrated greater physical activity among men; it can be that greater proportion of men own cars than women.

Discussion

This review attempted to capture studies related to gender differences in the relationship between built environment and non-communicable diseases. All the studies were cross-sectional in nature. Findings emphasized expected patterns of gender differences with respect to mental health or physical activity/obesity. None of the studies attempted qualitative exploration of these differences. Moreover, there was sparse evidence from developing nations. Gender differences related to access to and use of health services, health-seeking behaviour, treatment options, experience in healthcare settings, and outcomes and consequences, have not been explored. Cultural factors which are closely linked with the perception of built environment, which can largely affect the physical activity behaviours or access to destinations, have also been scarcely explored.

The reviewed articles addressed gender differences differently, while the Jamaican study brought out explicit gender differences according to gender norms/roles and access to resources, rest of the articles conveyed indications of gendered differences. Both perceived and objective measurement of built environment brought out gender differences in the relationship between built environment and mental health/physical activity/obesity. Among the reviewed articles, mental health symptoms were largely captured through subjective measures while physical activity and obesity were captured objectively. School-level and neighbourhood-level studies brought out different aspects of gender differences among boys and girls in relation to school games and recreational physical activity in the neighbourhood respectively. Therefore, both schools and neighbourhoods are important spheres of research for physical activity among children. Income-levels and ethnic backgrounds of the neighbourhood have also emerged to be influential in the gendered relationship between built environment and physical activity among men and women. Social relationships and cohesion surfaced out be decisive for both men and women to participate in outdoor or recreational activities.

Different aspects of the built environment affect women and men positively as well as negatively as evidenced from the reviewed articles. One reason is that gender roles/activities and norms/values cause women and men to occupy different physical as well as social spaces. With regard to mental health, the socio-economic standing of the community was a major factor for men, while cleanliness of the surroundings, paved roads/sidewalks, green space in the neighbourhood were important for women. In case of physical activity and obesity, while girls had preference for separate spaces for activities at school, women had preference for safety from harm/crime to engage in outdoor activities. In order to take part in recreational activity, women also gave importance to aesthetics and greenery in the neighbourhood, density of neighbourhoods, proximity of recreational facilities and safety from traffic. On the other hand, rural neighbourhoods and less access to recreational facilities affected young boys while young men had greater priority for access to destinations, proximity to workspace and high street connectivity to engage in transport-related walking.

Furthermore, congruent findings from the articles showed that biological factors make some impact on observed sex differences in the case of mental health as well as physical activity. However literature suggests that social constructed differences between girls/women and boys/men contribute significantly to the observed differences. The social constructed differences are related to the gender norms/ values, gender roles/activities and access to resources. While gender roles and activities have impact for women in terms of stress, lack of time and dual responsibilities at home and workplace, the most significant factors are those related to gender norms and access to and control over resources. Roles and norms affect mental health through the expectations on masculine and feminine behaviour as well as power differentials between men and women. Likewise norms affect physical activity, walking behaviour and outdoor play for both women and girls. Parental trust and concerns for safety of girl children were largely detrimental to physical activity and walking behaviours of girls. Preference of girls to have separate activity spaces in schools need to be acknowledged. Opportunities to socialise and maintain social relations also emerged to be important for women to take part in physical activity. Availability of green spaces within one's neighbourhood may improve women's ability to engage in physical activity both because they may not have the time and financial resources to go farther away or use paid gyms/recreational facilities; it may also be socialisation that physical activity defines masculinity whereas it is not so for women.

Exploring further on relationship between mental health or physical activity and perceived built environment could enlighten on greater gender differences. The strengths of this review are the robust method employed in the systematic review, and the attempt to integrate gender analysis using Gender Analysis Matrix. The use of only PubMed search engine for literature review could be a limitation.

Conclusions

Studies on chronic disease risk generally adopt a mechanistic model of risk factor leading to event. The risk factor in itself is the result of social, economic, cultural and other determinants largely beyond the control of the individual, and the *built environment* is an important mediator in this pathway from social determinants to final outcome. This review has brought out glimpses of how gender plays a major role in the relationship between built environment and non-communicable diseases. The way in which built environment affects women and men differentially implies that policies and interventions to modify NCD risk factors have to take into consideration gender differences. Smart cities and green cities could incorporate gender-based preferences such as access to recreational resources, safety from crime and safety from traffic to engage in walking and take part in physical activity. This is a largely unexplored area; large gaps exist in the literature. This calls for further studies using qualitative and quantitative approaches to explore lived experiences of men and women, and the bring out possible modifying role played by gender.

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Spatial Clusters of Diabetes and Physical Inactivity: Do Neighborhood Characteristics in High and Low Clusters Differ?

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Abstract

This study aims to find spatial clusters of diabetes and physical inactivity among a sample population in Kerala, India, and evaluate built environment characteristics within the high and low spatial clusters. Spatial clusters with a higher and lower likelihood of diabetes and physical inactivity were identified using spatial scan statistic at various radii. Built environment characteristics were captured at panchayat level and 1600 m buffer around participant location using Geographical Information Systems. Comparison of sociodemographic and built environment factors was carried out for participants within high and low spatial clusters using *t* tests. Ten high and 8 low spatial clusters of diabetes and 17 high and 23 low spatial clusters of physical inactivity were identified in urban and rural areas of Kerala. Significant differences in built environment characteristics were consistent for low spatial clusters of diabetes and physical inactivity in the urban scenario. Built environment characteristics were found to be relevant in both urban and rural areas of Kerala. There is an urgent call to explore spatial clustering of non-communicable diseases in Kerala and undo the one-size-fits-all approach for prevention and control of non-communicable diseases.

Keywords

spatial cluster, built environment, diabetes, physical activity, Kerala, India

What We Already Know

- Prevalence of non-communicable diseases continues to rise in low-and-middle-income countries.
- Interventions related to diet and physical activity behaviors have proven to be effective.

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What This Article Adds

- Spatial clusters of diabetes and physical inactivity exists in both urban and rural Kerala.
- Built environment characteristics differ significantly between high and low spatial clusters of diabetes and physical inactivity in Kerala.

Introduction

Prevalence of non-communicable diseases (NCDs) and their risk factors are on the rise in both developed and developing countries. Major risk factors for ischemic heart disease, cerebrovascular disease, and diabetes has been on the rise in India, with diet, high systolic blood pressure, high total cholesterol, and high body mass index contributing to a quarter of disability-adjusted life years.[1] Also, India has the largest diabetic population in the world and is projected to reach 100 million by 2020. Among the high epidemiological transition level states, Kerala ranks highest in the prevalence of ischemic heart diseases, high total cholesterol, and elevated systolic blood pressure.[2] Deaths due to diabetes alone contributed to 3.1% of all deaths in India in 2016, thereby mandating prompt attention.[3] Intervention studies related to diet and physical activity behaviors have been attempted across the years and found substantial evidence on their efficacies to lower prevalence of diabetes and reduce physical inactivity.

Evidence from various studies, mostly from developed countries, have shown that physical activity, obesity, and diabetes patterns vary between areas of residence. Few pieces of evidence from developing countries also point in the same direction, with distinct variations in built and food environment indicators.[4,5] However, gaps still exist in delineating the relationship of environmental factors with NCDs in countries that are undergoing rapid transitions, including Brazil, Russia, India, and China. Majority of the studies from European countries have established strong associations of neighborhood built environment factors with physical activity, obesity, and diabetes. Population density, intersection density, and diversity and density of recreational facilities are significantly favorable to engage in physical activity.[6]

Although epidemiological studies assume that the observations at small areas are distributed uniformly and is not dependent on nearby observations, spatial studies are based on the assumption that adjacent regions have a similar prevalence of chronic diseases.[7] Public health researchers in developing countries have overlooked the importance of "place" and "space" in disease occurrence, which have now been addressed better with advancements in spatial analytic software and geographic information systems (GIS). Studies identifying spatial clusters or hotspots of physical activity, sedentary behavior, obesity, and diabetes have been carried out mainly in the United States, while few are reported from low- and middle-income countries.[8-13] Despite the high burden of NCDs in India, research incorporating spatial clustering techniques is lacking.

Moreover, the capture of objective built environment characteristics has not been attempted in this country using GIS and open-source solutions. Hence, this study aims to find spatial clusters of diabetes and physical inactivity among a sample population in urban and rural Kerala. It also seeks to distinguish characteristics of participants located within high and low spatial clusters of diabetes and physical inactivity.

Methods

Study Setting and Participants

We used data from the "Prevention and Control of Non-Communicable Diseases in Kerala, India" Project, a project run by Sree Chitra Tirunal Institute for Medical Sciences and Technology (SCTIMST), with financial support from the Government of Kerala. A total of 11 033 participants from the state were selected using stratified cluster sampling, with equal representation from urban and rural areas. The lowest level of the elected government in the state is the "panchayat" in rural areas and municipalities in urban areas; each panchayat and municipality is further divided into 10 to 20 wards of around 500 households each. Participants in the project had been selected from 1345 sampling units (wards or panchayats) across the state of Kerala. Data were collected from June to December 2016. Ethical approval for the present study was obtained from the Institute Ethics Committee of SCTIMST (IEC/1164).

Spatial Clusters

Spatial clusters have been defined using SaTScan[14] to detect whether the disease is randomly distributed in space. We have employed a purely spatial Bernoulli model for the spatial scan statistic, since this model considers cases and controls represented by a 1/0 variable. Hence, as per requirement for the Bernoulli model, we used a case file (those with diabetes/who were physically inactive), controls file (those without diabetes/who were physically active), and coordinates file (location of participants) for each of the outcome variable to undertake the analysis.

We employed the spatial scan statistic for a maximum window of 5 km, 7.5 km, 10 km, and 15 km radii and ensured the consistency of spatial cluster locations. A 1600-m circular buffer was defined around each participant location to capture built environment characteristics. This was defined based on previous studies where 1600 m would be the distance attained on walking at a moderate-to-vigorous intensity pace within 30 minutes, as per the recommendation for daily physical activity among adults.[15,16] The overall prevalence of diabetes among the sample population in urban and rural Kerala was estimated to be 21.3% and 19.1%, respectively; these proportions were set as the cutoff points for detecting high and low spatial clusters of diabetes. Similarly, the overall prevalence of physical inactivity among the selected sample population in urban and rural Kerala was 26.1% and 20.1%, respectively. These were, respectively, set as criteria for detecting high and low spatial clusters of physical inactivity in urban and rural areas.

Participant Characteristics

Sociodemographic Characteristics. The data accessed from the project included age (in years), gender (male/female), marital status (single/married), educational background (primary school or less/higher secondary school/graduation and above), and occupation (unemployed/manual laborers/executives or businessmen).

Outcome Variables. Both diabetes and physical inactivity were binary variables extracted from the project data. The participants were considered to be diabetic if they were already on oral hypoglycemic agents or insulin for the past 2 weeks or had a fasting blood glucose $\geq$126 mg/dL. Self-reported time taken to engage in various activities, including vigorous physical activity, time to walk/cycle, for vigorous sports, for moderate sports, and to sit/recline, were captured. Total metabolic equivalent minutes were calculated for a week. Those participants who had a total metabolic equivalent minutes of $<$600 were considered to be physically inactive.

Built Environment Factors

Neighborhood-level characteristics. The neighborhood around each participant was defined by a circular buffer of 1600 m around the location of their household. The variables captured at the buffer level include the following:

1. *Land slope*: The land slope was obtained using the Digital Elevation Model data from the CGIAR CSI (Consultative Group for International Agricultural Research–Consortium

for Spatial Information) SRTM (Shuttle Radar Topography Mission) 90-m resolution digital elevation data. The median slope was taken as a measure of hilliness in the neighborhood.[17]
2. *Greenness and built-up density*: Normalized Differentiated Vegetation index measured the amount of greenness within the buffer area of 1600 m, while Normalized Differentiated Built index measured the amount of built-up density within the neighborhood. Both of these measures were captured from Landsat 8 Operational Land Imager images from the United States Geological Society archives.[18,19]
3. *Intersection density*: Intersection density was defined as the ratio of the number of 3-way or more intersections to the area of the buffer in square kilometers.[20] The road network was captured using OpenStreetMap where “highway” or “walkway” had true value.[21]

Panchayat-level characteristics. The following variables were captured from the panchayat/municipality that the participants belonged to:

1. *Population and residential density*: These were obtained from the Census of India 2011. The population density was defined as a total number of inhabitants per square kilometer, and residential density was determined as the total number of housing units per square kilometer.
2. *Safety from crime*: Crime rates for the year 2016 were collated from State Crime Records Bureau (the data holder for crimes and accidents under the directive of Central Government) for each police station. Crime rates were defined as the total number of crimes/total population.
3. *Safety from traffic*: Pedestrian accident rates was captured as a proxy to safety from traffic, which was defined as the number of pedestrian accidents/total population for each panchayat. Data were collated from the Road Accident Information System, State Crime Records Bureau, for the year 2016.

Statistical Analysis and Software

Spatial clusters were identified using SaTScan version 9.6. The depiction of clusters using maps was created using Quantum GIS software, version 3.4.4. Comparisons of participant characteristics were done using IBM SPSS Statistics, version 25, and R software, version 3.6.1. Categorical variables were analyzed using χ^2 statistics, and continuous variables were tested using *t* test statistics. A *P* value of less than .05 was considered to be the level of significance for all statistical tests employed.

Results

Spatial Clusters of Diabetes

A total of 5 high spatial clusters and 4 low spatial clusters were identified both in the urban and rural settings, given in Supplementary Table 1 (available online) and shown in Figure 1. Participants in the highest clusters of diabetes had almost 3 times higher likelihood of having diabetes in both urban (relative risk [RR] = 3.14, $P < .001$) and rural (RR = 2.68, $P < .0001$) settings. On the other hand, participants in the lowest spatial clusters of diabetes had 70% (RR = 0.30, $P < .001$) and 81% (RR = 0.19, $P < .001$) lower likelihood of having diabetes in urban and rural areas, respectively.

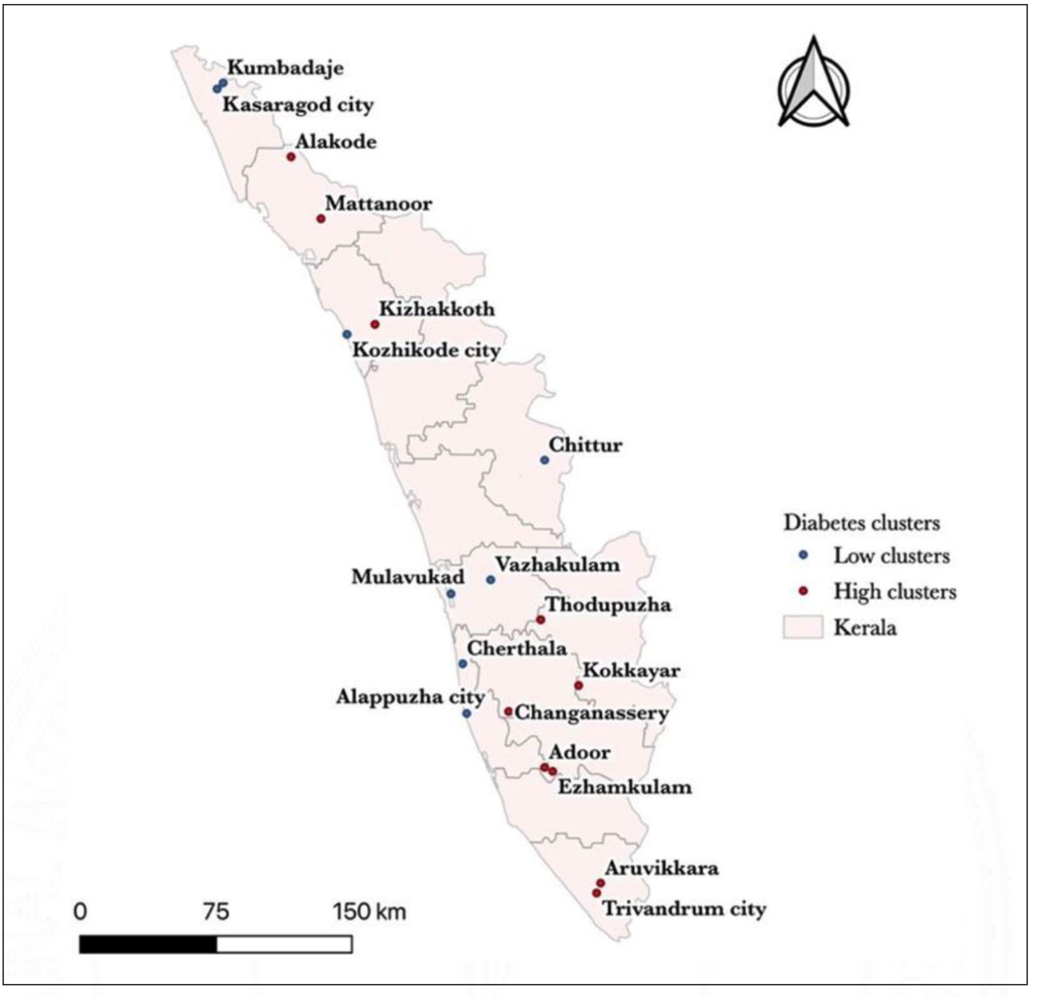

Figure 1. Map showing spatial clusters of diabetes among a selected population across Kerala.

Spatial Clusters of Physical Inactivity

A total of 10 high and 13 low spatial clusters of physical inactivity were identified in the urban areas while there were 7 high and 10 low spatial clusters in the rural areas, as given in Supplementary Table 2 (available online). The geographical locations of the top 5 high and low spatial clusters in urban and rural areas are shown in Figure 2.

Comparison of Sociodemographic Characteristics Between High and Low Clusters

There were significant differences in the sociodemographic characteristics of participants ($P < .01$), except for gender, within high and low clusters of diabetes in the urban setting. On the other hand, among the sociodemographic characteristics, only age ($P < .05$) and marital status ($P < .01$) showed a significant difference for participants within high and low spatial clusters of diabetes in the rural setting. For participants within high and low spatial clusters of physical inactivity in the urban environment, there were significant differences in gender, educational qualifications, and occupational status ($P < .01$), while not for age and marital status. In the rural

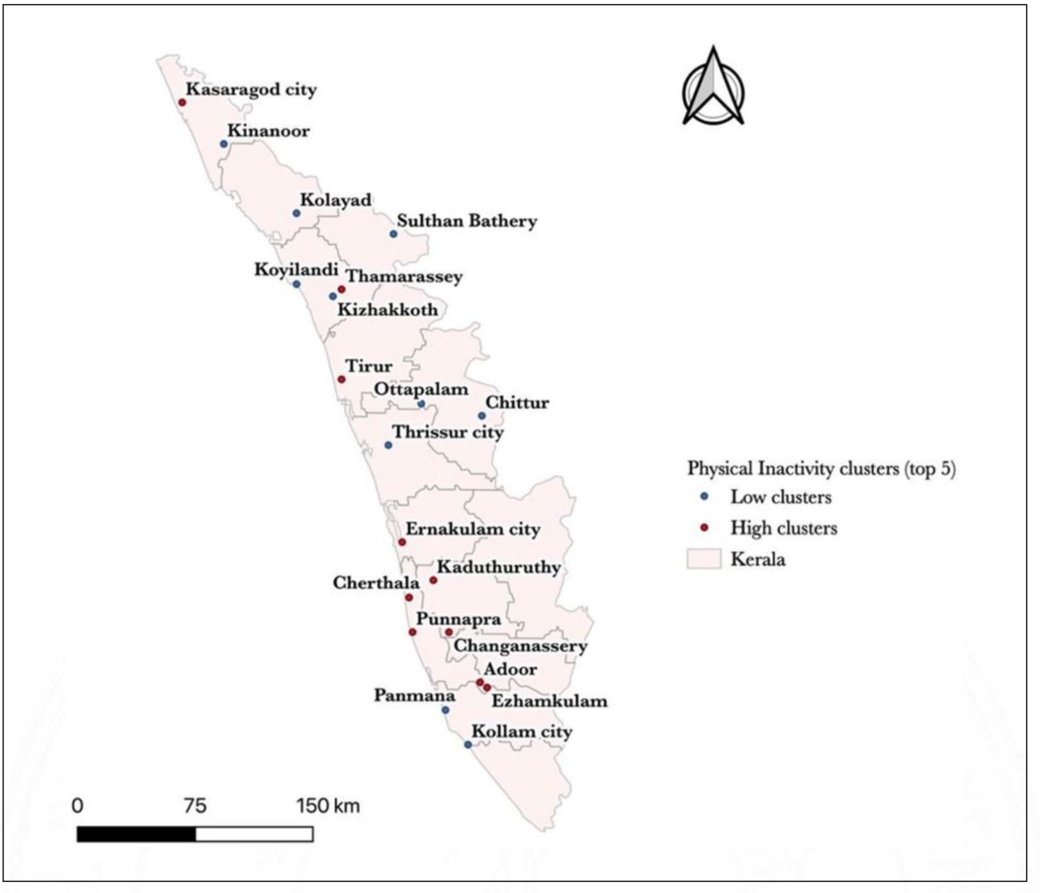

Figure 2. Map showing spatial clusters of physical inactivity among a selected population across Kerala.

setting, only educational status and occupation showed a statistically significant difference among participants belonging to high and low spatial clusters of physical inactivity ($P < .01$; Supplementary Table 3, available online).

Comparison of Built Environment Factors Between High and Low Clusters

Diabetes Clusters. Participants belonging to low spatial clusters of diabetes were located in panchayats with significantly higher population and residential density when compared with those belonging to high spatial clusters in both urban and rural settings. Moreover, panchayat-level crime rates and pedestrian accident rates were significantly lower for participants in low clusters in the urban setting, in comparison with those in high clusters. This scenario was reversed in the rural setting, with higher panchayat-level crime rates and pedestrian accident rates for participants in low clusters. A statistically significant higher neighborhood built-up density and lower neighborhood greenness and land slope were found for participants belonging to low clusters of diabetes, in both urban and rural settings. Intersection density in the neighborhood proved to be higher for participants in low clusters only in the urban setting.

Physical Inactivity Clusters. Panchayat-level population density and residential density were significantly lower for participants in low clusters of physical inactivity in comparison with those for participants in high clusters in rural areas. Crime rates and pedestrian accident rates were significantly lower in panchayats with low spatial clusters of physical inactivity in both urban and rural settings. Participants in urban low spatial clusters had statistically significant lower neighborhood greenness and higher built-up density when compared with those in high clusters. On the contrary, in the rural setting, those participants located in low clusters had significantly higher neighborhood greenness and lower built-up density in comparison with their counterparts in high clusters. Furthermore, higher neighborhood land slope and lower intersection density were found for participants located in low spatial clusters of physical inactivity in both urban and rural settings, when compared with those for participants located in high spatial clusters (Table 1).

Discussion

The objective of this study was to identify spatial clusters of diabetes and physical inactivity among a selected population of 11 033 participants from 1345 sampling units across Kerala using spatial scan statistics and to delineate differences in sociodemographic and neighborhood characteristics of those participants located within cluster locations. High and low spatial clusters of diabetes and physical inactivity were found in both urban and rural areas. There were statistically significant differences in the sociodemographic characteristics of participants in high and low clusters, no consistent pattern emerged.

However, built environment characteristics of participants within high and low spatial clusters of diabetes and physical inactivity showed significant differences. Population and residential density were found to be significantly higher for the low clusters of diabetes in both urban and rural settings. Though not documented for diabetes, other studies have identified similar trends for physical activity and obesity clusters, and for meeting physical activity recommendations.[6,22] Higher intersection density was found in low clusters of diabetes in the urban setting, while lower intersection density was found in low clusters of physical inactivity both in urban and rural settings. This contrast could be due to the difference in the capture of diabetes using objective methods and estimation of physical activity using subjective measures. Higher intersection density has been previously found to favor physical activity and walking behaviors.[23]

Crime rates and traffic rates were significantly lower for low clusters of both diabetes and physical inactivity in the urban setting, while not in the rural environment. The urban scenario was similar to previous studies from Canada, where a higher prevalence of diabetes was related to higher crime rates; from Chennai, India, where walkability was related to low crime rates; and from Ghana, where adults engaged in more elevated amounts of physical activity in neighborhoods with low crime rates.[4,24,25] Moreover, perceived safety from crime has also been related to physical activity, weight status, and walking.[26] Lower traffic rates have been earlier related to lower insulin resistance and lower prevalence of obesity.[27] Perceived safety from traffic has also been found contributing to meet physical activity recommendations.[28]

Higher built-up density and lower greenness indicating urbanicity were related to low clusters of diabetes and physical inactivity in the urban setting, which is in congruence with other studies from the United States, where land-use was associated with meeting physical activity recommendations, but contradictory to other findings from Philippines, which indicate urban areas to be obesogenic in nature.[29,30] Lower land slope within the neighborhood was found among low spatial clusters of diabetes in the urban setting, which seems to confute previous findings from Perth, Australia, where a hilly neighborhood was found to be protective of diabetes. Results from the rural setting on the land slope, greenness, and built-up density failed to establish concordance for both low clusters of diabetes and physical inactivity.

This study shows that there are regional differences in the prevalence of diabetes and physical inactivity, and that built environment characteristics within neighborhoods matter across the

Table 1. Neighborhood Characteristics of Participants in Spatial Clusters of Diabetes and Physical Inactivity[a].

Location	Urban		Rural	
Type of cluster	High	Low	High	Low
Diabetes clusters				
	N = 667	N = 808	N = 452	N = 632
Population density	**2331.82 ± 1245.86**	**3312.83 ± 803.04***	**1239.83 ± 586.77**	**1659.37 ± 634.43***
Residential density	**578.32 ± 311.12**	**709.79 ± 176.09***	**306.93 ± 144.83**	**401.01 ± 162.47***
Crime rate	**76.74 ± 35.17**	**14.97 ± 8.96***	**50.75 ± 44.11**	**109.03 ± 70.29***
Pedestrian accident rate	**113.91 ± 43.52**	**69.93 ± 12.81***	**61.53 ± 67.77**	**392.43 ± 382.55***
Greenness	**0.49 ± 0.06**	**0.39 ± 0.13***	**0.54 ± 0.11**	**0.38 ± 0.18***
Built-up density	**−0.21 ± 0.03**	**−0.18 ± 0.06***	**−0.24 ± 0.04**	**−0.16 ± 0.04***
Land slope	**2.82 ± 1.33**	**2.25 ± 0.97***	**6.96 ± 3.39**	**1.89 ± 1.33***
Intersections	**79.33 ± 72.07**	**90.49 ± 76.50***	22.57 ± 71.32	25.82 ± 33.42
Physical inactivity clusters				
	N = 1317	N = 2119	N = 1068	N = 1429
Population density	3120.63 ± 1720.13	3030.94 ± 1482.01	**1454.89 ± 569.43**	**1357.52 ± 752.87***
Residential density	719.47 ± 400.04	714.70 ± 353.92	**358.08 ± 139.58**	**329.87 ± 185.64***
Crime rate	**42.85 ± 39.63**	**32.92 ± 40.28***	**116.81 ± 74.53**	**76.46 ± 27.19***
Pedestrian accident rate	**95.27 ± 38.79**	**70.37 ± 52.42***	**174.57 ± 100.24**	**111.81 ± 74.53***
Greenness	**0.43 ± 0.13**	**0.41 ± 0.11***	**0.48 ± 0.08**	**0.54 ± 0.06***
Built-up density	**−0.18 ± 0.05**	**−0.17 ± 0.05***	**−0.19 ± 0.04**	**−0.22 ± 0.05***
Land slope	**2.30 ± 1.59**	**2.42 ± 1.52**	**2.50 ± 1.75**	**5.28 ± 4.19***
Intersections	**144.09 ± 175.15**	**103.33 ± 111.18***	**17.47 ± 19.12**	**12.96 ± 18.21***

[a]All values are given as mean ± standard deviation.
*Denotes P value <.01, boldface depicts significant relationship (P < .05).

state. It substantiates the importance of exploring the role of place on health status and prevention of disease even in low- and middle-income countries. Urban and rural differences in both prevalence and built environment characteristics within high and low spatial clusters indicate that a "one-size-fits-all" method cannot suffice to curb the rising incidence of NCDs in Kerala. These findings could establish the effectiveness of spatial data analysis as a necessary tool for tailor-made interventions by both public health professionals and policymakers.

The present study has several limitations. The cross-sectional nature of the survey cannot aid in establishing causality between the neighborhood characteristics and NCDs. Moreover, the spatial patterns may change depending on the spatial scale used and also taking into cognizance that areal units in geographical studies are arbitrary and modifiable. The physical activity measure was not measured objectively, hence could produce inconsistent results. This study was confined to a 15-km radius; therefore, ward-level or panchayat-level clustering could not be performed.

Conclusion

This study serves as underpinning research to find spatial clusters of diabetes and physical inactivity, and in the relationship between the built environment and NCDs in Kerala. Consistent patterns of lower crime rates, pedestrian accident rates, greenness, and higher built-up density were found in low clusters of diabetes and physical inactivity in the urban areas. However, low spatial clusters of diabetes and physical inactivity in the rural setting showed contradictory differences in the built environment characteristics. These findings lay down the need for further exploration in spatial clustering of diabetes/physical inactivity in the state of Kerala. Results of this study could aid in the design and implementation of a focused intervention based on geographical location of participants.

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Supplemental Material

Supplemental material for this article is available online.

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Original Article

Using Open-Source Data to Explore Distribution of Built Environment Characteristics Across Kerala, India

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Abstract

Background: Built environment characteristics in the neighborhood are of utmost priority for a healthy lifestyle in the fast-urbanizing countries. These characteristics are closely linked to the disease burden and challenges in low- and middle-income countries (LMICs), which have been unexplored using open-source data. The present technology offers online resources and open source software that enable researchers to explore built environment characteristics with health and allied phenomena. **Objectives:** This article intends to delineate methods to capture available and accessible objective built environment variables for a state in India and determine their distribution across the state. **Methods:** Built environment variables such as population density and residential density were collated from the Census of India. Safety from crime and traffic were captured as crime rates and pedestrian accident rates, respectively, acquired from State Crime Records Bureau. Greenness, built-up density, and land slope were gathered from open-source satellite imagery repository. Road intersection density was derived from OpenStreetMap. Processing and analysis differed for each dataset depending on its source and nature. **Results:** Each variable showed a distinct pattern across the state. Population and residential density were found to be closely related to each other across both districts and subdistricts. They were both positively related to crime rates, pedestrian accident rates, built-up density, and intersection density, whereas negatively related to land slope and greenness across the subdistricts. **Conclusion:** Delineating the distribution of built environment variables using available and open-source data in resource-poor settings is a first in public health research among LMICs. Cost-effectiveness and reproducible nature of open-source solutions could equip researchers in resource-poor settings to identify built environment characteristics and patterns across regions.

Key words: Built environment, distribution, geographical information systems, low-and-middle-income countries, open-source, public health

Introduction

The place where we live matters a lot. The relationship between health and place has been of great interest in the present health scenario. Broadly, the built environment encompasses the place where we live and have been modified by people. It is inclusive of indoor and outdoor physical environments (including climate and air quality) and social environments which comprise civic participation and community investment. Another definition says that "it includes man-made buildings, infrastructures and cultural landscapes that constitute the physical, natural, economic, social, and cultural capital of a society."[1] Yet another useful definition states "built environment consists of all buildings, spaces, and products that are created or modified by people."[2] Relationship of the built environment with health has been broadly inclusive of the built environment and physical activity, built environments and food, built environments and mental health, and urban planning and health. The variables documented to capture the built environment ranges from population density, residential density, land-use mix, street connectivity, greenness, land slope, safety from crime, and safety from traffic to capture of food environments (density of restaurants, distance to food destinations, etc.). Furthermore, types of data used for measuring built environment characteristics encompass objective measures (e.g., systematic scans or audits), perceived

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measures (e.g., by personal interviews or questionnaires), and archived datasets analyzed using geographical information systems (GIS).[3]

Large epidemiological studies have been undertaken in the developing nations to estimate the prevalence and identify contributing factors of communicable and noncommunicable diseases. However, the relationship between health conditions with built environment features has not been explored adequately in these nations. Recent advancements in spatial analysis, capacity building, and availability of spatial data have been crucial for researchers in low- and-middle-income countries (LMICs) to spearhead studies on the built environment. Besides, open-source solutions such as quantum GIS (QGIS), Google Earth, OpenStreetMap (OSM), and satellite data availability provide cost-effective platforms to undertake research involving spatial data.[4] Advancements in geospatial applications enhanced computational power, and increased availability of spatial data have empowered researchers to incorporate GIS to capture objective built environment measures over large areas, using publicly available data.[5,6] Taking into account the recent trend toward building healthy communities, this methodology using GIS and available data would also help gauge communities/neighborhoods based on land use and safe infrastructure to walk/bicycle.[7]

On this backdrop, this study is aimed to: (a) delineate methods to capture built environment variables using open-source solutions for a state in India and discuss the challenges thereof, (b) examine the distribution of built environment variables across Kerala.

Materials and Methods

Study site

Kerala, one among the states with a high epidemiological transition level, is the lowermost southwestern State in India. It has 14 districts with 64 sub-districts. It is topographically diverse, with lowlands in the western coasts and extending toward midlands and highlands in the eastern regions.[8] It is well known for its biodiversity and very high social indicators among the Indian States.[9] In terms of health indicators, Kerala fares excellent in neonatal and maternal mortality rates but faces the greatest challenge to curb lifestyle diseases, including diabetes, coronary heart disease, renal disease, cancer, and geriatric problems.[10] The urban share in Kerala among the total population has doubled from 26% in 1991 to 48% in 2011, which is the highest in India.[11] Problems due to unplanned urbanization continue to prevail in urban Kerala, including the rise in transportation costs, urban poverty, and urban sanitation problems.[12]

Data sources

This study has compiled data from the following sources:

Census data

Population density and residential density were obtained from the Census of India, 2011 (http://censusindia.gov.in).

State Crime Records Bureau

Crime rates and pedestrian accident rates were accessed from the State Crime Records Bureau, the authorized data holding agency under the Government of India directive. Rates were available for all 498 police stations in Kerala. Each police station was linked to the corresponding district and sub-district using jurisdiction details from the corresponding Kerala Police station websites. All 498 police station websites were visited to confirm their jurisdiction. Crime was defined as total crimes inclusive of all cognizable crimes in the Indian Penal Code.[13]

Spatial data

Greenness was measured using normalized differentiated vegetation index, and built-up density was estimated using normalized differentiated built index from Landsat8 images accessed from the United States Geological Society archives.[14,15] The land slope was measured from digital elevation model data retrieved from Shuttle Radar Topography Mission (SRTM) 90 m resolution images through Consortium for Spatial Information.[16,17] Intersection density was calculated as the number of three-way or more road intersections per square kilometer area in a district or sub-district. This was captured from the road network layer for the state of Kerala using OSM.[18,19] The timeline for data capture was between February and April 2018.

Data processing

Nonspatial data

The population density was defined as the number of inhabitants per square kilometer area of district or sub-district. In contrast, residential density was defined as the number of residential units per square kilometer area of district or sub-district. Crime rates were calculated as the number of crimes reported per thousand population in district or sub-district. Pedestrian accident rates were calculated as the number of pedestrian accidents reported per one lakh population in district or sub-district.

Spatial dataset

Search criteria of place names of Kerala, Kasaragod, Thiruvananthapuram, and Kanyakumari, with a data range of the year 2016 and a cloud cover <10% yielded 25 Landsat 8 operational land image images. Similarly, a search criterion for Kerala in the SRTM repository produced three SRTM images, which were merged and clipped for calculating the land slope for the extent of Kerala. The OSM layer was also clipped to the extent of Kerala. District and sub-district-level measures of greenness, built-up density, and land slope were captured using Zonal statistics plugin. In contrast, intersection density was obtained using points in the polygon tool in the QGIS software 3.4.4 (QGIS Development Team, 2009). Data validation and quality check measures were placed in each step of processing, beginning with the download of data, filling of no data values, calculation of composite measures, and scrutiny of raster histograms. The data processing methods are summarized in Table 1. Approval for this research was obtained from the Institutional Ethics Committee (IEC/1164).

Table 1: Data processing methods and definitions (source: Original)

Characteristic	Source, years	Definition	Processing/process	Variable
Population density	Census, 2011	The total number of inhabitants per area/km^2	As available	Population density/km^2
Residential density	Census, 2011	The total number of households per area/km^2		Residential density/km^2
Safety from crime	SCRB, 2016	Total number of crimes/ total population	Each police station was mapped to district/ subdistrict according to jurisdiction details in each police station website	Crime rate/1000 inhabitants
Safety from traffic	SCRB, 2016	Total number of pedestrian accidents/total population		Pedestrian accident rate/100,000 inhabitants
Greenness	Landsat 8 OLI images, 2016	Greenness within each district and subdistrict	Band 4 and Band 5 images were simultaneously loaded after atmospheric correction of each image. Raster calculator tool in QGIS could generate NDVI. Zonal statistics tool could generate NDVI statistics in each district and subdistrict	Mean NDVI
Built-up density	Landsat 8 OLI images, 2016	Amount of urban area distribution within each district and subdistrict	Band 5 and Band 6 images were simultaneously loaded after atmospheric correction of each image. Raster calculator tool in QGIS could generate NDBI. Zonal statistics tool could generate NDBI statistics in each district and subdistrict	Mean NDBI
Land slope	SRTM images, 2016	The on-ground terrain within each district and subdistrict	DEM data with a cell size of 90 m×90 m were used. Terrain models in raster analysis were used to calculate the slope. Zonal statistics tool could generate slope statistics in each district and subdistrict	Mean slope
Intersection density	OSM layer, 2016	The number of three-way or more intersections/km^2. Within each district and subdistrict	The subset of roads from the OSM layer was created. Using line intersections tool in vector analysis, point features were created where the lines intersect each other	The number of points/ km^2

GIS: Geographical information systems, SCRB: State crime records bureau, OLI: Operational land image, SRTM: Shuttle radar topography mission 90m elevation data, OSM: OpenStreetMap, QGIS: Quantum GIS, NDVI: Normalized differentiated vegetation index, NDBI: Normalized differentiated built index, DEM: Digital Elevation Model

Data analysis

Geographical distribution of population density, residential density, crime rates, pedestrian accident rates, greenness, built-up density, intersection density, and land slope were summarized using both tables and choropleth maps across districts and subdistricts of Kerala. Choropleth map generation was done using *sp* package in R software version 3.6.1 (R Core Team, 2019). Correlation between these variables was also examined.

Results

Distribution of built environment variables – district-wise

The built environment variables were captured for districts and sub-districts, and geographical distribution of the same are shown in Figures 1 and 2. Thiruvananthapuram district was the most populous and had the highest density of housing units in the State. Crime rates were recorded to be the highest in Ernakulam and lowest in Malappuram districts. Pedestrian accident rates were reported to be highest in Kollam, whereas lowest rates were reported from Malappuram district. Ernakulam district had the highest built-up density and lowest greenness, while Kozhikode had the lowest built-up density, and Wayanad had the highest greenness. The most upper median land slope was found for Idukki, while the lowest was for Alappuzha district. Ernakulam was found to have the highest intersection density, while Idukki had the lowest number of road intersections per square kilometre.

Distribution of built environment variables – sub-district-wise

The highest land slope was in the Devikulam sub-district in Idukki, while the lowest was found to be in Aleppey sub-district in Alappuzha. Cochin subdistrict had the lowest greenness, while Ranni in Pathanamthitta recorded the highest. Kuttanad in Alappuzha recorded the lowest built-up density while the highest built index was recorded for Cochin in Ernakulam. Pirmed in Idukki was the least populous and had the lowest number of housing units per square kilometer while Cochin city recorded the highest population and residential density. Kanayanur and Cochin subdistricts in Ernakulam ranked lowest and highest, respectively, in crime and pedestrian accident rates. Intersection density was highest in Kanayanur and lowest in Ambalappuzha subdistricts.

Correlation of built environment variables-district-wise

Correlation between built environment variables among districts and subdistricts are summarized in Table 2. Across districts, population density and residential density were highly correlated to each other. The population density was also positively related to three-way road intersection density

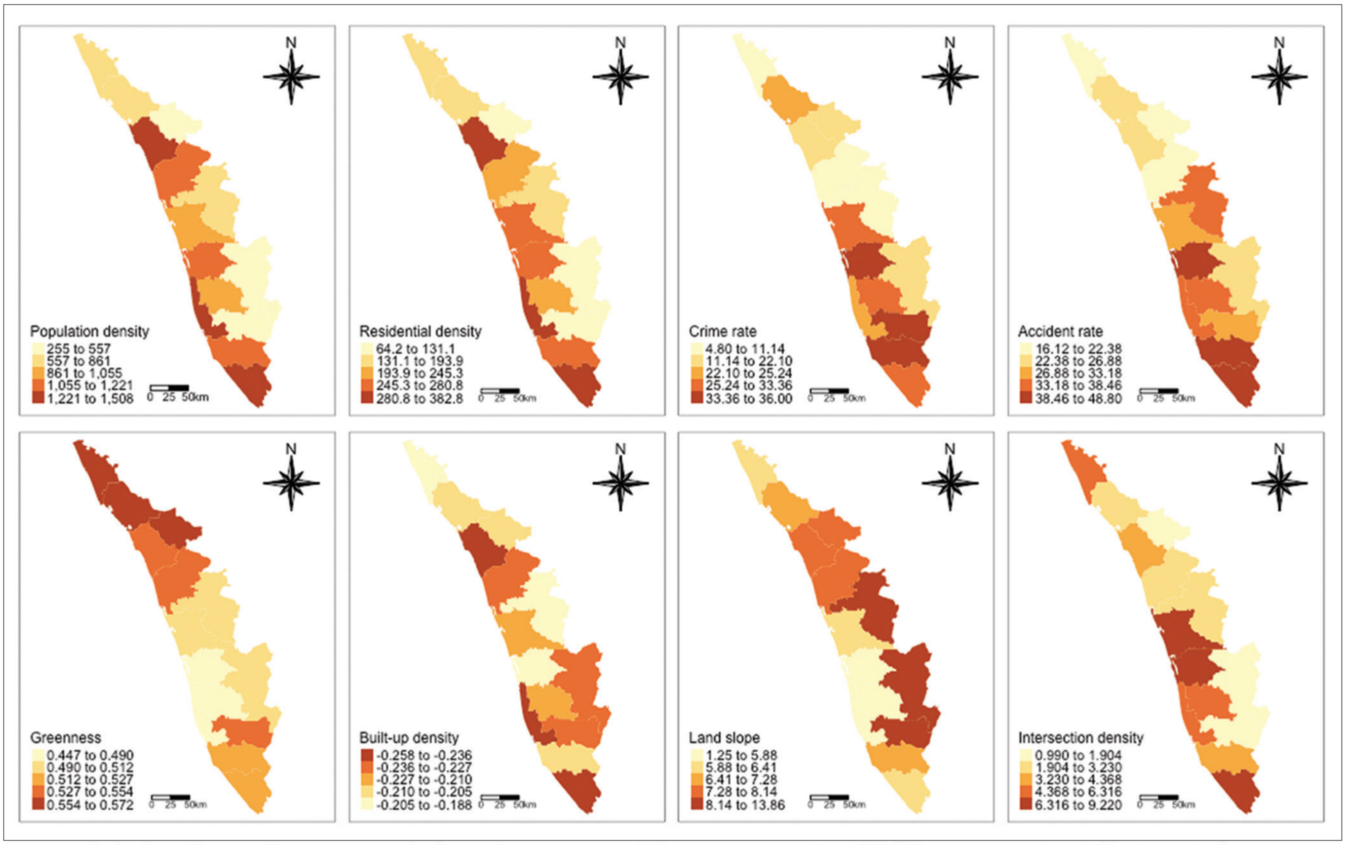

Figure 1: Distribution of selected built environment variables across districts in Kerala (Source: Author generated).

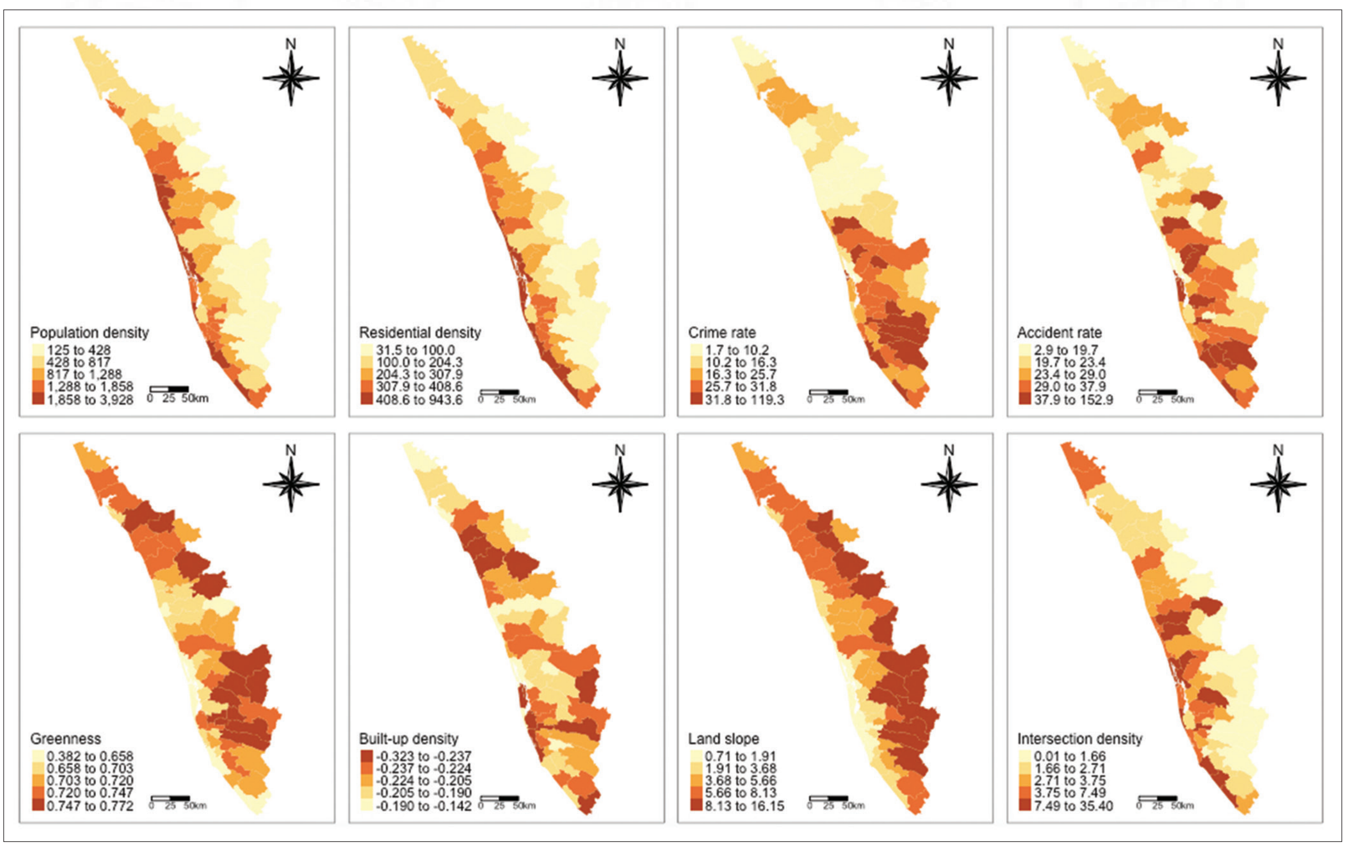

Figure 2: Distribution of selected built environment variables across sub-districts in Kerala (Source: Author generated).

Table 2: The correlation among built environment variables across districts and subdistricts (source: Original)

Built environment variables	Across districts							
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
X_1	1.00							
X_2	0.98*	1.00						
X_3	0.14	0.30	1.00					
X_4	0.40	0.54†	0.78†	1.00				
X_5	−0.17	−0.25	−0.47	−0.57†	1.00			
X_6	−0.29	−0.27	0.22	0.29	−0.10	1.00		
X_7	0.57†	0.62†	0.44	0.60†	−0.45	0.36	1.00	
X_8	−0.74*	−0.72*	0.03	−0.36	0.19	−0.26	−0.66†	1.00
Built environment variables	**Across subdistricts**							
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
X_1	1.00							
X_2	0.99*	1.00						
X_3	0.27†	0.32*	1.00					
X_4	0.34*	0.37*	0.81*	1.00				
X_5	−0.83*	−0.83*	−0.43*	−0.54*	1.00			
X_6	0.26†	0.26†	0.27†	0.33*	−0.50*	1.00		
X_7	0.69*	0.73*	0.29†	0.28	−0.71*	0.47*	1.00	
X_8	−0.67*	−0.67*	−0.06	−0.21†	0.60*	−0.20	−0.41*	1.00

*P<0.01, †P<0.05. X_1: Population density, X_2: Residential density, X_3: Crime rate, X_4: Pedestrian accident rate, X_5: Greenness, X_6: Built-up density, X_7: Intersection density, X_8: Land slope

and negatively related to the land slope. A similar relationship was reflected for residential density with the density of road intersections and land slope. Pedestrian accident rates were directly related to the density of houses per square kilometer, crime rates, the density of road intersections, and inversely related to greenness. The density of road intersections per square kilometer tended to decline with higher land slope.

Correlation of built environment variables-sub-district-wise

The population and residential density of sub-districts also were highly correlated to each other. Both population and residential density were directly related to crime rates, pedestrian accident rates, urbanicity, and road intersection density, but were negatively related to greenness and land slope. Crime rates had a tendency to be higher with higher intersection density, built-up density, and pedestrian accident rates, while an inverse relationship was found with greenness. A lower inclination of pedestrian accident rates was found with higher greenness, higher land slope, and with lower built-up density. Higher intersection density was related to low greenness, high built-up density, and low land slope. Higher greenness was related to higher land slope and low built-up density.

Discussion

This study intended to capture the available built environment variables using open-source data and examine their distribution across districts and subdistricts of Kerala. The distribution of variables under study showed distinct patterns across districts and sub-districts.

Capturing data and assimilating them continues to be a great challenge for researchers in LMICs.[20] Seeking due permission from government authorities to access data in LMICs continues to be a hurdle. Obtaining spatial data from government-owned sources, for example, Bhuvan in India entails procedural delays and charges.[21,22] However, the linking of various data sources has its constraints of compatibility, and standardization, for example, police station jurisdiction and census blocks jurisdiction, may not be the same. Majority of the existing evidence depicts the capture of the walkability index, which may be impossible to capture objectively in LMICs, because of the paucity of data regarding land use and accessible destinations. Land use data available from government sources in India depicted agricultural land, barren land, and cropland, which could not be used for examining walkable environments while developed countries had specifics of residential/institutional/commercial use.[6] The digitization of such variables may be plausible in the forthcoming decade, due to advancements in technology and expertise in handling spatial data.

District and subdistrict distribution showed that population density and residential density were highly correlated, which were related to accident rates, intersection density, and land slope within the districts. Within the sub-districts, both higher population density and residential density reflected higher built-up density, higher intersection density, and lower land slope and greenness, with higher rates of crimes and accidents. These could determine the urbanicity of the districts and subdistricts. These results coincide with previous pieces of evidence, where population density has been related to built-up growth and an increase in the built-up area.[23,24] Moreover, there has been an established relationship between population density and crime rates, particularly a negative relationship with property crimes.[25] Higher crime rates were also reported in the populous districts of Istanbul.[26] Residential density beyond a threshold has also been evidenced to reduce violent crimes in urban neighbourhoods.[27] Furthermore, higher population densities have resulted in the lowering of maximum vegetation fraction in the United States.[28] Greenness was found to be inversely related to population density, crime rates, and pedestrian accident rates. This has been previously documented in Portland, where greenness has resulted in reduced violent crimes.[29] Moreover, greenness has been found to reduce stress and mental fatigue in urban settings, thus facilitating a converse relationship between greenness and crime. Fewer police crime reports were also reported in higher vegetated regions in Chicago, and a negative correlation has also been found between tree cover and crime rates.[30] Pedestrian accident rates with higher casualties were found to be higher in extremely dense areas, and pedestrian collisions were also higher in high-density urban neighborhoods and areas with a higher percentage of street space.[31]

The present study showed that it is possible to capture all available built environment variables using open-source data, which could be reproducible across LMICs. It is a first of its kind attempt in public health research from LMICs. Such an exploration is cost-effective and maximizes the use of available resources in public health research. It could be replicated for comparison across different settings or investigate changes in the neighborhood across time series. Such exploration could provide opportunities to answer a multitude of plausible research questions, including relationships to health and disease. This method of spatial data capture using open-source data demonstrated the relationship of built environment characteristics in the neighborhood with diabetes and physical inactivity.[32] Nevertheless, limitations such as standardization across datasets and jurisdiction boundaries need to be taken care of. This study has also attempted to capture only a few of the variables of the built environment. All the objectively captured data were not originally captured for research purposes, especially crime and pedestrian accident statistics; hence, we may not be assured of quality. GIS data captured as a single estimate for the whole state may not exactly reflect the true phenomenon, which has not been evaluated for validity and reliability. Certain open-source data sources, for example, the OSM is updated through crowd-sourcing, and hence may not be complete and reliable as for the developed countries.

Conclusion

Objective measurements of the built environment can be captured using open-source data and freely available datasets in resource-poor settings. Capturing built environment data for public health research continues to be challenging in LMICs. However, the available solutions prove to be beneficial in delineating distribution across a state and have the potential to be replicated. These could be used to identify and compare built environment features across neighborhoods in LMICs.

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Conflicts of interest

There are no conflicts of interest.

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