A Framework for Applying Computational Methods to Identify Optimal Open Space Location for Physical Activity

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Abstract: The public health field is faced with much concern about low levels of physical activity (PA) and increased risks of chronic diseases which are associated with numerous health conditions and generally lead to lower life expectancy in most developed countries. Open spaces such as parks, plazas, and greenways play a critical role in promoting PA in communities by providing accessible and convenient settings where people can engage in various forms of PA.

This paper presents a well-structured framework that uses a streamlined approach to analyse multiple physical and environmental factors influencing the use of open spaces for PA. Using vector data, scripts were developed to automate geospatial analysis including network analysis, proximity analysis, transit access density analysis, and the Shannon diversity index through the QGIS Python API. The results demonstrate the potential of computational methods to fully automate workflows for identifying optimal open space locations that support convenient PA engagement in communities.

Keywords: Framework, computational methods, optimal location, open spaces, physical activity

1 Introduction

Studies show that the amount of PA has decreased remarkably in recent years (FATHI et al. 2020), leading the World Health Organization (WHO) in 2022 to again identify inactivity as the fourth leading risk factor in the global mortality rate. (WHO 2022). Research shows an increase in chronic diseases relate mainly to the lack of PA with other contributors such as poor food, and personal habits such as drinking and smoking (WHO 2022). Most adults in the United States do not meet the current Center for Disease Control (CDC) PA guidelines recommending that adults get at least 150 minutes of moderate-intensity aerobic PA or 75 minutes of vigorous-intensity PA, or an equivalent combination each week. On a global spectrum, studies show that currently, one-third of adults in the world are physically inactive (WHO 2022). These findings highlight the critical issue of physical inactivity and the role of the built environment in facilitating convenient opportunities for PA. Since the early 21st century, there has been a growing interest in how the built environment influences health-promoting behaviours, prompting research on designing spaces that encourage diverse forms of PA (BEDIMO-RUNG et al. 2005). Researchers like Frank et al. (2006) and Leslie et al. (2007) examined the association between walking and the built environment features such as mixed land uses, street connectivity, net residential density (dwelling density), and retail floor-area ratio. Their study found that single land-use, low-density land development, and disconnected streets are positively associated with auto dependence and negatively associated with walking, the most common form of PA. A large body of literature provides some answers about features such as design elements (GILES-CORTI et al. 2008, KARIMI 2012, KACZYNSKI et al. 2008, FATHI et al. 2020, WANG & STEVENS 2020), proximity to open spaces (STEWART et al. 2016, HURVITZ et al. 2014, GILES-CORTI & DONOVA, 2002, GILES-

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CORTI et al. 2008, HAN et al. 2013), access to open spaces (GILES-CORTI et al. 2008, STEWART et al. 2016, BARAN et al. 2008, ALFONZO, 2008), and amenities (FORSYTH et al. 2008, MCCORMACK et al. 2004) and how these physical environmental factors broadly influence active living and engagements in PA. The built environment has become a fundamental factor in discussions on PA, particularly regarding open spaces as accessible public destinations for PA.

One major challenge faced by proposing new and or existing open space is identifying an optimal location for an open space that can be conveniently accessed and utilized for PA. The location of an open space plays a critical role in promoting active lifestyles, as accessible public destinations for PA.

In this study, we define an open space as a publicly accessible space that is designated for outdoor recreational activities and social interaction (MADANIPOUR 2003, ROGERS 1999, WOOLEY 2003). These spaces can take many forms, including parks (CHIESURA 2004, NEWMAN 1973), squares, plazas (MILLER 2007), playgrounds (WOOLLEY 2003), gardens (NEWMAN 1973), and other types of green or natural areas (LITTLE 1995). Open spaces have been found to play an essential role in providing opportunities for people to engage in PA (WANG et al. 2021) as studies have found that children (BAEK et al. 2015), young adults (O'LOUGHLIN et al. 2022, LESLIE et al. 2001), and older adults can benefit from having access to a range of open spaces such as playgrounds, parks, open fields, trails and sports fields (WOOLLEY 2003). However, the lack of open spaces (TINSLEY et al. 2002) and their unequal distribution (KING 1995) have discouraged users from using these spaces to engage in PA. One major challenge faced by proposing new and or existing open space is identifying an optimal location for an open space that can be conveniently accessed and utilized for PA. The location of an open space plays a critical role in promoting active lifestyles, as accessibility and proximity significantly influence the likelihood of people engaging in PA (MCCORMACK et al. 2010). Therefore, determining the most optimal location requires careful consideration of various physical and environmental factors, making it a complex yet essential task. This research introduces a framework that applies the concept of spatial location optimization, a computational approach for identifying optimal sites for activities, services, or facilities within a geographic area. This method integrates spatial data, algorithms, and analytical techniques to balance factors such as accessibility, proximity, demand, cost, and environmental impact (WEI et al. 2022, CHEN et al. 2023). In planning and design, spatial location optimization has been applied to identify locations that maximize benefits to users while minimizing negative impacts, such as travel distance or resource consumption (KACZYNSKI et al. 2014). Similarly, this study applies the spatial location optimization method by analysing physical and environmental factors using geospatial data (vector layers) and computational methods.

2 Methods

This section provides an overview of the analysis and computational methods applied in this study to develop a well-structured framework. The discussion begins by introducing the physical and environmental factors analysed within the framework, followed by an overview of the QGIS platform and its suitability for geospatial analysis. The following sub-sections discuss using vector data for geospatial analysis, focusing on vector-based spatial analytical methods such as network analysis and density measurement. Subsequent sub-sections present the study area, and the different analyses computed within this framework.

2.1 Physical and Environmental Criteria for Framework Analysis

In developing the physical and environmental factors analysed in this study, insights were gathered from a semi-structured interview conducted between May and September 2023 using a purposive sample of experts. The goal of the study was to understand the key factors influencing the use of open spaces for PA. Participants included 18 academic and industry experts from public health, urban design, planning, and architecture fields.

Findings from the study helped establish a well-defined theoretical basis, which was further synthesized using the Analytical Hierarchical Process (AHP) and a systematic approach involving weight scoring and rationale-based selection, which helped the researchers to identify the most relevant factors based on three criteria: (1) alignment with the research objectives, (2) feasibility of measurement using computational methods in QGIS, and (3) contribution to a focused and manageable analysis. These criteria ensured that the selected factors effectively addressed the study goals while remaining practical for computational implementation. Figure 1 presents the final set of factors and sub-factors that serve as the foundation for the spatial analysis applied in this study.

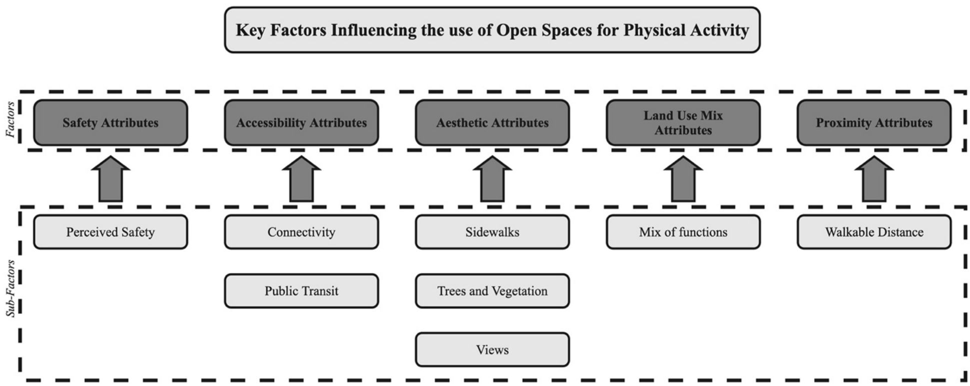

Fig. 1: Key Factors Influencing the Use of Open Spaces for Physical Activity (Source: Authors)

2.2 Development Environment for Geospatial Analysis

QGIS is a free and open-source GIS software known for its flexibility, extensive plugin ecosystem, and unrestricted access to geospatial analysis tools. Unlike proprietary software such as ArcGIS, AutoCAD Map 3D, and Bentley Map, which impose license restrictions on many functional modules, QGIS provides unrestricted access to its features, making it an attractive choice. It supports C++ and Python, with the PyQGIS library enabling seamless scripting and automation of processes (HUANG et al. 2024). The built-in Python API allows for efficient geospatial data processing and integration with external libraries, making QGIS an ideal platform for computational analysis. PyQGIS library is contained within the qgis package, which comprises four main sub-packages: qgis.core, qgis.gui, qgis.analysis, and qgis.server.

The qgis.core package handles reading, processing, and managing raster and vector data, while qgis.gui provides tools for designing user interfaces in QGIS. The software supports various geospatial functions and analyses, enabling users to perform a wide range of spatial analyses and visualize results. Given its open-source nature and scripting capabilities (WEGMANN et al. 2020), QGIS provides the necessary flexibility for implementing the various geospatial analyses undertaken in this study.

2.3 Vector Data for Geospatial Analysis

Vector data is one of the two types of spatial data used to represent geographic features in GIS. It uses points, lines, and polygons from Euclidean geometry to represent geographic entities with precise location identification and attribute connections, enabling accurate measurement of spatial properties (DAS et al. 2024).

Its relevance in spatial representation and computational analysis stems from its accessible format and ability to support processes such as buffering, overlaying layers, measurements and pattern analysis (KUMAR et al. 2023). Additionally, vector data preserves spatial relationships during geometric transformations, ensuring topological integrity which is critical for accurate network analysis, proximity calculations, and spatial modelling within a network. This feature of vector data is essential to this study, where connectivity and density influence geospatial assessments. The primary analytical aspects of vector data used in this study are network analysis and density measurements.

2.4 Network Analysis

Network analysis is the practical application of graph theory to study the real-world relationships and interactions within a network, whether physical (e. g., roads, utilities, pedestrian pathways) or abstract (e. g., social connections, communication systems). It examines nodes (points) and edges (connections) to analyse patterns of connectivity, flow, accessibility, and centrality (PORTA et al. 2006).

In architecture, network analysis has been used to model spatial and functional relationships, where rooms and corridors are represented as nodes and their connections (doors, hallways, or paths) as edges (JABI 2016). In geospatial studies, it has been widely applied in GIS for transportation route optimization (BAST et al. 2016), accessibility measurement (TURNER 2001), and urban system modelling (PORTA et al. 2006). Studies show its effectiveness in analyzing street connectivity (HILLIER et al. 1987, TURNER, 2001), transport networks (BAST et al. 2016), and the spatial distribution of services like utilities, telecommunications, and retail (PORTA et al. 2010).

Network analysis efficiently processes complex, interconnected datasets, making it ideal for large-scale spatial analysis. Space Syntax applies network analysis to study spatial systems, focusing on integration and connectivity to reveal how spatial arrangements influence social behaviors like crime rates, wayfinding, and movement (HILLIER and HANSON 1989). Depthmap, an extension of this methodology, measures relative accessibility and connectivity while enabling visibility graph analysis for buildings and urban environments (TURNER 2001). This study primarily employs network graphs to analyse spatial relationships on vector datasets because network data consists of points (nodes) and lines (edges) that align directly with graph structures used in network analysis. Integrating network-based measures enhances the understanding of spatial relationships, complementing other geospatial analyses in identifying optimal locations for PA.

2.5 Density Measurement

Density measurement is a key analytical technique in vector data used to evaluate the spatial distribution and concentration of features within an area or network system. It is commonly applied to points (e. g., trees, buildings), lines (e. g., roads, pathways), and polygons (e. g., land-use zones) to analyse patterns of accessibility, connectivity, and environmental quality (BORRUSO 2005).

In geospatial analysis, vector-based density measurements include point density (counting point features within a defined area), line density (measuring the total length of network features), and polygon density (calculating feature concentration within administrative boundaries) (HARRIS & CHEN 2005). Kernel Density Estimation (KDE) is widely used to create gradient maps that highlight variations in density across a continuous surface.

This study applies density measurements to evaluate the spatial distribution of built environment features by analysing the concentration of elements such as pedestrian pathways, transit stops, and tree canopy cover.

2.6 Study Area

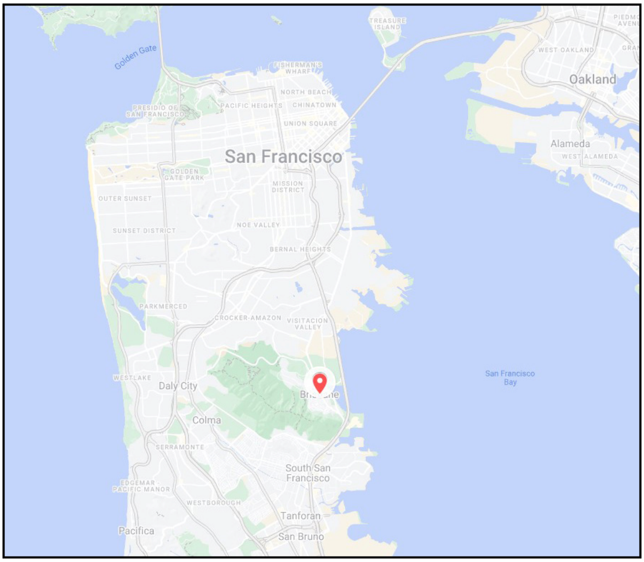

Fig. 2: Map of Brisbane, the Study Area Where Framework was Tested (Source: Authors)

The study area for this research is Brisbane, a small city in San Mateo County, located on the southern end of San Francisco city limits on the San Francisco Bay. Brisbane is characterized by its proximity to a major metropolitan centre and its mix of residential, commercial, and industrial zones. The city is bordered by natural spaces, including San Bruno Mountain State Park, which offers opportunities for exploring interactions between built environments and natural spaces. Brisbane's role as a commuter hub and its evolving urban infrastructure reflects broader trends in the San Francisco Bay Area, making it a microcosm of regional development challenges and opportunities. Its compact size and diverse population make it an ideal study site for experimenting the various geospatial analyses presented in this study on a manageable scale.

2.7 Computational and Geospatial Analysis

This section presents geospatial analyses organized within the framework to assess the physical and environmental factors within Brisbane, California. The following subsections outline the four main stages of the framework, with each stage building upon the previous one to ensure a logical progression from data collection to final evaluation and results.

Stage 1: Data Collection

The vector data used in this study were primarily obtained from the HOT Export Tool, a web-based platform developed by the Humanitarian OpenStreetMap Team (HOT) that allows users to export OpenStreetMap (OSM) data in various vector formats. These open-source vector data are user-friendly and well-suited for GIS, mapping, and geospatial analyses. For each physical and environmental factor assessed in this framework (see Tab. 1), various vector datasets were downloaded from the HOT Export Tool

Because tree canopy vector data were not available through the HOT Export Tool, the datasets were sourced from California State Geoportal (gis.data.ca.gov). Transit stop data were obtained from the California Open Data Portal (data.ca.gov/dataset/ca-transit-stops). Additionally, a geographic boundary layer was downloaded to define the limits of the study area and ensure that all analysis aligned accurately with the study area and produced geographically valid results. All vector data used in this study were in shapefile format.

Table 1: Methods of Analysing Physical Environmental Factors

Physical and Environmental Factor(s)	Description	Vector Layer(s) Used	Methods
Aesthetic Attributes			
Sidewalks	Assesses the presence of sidewalks to facilitate easier, safer and more attractive access to open spaces.	• Road • Sidewalks	Pedestrian Path Density Analysis
Trees and Vegetation Coverage	Assesses the presence of trees to create shade and mitigate heat. Also improve air quality and enhance visual attractiveness of an open space.	• Trees • Study area boundary	Tree Canopy Cover Analysis
Views	Assesses for the presence of views (such as natural landscapes, open vistas, urban skyline) that could make a space more attractive and enjoyable for both active and social uses.	• Potential Open Space • Buildings • Water bodies • Hills/Mountains • Study area boundary	Vista Quality Assessment

Physical and Environmental Factor(s)	Description	Vector Layer(s) Used	Methods
Accessibility Attributes			
Connectivity	Evaluate connectivity, as well-connected locations facilitate ease of travel and encourage active transportation, increasing the likelihood of frequent visits to an open space.	• Roads • Pedestrian paths • Study area boundary	Network Analysis: Using centrality measures
Public Transit	Assess for the presence of public transit infrastructure such as bus routes, bus stops and commuter rail as they encourage open space visit by providing affordable, reliable transportation options.	• Transit Stop • Transit Route • Road (optional) • Study area boundary	Transit Access Density Analysis
Land Use Mix Attributes			
Mix of Functions	Examines the diversity of nearby land uses, as mixed functions create a vibrant and multifunctional environment making an area more interesting for PA.	• Land use • Study area boundary	Shannon Diversity Index (SDI) for Land-Use Categories
Safety Attributes			
Perceived Safety	Evaluates the perception of safety in the area as a safe area fosters a sense of security, encouraging people to visit open spaces and stay longer.	–	–
Proximity Attributes			
Walkable Distance	Determines the proximity of existing residential areas to potential open space locations.	• Residential area • Vacant land • Road • Study area boundary	Proximity Analysis

Stage 2: Data Preprocessing

Prior to each analysis, the downloaded vector data were pre-processed to standardize formats to address inconsistencies and align spatial attributes with the study objectives, as shown in Figure 3. For instance, vector data, such as transit stops and tree cover datasets, covered a larger geographic area than the defined study boundary and were clipped to the extent of the study area to focus the analysis and include only relevant features. Data validity was verified in QGISPY by running a simple code that loads a vector layer. Additionally, it was noted that the downloaded vector data came in different coordinate reference systems (CRS), requiring reprojection into a uniform CRS to avoid issues with analysis and visualisation. Brisbane is in the UTM Zone 565 and uses the EPSG 32756 CRS. For analytical methods, projected coordinates (in meters) were preferred over geographic coordinates (in degrees), as they provide consistent, linear measurements suitable for spatial analysis, unlike degrees, which vary in distance depending on latitude. All the coordinates in this study were projected in meters to ensure accurate and uniform scaling for the calculations.

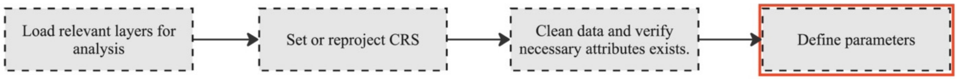

Fig. 3: Workflow illustrating the general steps for data preprocessing prior to spatial analysis (Source: Authors)

Stage 3: Analytical Methods

This section presents the geospatial analytical methods used to assess the physical and environmental factors, as shown in Table 1.

Analysis of Aesthetic Attributes

Sidewalk Density

Sidewalk density was analysed using a Python script developed in PyQGIS. The script divides the study area into equal-sized grid cells clipped to match the study boundaries. The presence of sidewalks within each cell was measured and normalized by cell area to determine the density. A higher sidewalk density indicates better pedestrian access and walkability, whereas a lower density suggests reduced walkability. This analysis used vector data of the existing sidewalks and study area boundaries.

Trees Coverage

Tree coverage was assessed using tree canopy cover analysis. This analysis evaluated the density of tree coverage to identify areas where the tree canopy cover exceeded a defined threshold of 60%, illustrating the presence of more trees. On PyQGIS, the total tree canopy area was calculated within each study area, and the percentage of canopy cover relative to each grid cell was computed. Cells exceeding the 60% threshold were identified (Figure 5). This method efficiently measures tree coverage by analysing the spatial extent of canopies rather than by counting individual trees.

Vista Quality Assessment

Vista quality analysis was conducted in QGIS to evaluate the scenic value of potential open spaces based on their proximity to and spatial intersection with key visual elements (e. g., building skylines, water bodies, and mountains). This analysis calculates the Vista score for each feature in the potential open space vector layer by counting the number of intersecting features from other geographic layers. The location with the highest Vista Score was identified as the optimal spot for the picturesque view. The analysis generated a new vista layer highlighting areas with varying scores to represent their scenic value.

Analysis of Accessibility Attributes

Street Connectivity

Street connectivity was assessed using NetworkX and centrality analysis. The process began by importing the necessary libraries, such as GeoPandas, to handle geospatial data and NetworkX for network analysis. Geospatial data for nodes (e. g., intersections) and edges (e. g., roads) are loaded into Geodata Frames. A graph object was then initialized in Network X to represent the street network, with nodes added based on their coordinates and edges derived from road segments connecting these nodes.

To ensure that the graph accurately represented the connectivity, its coherence and structure were further evaluated. Closeness centrality was computed to determine the importance of each node based on its proximity to others in the network. This study employed closeness centrality, referencing KIM & LEE (2016), who found that centrally located schools had higher proportions of students walking to and from the school. The results of this analysis would identify the most connected areas, highlighting nodes with the highest centrality scores as optimal locations for well-connected open spaces.

Transit Access

To evaluate public transit accessibility, this study employed transit accessibility density analysis to identify areas with high public transit access. The analysis calculated the density of transit stops along each route within the study area.

On PyQGIS, transit stop locations were buffered to create polygon geometries representing their spatial coverage. The density of stops along each route is computed and visualized. Areas with a higher concentration of stops were identified as optimal locations for open spaces, ensuring accessibility for transit-dependent populations, such as older adults, low-income individuals, and adolescents not yet of driving age.

Analysis of Land Use Mix Attributes

Mix of Functions

To identify areas with a high land-use mix, which enhances the use of open spaces for PA by creating vibrant, multifunctional environments, this study applied the Shannon Diversity Index (SDI). SDI is a mathematical measure widely used in ecological and environmental studies to assess diversity.

This framework used SDI to calculate the diversity and distribution of land use categories within the study area. The results were visualized using a graduated renderer with color-coded intervals to classify the different SDI values (see Figure 9). This approach effectively highlights areas with high land-use diversity and those with a lower land-use diversity. It is calculated using the following formular:

$H = -\sum[p_i \times \ln(p_i)]$

H' = Shannon Diversity Index (measure of diversity within a dataset
p_i = Proportion of individuals (or observations) belonging to species i^{th} category
$\ln(p_i)$ = Natural logarithm of p_i

When applied to land use, SDI measures the land use diveersity by treating different land use type (e. g., residential, commercial, industrial, and recreational) as the 'species' or 'categories' in the formula.

Analysis of Proximity Attributes

Walkable Distance

This study used proximity analysis to evaluate proximity by measuring the distance between existing vacant land (potential open space sites) and residential areas (catchment areas). Using spatial geometric functions, the analysis calculated a combined score to identify the closest vacant land sites.

A scoring function, 1 / (residential proximity + 1), was applied to ensure that closer proximity resulted in higher scores. The vacant land sites with the highest scores were identified as optimal locations for open spaces, as they were closest to residential areas and were thus more accessible to potential open-space users.

3 Results

This study analysed key physical and environmental factors, including aesthetics, accessibility, land-use mix, and proximity, to identify optimal locations for open spaces in Brisbane. Using different computational methods including pedestrian path density analysis, tree canopy cover analysis, vista quality assessment, network analysis, transit accessibility density analysis, Shannon Diversity Index analysis, and proximity analysis to identify areas most suitable for open spaces based on each analysis.

To assess aesthetic attributes, this study measured sidewalk density, tree canopy coverage, and locations with picturesque views. Sidewalk density analysis evaluated the distribution of sidewalks within the study area by classifying them into high-, medium-, and low-density regions. To ensure an accurate representation, the analysis applied a grid overlay to resolve any layer geometry misalignment and create a clear visual distinction between different sidewalk densities. As shown in Figure 4, the results indicate that most of Brisbane lacks sidewalks, some areas have a moderate sidewalk density, and only a few locations have a high sidewalk density.

The tree canopy cover percentage was also analysed using a grid-based approach that divides the study area into smaller, manageable cells. Each grid cell served as a spatial unit for calculations, ensuring uniformity and ease of visualisation across the study area. Unlike sidewalk density analysis, larger grid cells were used for tree canopy analysis because of the polygonal nature of tree canopy data, whereas sidewalks were analysed using line data. The results shown in Figure 5 indicate a relatively even distribution of tree canopy coverage across Brisbane, with most areas having adequate tree canopy cover.

Figure 6 shows the results of the Vista Quality Assessment analysis, which indicates that most of Brisbane, particularly the northern and central regions, have low Vista quality, likely due to obstructions such as dense vegetation or terrain limiting visual openness. In contrast, zones of high vista quality are found in the southern and southwestern parts of the city, where open landscapes and elevated viewpoints enhance visual access. Moderate vista-quality areas were scattered throughout the site, highlighting a mix of visual openness levels. These findings reveal apparent spatial disparities in visual openness, emphasizing the variations in scenic quality across different parts of the city.

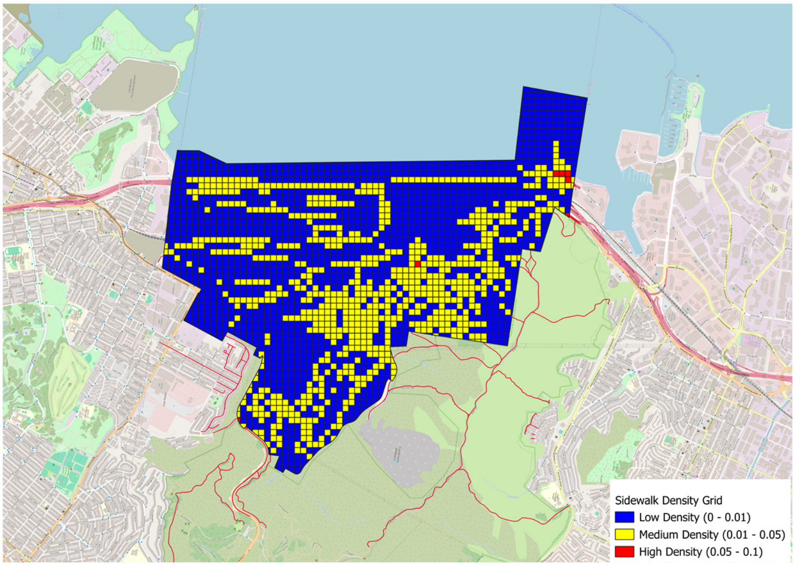

Fig. 4: Map Showing Sidewalk Analysis (Source: Authors)

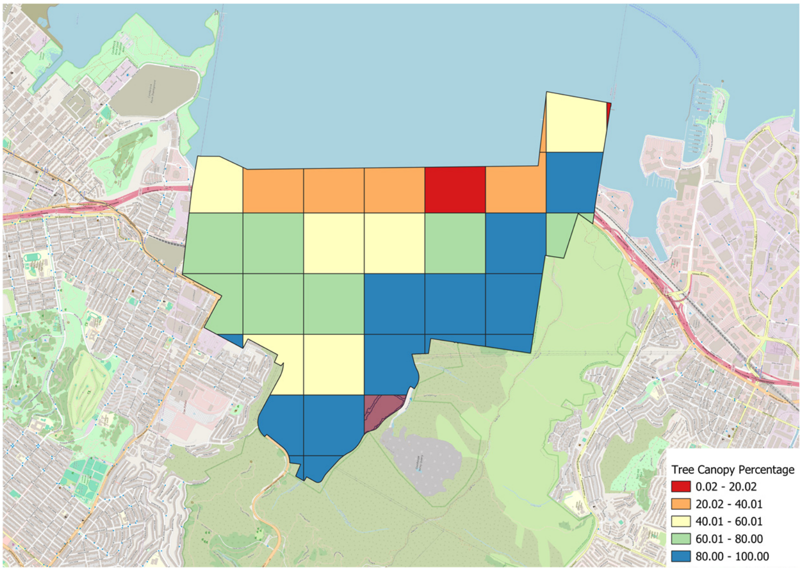

Fig. 5: Map Showing Tree Canopy Percentage (Source: Authors)

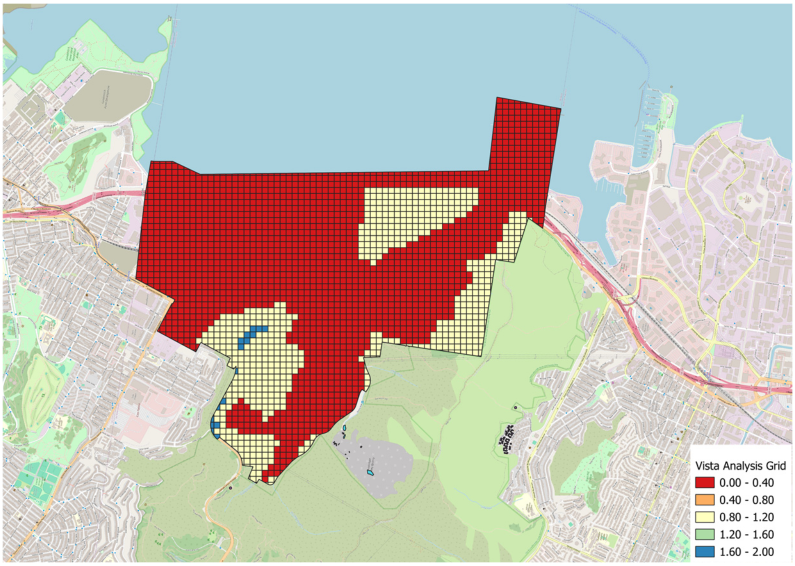

Fig. 6: Map Showing Visual Quality Assessment Analysis (Source: Authors)

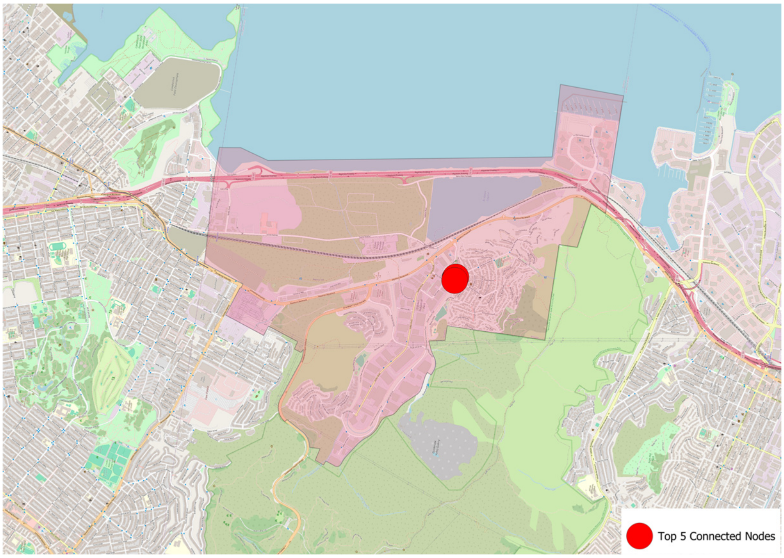

Fig. 7: Map Showing Top Five Connected Nodes (Source: Authors)

To measure accessibility, this study analysed street connectivity and public transit access. Figure 7 presents the graph theory network analysis results, which evaluate node connectivity using closeness centrality derived from road vector data. During the analysis, some road segments (edges) were disconnected. To address this problem, a minimum spanning tree (MST) was applied to ensure that all nodes were connected for the analysis. The top five nodes with the highest centrality values were identified and visualized as point layers to highlight the most connected locations, as shown in Figure 7.

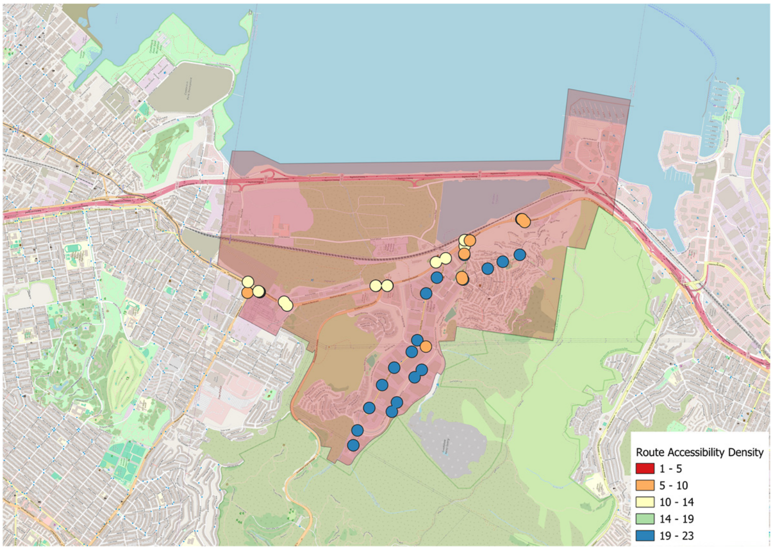

Fig. 8: Map Showing Route Accessibility Density (Source: Authors)

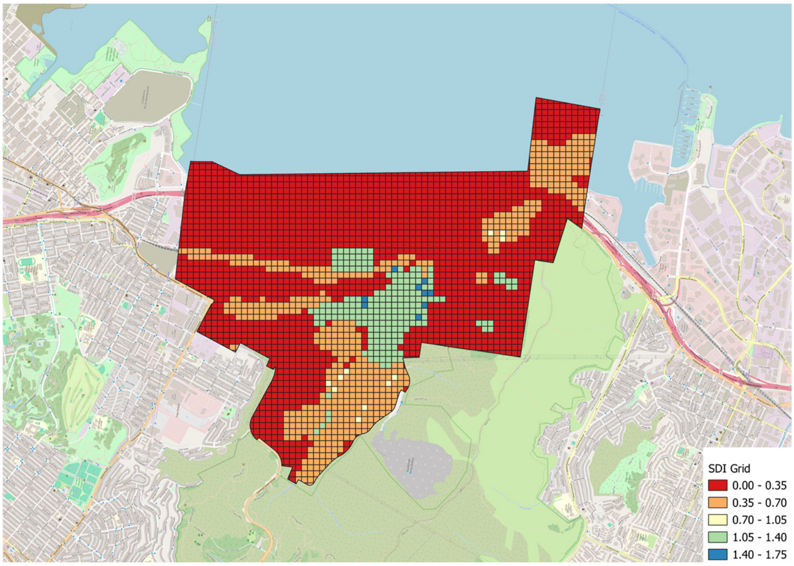

Fig. 9: Map Showing Shannon Diversity Index Analysis (Source: Authors)

After calculating the density of transit stops along each route and buffering them to create a polygon layer representing their spatial influence. The results of the accessibility analysis were best visualized using nodes, highlighting the critical points within the transit network. Figure 8 reveals a moderate-to-high transit density within Brisbane, with the western part of the city having a higher transit density than other parts.

Within this framework, land-use mix was analysed using the Shannon Diversity Index (SDI) to assess spatial variations in land-use diversity. Figure 9 shows that most of Brisbane has low land-use diversity (red zones), particularly in the northern and central regions. In contrast, higher land-use diversity is concentrated in the southern and central regions. The map shown in Figure 9 suggests that land use was unevenly distributed, with some areas having a greater mix of functions than others.

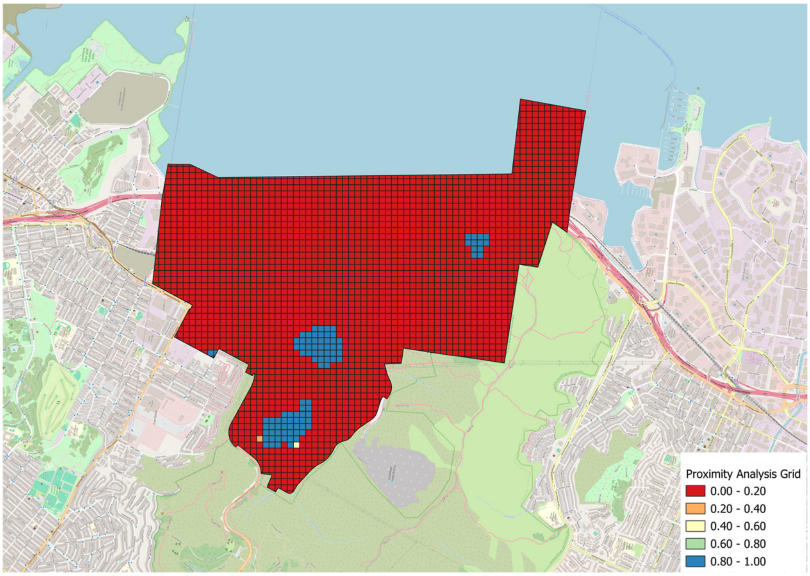

Fig. 10: Map Showing proximity Analysis (Source: Authors)

The proximity analysis in this study assessed the distance between existing vacant land (potential open space locations) and residential areas (catchment areas), assigning a value representing the minimum distance for each potential open space site. A combined score is computed for each parcel. As shown in Figure 10, the results indicate that proximity to residential areas is generally low across the city, with higher proximity areas (blue zones) concentrated in the southern and central regions. This reveals a stark contrast between walkable pockets and large areas of low proximity. This pattern may be influenced by the uneven land use distribution shown in Figure 9. While this study used residential areas as catchment zones, future applications of this analysis could incorporate commercial, industrial, or educational areas to refine the proximity assessments.

This framework successfully analysed key physical and environmental factors, safety, previously identified as a relevant factor influencing open space use for PA, was not included due to challenges in applying standardized methodologies to measure safety accurately in QGIS. However, efforts to integrate safety analysis into this framework are ongoing.

4 Conclusion

The research presented in this paper demonstrates an organization of different analyses in a well-structured framework applying different scripts developed on PyQGIS. Each analysis contributes valuable insights and, together, forms a computationally efficient and streamlined approach that leverages open-source data. While existing studies provide evidence of applying complex computational methods to evaluate specific physical and environmental factors in the built environment, the challenge remains in developing a streamlined approach that analyses multiple factors using different computational methods on a single platform, which is ultimately what this framework presents.

This study found PyQGIS to be a versatile platform due to its seamless integration of Python scripting with QGIS's geospatial capabilities to automate spatial analysis that would otherwise require complex tasks. The grid-based approach provides several advantages for spatial analysis, particularly its ability to examine small-scale features, such as sidewalks, within a larger area, resulting in visually interpretable maps. This method proved especially effective in the sidewalk density assessment. However, challenges arose when applying the grid approach to more complex geographic contexts, such as intersections involving water bodies and mountainous terrain. These challenges highlight the need further to explore alternative methods or refinements to the grid-based approach to enhance its versatility and accuracy in such scenarios.

Several limitations were encountered in developing this framework. Data availability posed significant challenges with some vector layers. For instance, the mountain vector layer for vista quality assessment was difficult to access for the study area; hence, the researchers manually created it. This manual intervention may have introduced fractures to the dataset, possibly impacting the accuracy of the results. Furthermore, some vector layers acquired from Hot Export Tool contained incorrect features or incomplete attributes, necessitating additional processing that may have affected the overall analysis. Automating analytical tasks using the QGIS API also presented limitations, particularly in achieving consistent workflows for complex spatial analyses. Visualisation inconsistencies, such as using grid-cells in most analyses and node-based representations in others (e. g., connectivity and transit density), highlight the need for greater visual consistency in future studies.

Despite these challenges, the computational methods presented in this paper establish a first-of-its-kind framework, laying the groundwork for exploring further possibilities in built environment and health-related research. Notably, the study did not aim to identify an optimal location for an open space within the study area but to test the organization of different analyses within a framework. Future research will focus on refining the computational methods to enhance predictive accuracy, standardizing visualisation across analyses, and applying them to larger urban datasets to visually identify optimal locations for open spaces where PA can be conveniently engaged.

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