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Job accessibility and spatial equity

A City of Cape Town case study

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Abstract: Addressing unemployment and income inequalities in transport and land-use policies is important, particularly in South Africa, which is currently experiencing one of the highest unemployment rates and income inequality in the world. This research investigates the horizontal (geographical distribution) and vertical (distribution between income groups) impact of job accessibility within the City of Cape Town. Two accessibility measures were estimated using unique tax administrative data together with TomTom road network and speeds data to determine job accessibility, differentiating between suburbs, industries, income groups, and different travel times. The research findings show the spatial divide between worker's residence and jobs and highlight the difference in this spatial mismatch between different income levels. The results highlight the unequal distribution of accessibility across space and between different income groups and show that the impact of congestion has a greater effect on access to job opportunities for residents of low-income locations compared with those from high-income locations. This reinforces spatial inequality. This research provides insights into where transport investments should be made to increase access to jobs and reduce inequality in accessibility, which could drive further income inequality and unemployment.

Key words: job accessibility, spatial inequality, spatial mismatch, congestion, travel time, developing country

JEL classification: D63, R1, R41, O1

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1 Introduction

The World Bank (2022) reports that globally 56% of people live in cities and that this is expected to increase to 7 out of 10 people living in cities by 2050. Cities are the drivers of economic growth, with currently 80% of the global gross domestic product generated in cities (World Bank 2022).

The relationship between urbanization and economic growth can be explained by the urban economic theory of agglomeration economies (O'Sullivan 2019). Firms cluster in urban areas to maximize their profit through agglomeration benefits, such as tapping into a common labour pool, sharing intermediate inputs, improving skills matching and sharing knowledge. This decreases their cost of production. These agglomeration benefits increase labour productivity and wages, which then attract individuals to cities. Individuals seek to maximize their utility by benefiting from the economics of production through higher wages, and from the economics of consumption through the greater variety of goods and services available in urban settings. These agglomeration benefits can thus lead to higher productivity and economic growth, also known as the urban dividend.

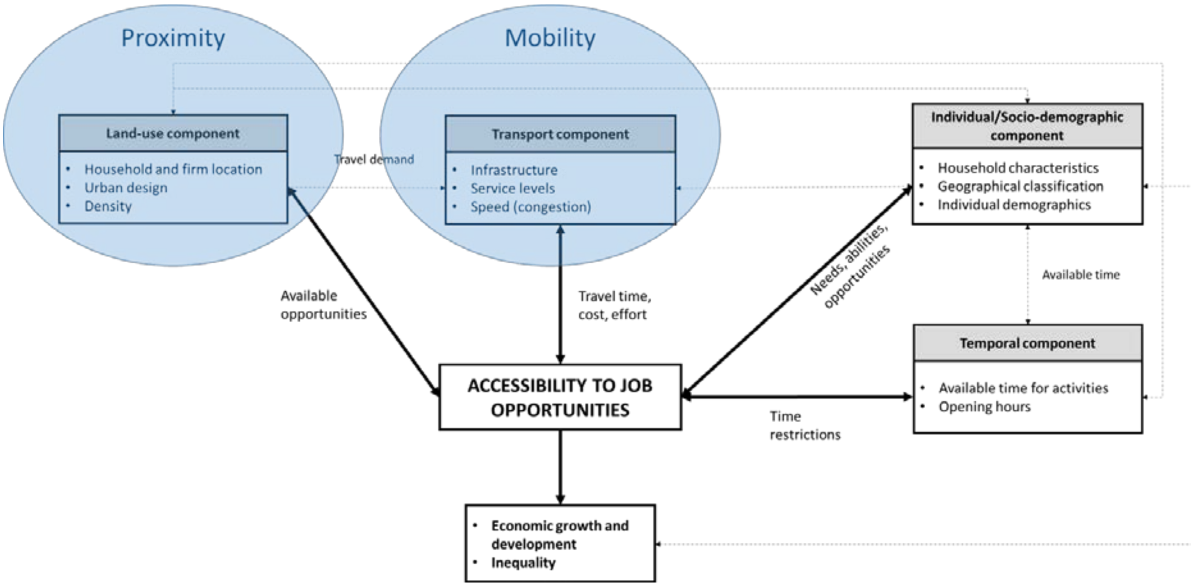
Poor spatial, land-use, and transport policies, which can lead to diseconomies of agglomeration, can erode the potential economies of agglomeration and ultimately influence economic growth and development. If transport is expensive and land use is not well planned, it decreases the urban dividend. In Africa, it is still better for people to be in cities than in rural areas because of the existence of an urban dividend (Nakamura et al. 2016). The question is whether this urban dividend is as high as it should be. Compared with cities in other countries with similar urbanization rates and comparable natural resources, cities in Africa are not living up to their potential (Page et al. 2020; Nakamura et al. 2016).

South African cities also experience constrained growth caused by poor urban planning and poor transport services that restrict access to productive activities and, in particular, job opportunities. This causes a spatial mismatch between where people live and where jobs are located. The government is responsible for creating an environment where individuals get access to employment to benefit from urbanization, resulting in agglomeration economies. However, the spatial divide between the location of housing and jobs makes it difficult for the government to plan and provide services that lead to higher economic growth and development.

Three constraints to economic growth and development were identified in the African Growth Initiative study (Page et al. 2020): (i) constraints within the business environment, (ii) public-sector governance, (iii) and accessibility, which is broadly defined as the ability to access opportunities within a city (Page et al. 2020). This paper focuses on accessibility, which is affected by land-use, transport, and temporal and individual components (Geurs and van Wee 2004), as illustrated in Figure 1.

The distance between where firms (jobs) are and where the working population is located determines the proximity of individuals to reaching employment. Poor proximity to jobs increases the need for workers to travel and puts pressure on the transport component, which influences mobility. The transport component comprises transport infrastructure, service levels, and speed. Poor transport planning and the lack of transport infrastructure can lead to higher congestion levels and thus influence travel speed, ultimately decreasing accessibility.

Figure 1: Conceptual framework for factors affecting the accessibility to job opportunities



Source: authors' construction.

Researchers and policymakers can use accessibility measures to measure the impact of transport and land use on an individual's ability to reach activities, especially job opportunities. It is important to understand the levels of accessibility to job opportunities, as several studies have shown the impact of accessibility on employment levels and wages (Johnson et al. 2017; Knudsen et al. 2022). These studies point out the differentiated impact of accessibility on employment/wage outcomes for different industries and argue the importance of including accessibility impacts in the economic evaluations of transport infrastructure projects.

1.1 Spatial equity and accessibility

It is also important to consider the fairness of the distribution of accessibility. Lucas et al. (2016) discussed a method for evaluating equitable accessibility and the distribution of access across demographic groups. They also used accessibility measures to determine what percentage of the population cannot reach an acceptable level of access according to a minimum threshold.

Equity aspects in accessibility can be referred to as 'spatial equity'. Spatial equity means the 'provision of benefits at a level that is consistent or fair throughout a geographical space' (Tsou et al. 2005). Litman (2007) and Ricciardi et al. (2015) refer to horizontal equity and vertical equity, respectively. Horizontal equity refers to equal accessibility across all groups across space, whereas vertical equity refers to the equal distribution of accessibility across different demographic groups, such as income groups. In South African cities, in most cases horizontal and vertical equity go hand in hand because of historical spatial segregation during the apartheid era. A study in Perth, Australia, evaluated the usefulness of incorporating spatial equity aspects in accessibility for the planning of transport and spatial investments. This study by Kelobonye et al. (2019) found that households on the periphery of the city are generally poorly served by transport, with no or limited accessibility to job opportunities. They found that more housing developments on the periphery of the city not only created a mismatch between residential areas and job opportunities in the inner city but also increased the number of individuals being disadvantaged regarding access to jobs (Kelobonye et al. 2019).

1.2 Congestion and accessibility

Congestion is an input variable in the transport component affecting accessibility and 'arises when demand levels approach the capacity of a facility and the time required to use it (travel through it) increases well above the average under low demand conditions' (Ortúzar and Willumsen 2011: 5). Congestion affects a firm's location decision because higher congestion increases employees' overall transport cost, travel time, and reliability. It also affects its input and output cost (e.g., labour inputs and access to market, respectively). Congestion can lead to firms and populations moving out of major employment centres that are smothered by high congestion levels, encouraging sprawl and lowering densities on the urban edge. Sprawl induces longer travel times and makes public transport less viable. It also has an impact on a firm's logistics systems by affecting timely deliveries, meaning that businesses have to keep a higher inventory stock. Ultimately, it affects overall firm productivity and economic growth. It is important to understand the impact of congestion on accessibility outcomes since increased congestion not only affects private car users but also road-based public transport modes that do not have a dedicated right-of-way infrastructure.

A study in Italy investigating local public transport researched the impact of congestion on the functioning of the labour and real estate markets (Mocetti and Roma 2021). The researchers highlight the impact of congestion, which, by increasing travel time to work, decreases the geographical range in which individuals would accept jobs. This leads to longer job-search times, resulting in higher periods of unemployment and individuals choosing to work in a job lower than their experience and education level (Mocetti and Roma 2021). This influences productivity.

South African cities are no exception regarding congestion and a spatial divide between homes and jobs (Van der Merwe and Krygsman 2020). The lack of a government public transport service and infrastructure provision has resulted in public transport relying on the wrong transport technology, such as minibus taxis, to transport most captive commuters. The rail services in the country have decreased significantly, with almost no rail services currently operating within the metropoles. Past rail commuters are now making use of road-based public transport modes, mostly minibus taxis, leaving these commuters and minibus taxi operators exposed to the impacts of congestion (Van der Merwe and Krygsman 2022).

Studies have investigated levels of congestion in urban areas from an engineering perspective. There is a gap in the literature to investigate the impact of congestion on accessibility and, particularly, the impact of congestion on spatial equity. The question is: which social demographic groups (from a commuter perspective) or industries (from an employer perspective) are affected the most by congestion regarding accessibility to employment opportunities?

This paper will use the City of Cape Town as a case study for South African cities to understand the current horizontal (geographical) and vertical (across different income groups) distribution of accessibility to employment. By using unique spatial tax administrative data, referred to as 'spatial tax panel data', combined with TomTom road network and speeds data, this research makes a unique contribution to existing accessibility analysis. Using these distinctive datasets allowed for accessibility analysis under different travel-time conditions to assess the differentiated impact of congestion on different income groups. This has not been done previously in equity analysis. Understanding the horizontal and vertical accessibility distribution within the City of Cape Town can help policymakers to prioritize interventions to improve accessibility to jobs in underserved areas and help to identify population groups that may face barriers to accessing job opportunities to reduce further societal and income inequalities and exclusion.

2 Methodology

2.1 Data

Three data sources are required for conducting accessibility analysis.

- Employment data: data on where the job opportunities are located.
- Population data: data on where the population resides.
- Travel-time data: travel cost or travel impedance between zones.

First, employment data were obtained from the South African Revenue Services (SARS) spatial tax panel datasets made publicly available in 2022 as part of the Cities Support Programme project (Nell and Visagie 2022). These datasets provided information on the number of jobs (full-time equivalent (FTE) employees) by industry and wage band on spatial hexagon level. These spatial zones (hexagons) each cover an area of ± 5 km^2 with the City of Cape Town divided into 330 hexagons as indicated in Appendix Figure A1. Annual data are available for the tax years from 2014 to 2021 (i.e. from March 2013/end February 2014 to March 2020/end February 2021). COVID-19 affected the employment figures significantly compared with the previous employment trend. This analysis only uses employment data over a 6-year period from the 2013/14 to the 2019/20 tax years, which only includes data up to before the first lockdown announcement in South Africa in March 2020. The SARS datasets represent formal employment only and do not report on jobs in the informal sector.

Second, population data were obtained from the Council for Scientific and Industrial Research (CSIR) in South Africa and spatially reported on at mesozone level (see Appendix Figure A2). Population data were derived from the 2001 and 2011 census population data on small area layer (SAL) as well as the 2016 community survey. Cape Town consists of 59 mesozones, each being approximately 42 km^2 (CSIR 2023). This data release forms part of the stepSA[1] collaborative research initiative. The methodology showing how the population data are derived can be obtained from the CSIR website (see CSIR 2023) and the technical document (Naudé et al. 2007). Linear extrapolation was used to derive population and working population figures for the period 2014–20 to overlap with the spatial tax data.

A limitation of this population dataset is that researchers cannot accurately determine whether there was a shift in location of households from the last census conducted in 2011. The 2014–20 population locations only consider growth in population for each area, but no shift in residential locations. This dataset can be improved in future research when the expected 2022 census results become available in 2024.

Income levels on SALs (refer to Appendix Figure A3) were obtained from the 2011 census (Stats SA 2011). The union function in ArcGIS Pro was used to calculate the percentage overlap between SALs and hexagons, and between mesozones and hexagons to obtain all population, income, and employment data at the hexagon level. An income quartile variable was derived at the hexagon level using the 2011 census data weighted by the working population in each hexagon.

[1] stepSA (Spatial Temporal Evidence Planning in South Africa) is a collaborative research initiative aimed at building the capability and evidence base to support high impact and transformative investment decisions in South Africa's cities, towns, and settlements (see stepSA 2023).

Finally, the free-flow and congested travel-time matrix between each hexagon was derived using the TomTom road network and speeds data. The TomTom Move user interface (see TomTom 2023) provides historical floating car data (FCD) and includes road network and speed data. The FCD is obtained from in-vehicle navigation devices and applications. The road network for the City of Cape Town was selected using an area analysis tool, which classifies the roads into eight[2] functional road classes (FRCs) ranging from a high-order road classification (FRC 0), which is classified as motorways, freeways, and major roads, to the lowest-order road classification (FRC 7), which is classified as local roads of minor importance. The City of Cape Town has a road network of more than 30,000 km, divided into road segments of approximately 100 m.

The limited number of GPS devices used in South Africa is of concern, considering the country's income distribution. This raises the question whether the speed profiles obtained from the TomTom data represent all income groups. A paper published by Bruwer et al. (2022) analysed the potential bias of FCD speeds in the South African context. By comparing FCD speeds with benchmarking speeds, the results of this paper indicate that the speeds of TomTom FCD in various metropolitan areas are well within the accuracy levels.

The harmonic mean speeds for each hour of all road segments were obtained from TomTom FCD for the month of February 2019. This month represents the most appropriate period because it does not contain any public or school holidays, and weather conditions in the Western Cape also have a limited impact during February.

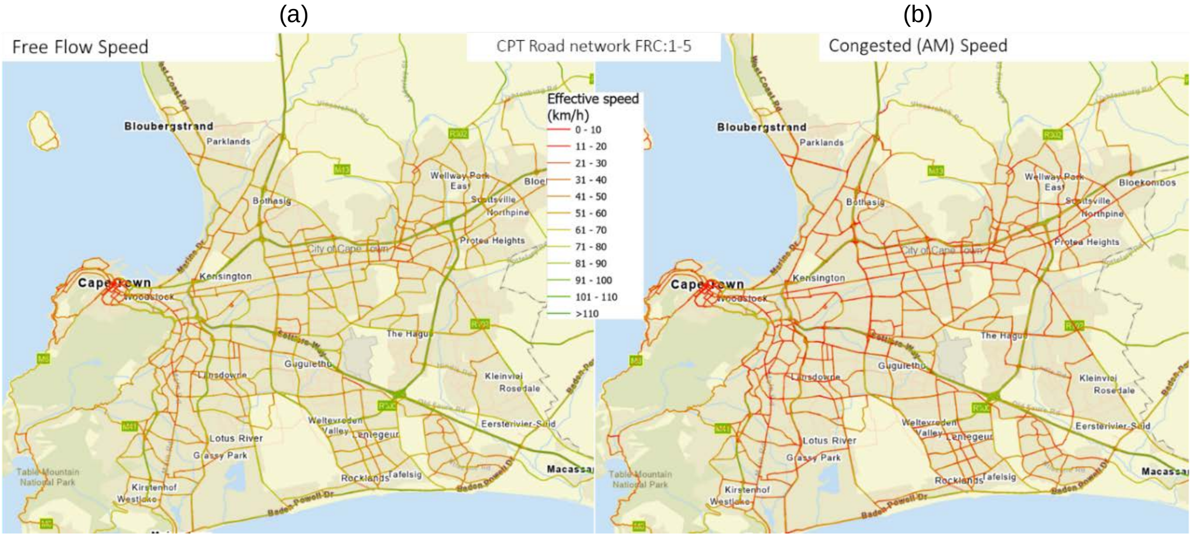
According to the *Highway Capacity Manual*, the widely used reference for transportation engineering, free-flow speed (FFS) is defined as 'the average speed of vehicles on a given segment, measured under low-volume conditions, when drivers are free to drive at their desired speed and are not constrained by the presence of other vehicles or downstream traffic control devices' (National Academies of Sciences, Engineering, and Medicine 2022: 10).

The average of the harmonic speeds for the period between 00.00 and 05.00 on weekdays was used to calculate the FFS, and harmonic speed data for the morning peak period (06.00–07.00, 07.00–08.00 and 08.00–09.00) was used to calculate the peak congestion speeds. These speeds were used to calculate effective travel time during free-flow and congested periods. Appendix Table B1 shows the difference in FFS and congested speed by functional road class and speed limit.

The difference between FFS and congested speed is depicted in Figure 2. The map shows the different speeds in the City of Cape Town for February 2019 for FRC 1–5.

[2] The City of Cape Town does not have an FRC 3 in the TomTom data. This can be because of different road classifications by the provincial Western Cape government or the metropolitan municipality.

Figure 2: (a) Free-flow speed and (b) congested speed by road segment (FRC 1–5)



Source: authors' construction using TomTom speed data.

The SARS individual and spatial tax panel datasets, as well as the TomTom road networks and speeds data, have not been used in transport and accessibility analyses before. Applying these unique datasets contributes to existing accessibility research in the following ways:

- Information on where jobs are located was previously not available in South Africa as employment data from the Quarterly Labour Force Survey (QLFS) is only reported at the provincial level. Some of the major metros collect employment information as part of their transport models and transport planning processes where employment is typically extracted from land-use maps of built-up areas and land-use type. A trip-generation factor for square metre built-up area by land use (commercial, services, residential, etc.) is used. By using the SARS spatial tax panel data in this study, employment data are provided on a more disaggregated level, by wage band and industry.
- The SARS spatial tax panel data provide employment data over time, which makes it possible to investigate employment changes over time.
- The TomTom road network transport data used in this study allow researchers to investigate the impacts of accessibility for different time periods, such as differentiating between FFS and morning and afternoon peak times. By contrast, publicly available datasets, such as the OpenStreetsMap road network, only provide speed limits for each road segment and require researchers to make assumptions on effective speeds by time of day.

Accessibility using the public transport network is excluded from this research because of the lack of publicly available data on the public transport network and travel times. In South Africa, public transport is predominantly road-based: 92% of all public transport trips to work in the City of Cape Town are reported as road-based trips according to the 2020 National Household Travel Survey (Stats SA 2021) which is thus well represented by the speeds presented in the TomTom data.

The data sources applicable to the accessibility analysis are summarized in Table 1. Variable descriptions are summarized in Appendix C.

Table 1: Employment, population, and travel-time data source for the City of Cape Town

Data source	Derived variables	Time period	Spatial level (number of zones in Cape Town)[a]
Employment data			
SARS spatial tax panel	Number of jobs (FTE) by industry type and wage band	2013/14–2019/20 tax years	Hexagons (330)
Population data			
CSIR population data	Population	2011, 2016	Mesozones (59 zones)
Census 2011	Population by wage bands and household income	2011	Small area layer (5,374 zones)
Road network / travel-time data			
TomTom road network and speeds	Road network (disaggregated to local roads); free-flow speed and congested (morning peak) speed	February 2019	Lines
ArcGIS Pro / Flowmap	Travel-time matrix using road network	February 2019	Origin–destination matrix (between hexagons)

Note: [a] shown in Appendix A.

Source: authors' construction.

2.2 Methods

Descriptive analysis and spatial mapping were used to indicate the employment and population densities on hexagon level within the City of Cape Town, highlighting employment by industry, wage bands, and employment changes over time.

The employment and population data on hexagon level were then used to calculate the job/worker mismatch by income quartile. The job/worker mismatch is the difference between the number of FTE employees (*$Jobs_i$*) and the number of working population (*$Workers_i$*) between the ages of 15 and 64 years within each hexagon *i*. The job/worker mismatch was calculated using Equation 1, and spatially mapped:

$$Job/worker\ difference\ (absolute)_i = Jobs_i - Workers_i \tag{1}$$

Two accessibility measures were calculated using the employment, population, and travel time datasets.

Accessibility proximity coefficient

An accessibility proximity coefficient (*A_prox*) was calculated to compare the rate at which jobs in an area can be reached. The proximity coefficient is a relative measure to compare the cumulative proximity count of the location of any hexagon (*i*) to the maximum number of jobs (*J*) hexagon *i* can reach within the timeframe [0, *t**], where *t** is the travel time it takes the best-located hexagon *i** to reach 100% of total jobs (*J*). The proximity count is the number of job opportunities that can be reached within 1-minute time intervals. Equation 2 represents the calculation for the accessibility proximity coefficient for each hexagon *i*:

$$A\_prox_i = \frac{\sum_{t=0}^{t^*} Proximity\_count_{it}}{Jt^*} \text{ for all } i = 1, \dots, N \tag{2}$$

The mean accessibility proximity coefficient over all hexagons (*N*) is then calculated for each income group under congested speed and FFS conditions weighted according to the population size of hexagon *i*. The total population size over all hexagons is denoted as *P*, and the population size in hexagon $i=p_i$. The population weight (W_i) for each hexagon is calculated as

$$W_i = \frac{p_i}{P} \tag{3}$$

The mean proximity coefficient over all hexagons (*N*) is calculated as

$$Mean\ A\_prox = \frac{\sum_{i=1}^{N} W_i A\_prox_i}{N} \tag{4}$$

Contour accessibility measure

The contour accessibility measure was then calculated to report on the number of job opportunities (proximity count) that can be reached within a certain travel-time threshold. This is a snapshot of the cumulative distribution function (derived to calculate the proximity coefficient) to reach job opportunities at a travel-time threshold. The contour accessibility measure, also known as the isochronic measure or cumulative opportunity measure, falls under the location-based accessibility measures discussed in Geurs and van Wee (2004). It has the advantage of easily interpreting and communicating the results, such as '*x*% of jobs can be reached within a 30-minute travel-time threshold'. This is more easily interpreted than the accessibility proximity coefficient, which only allows for the comparison of results between zones. The disadvantage of this method is that it does not take distance decay or competition for jobs into account. The contour accessibility measure has the following form:

$$A_{ik} = \frac{\sum_{j=1}^{J} B_j O_{jk}}{\sum_{j=1}^{J} O_{jk}} \tag{5}$$

where A_{ik} is the percentage of job opportunities within industry *k* that can be reached from hexagon *i*; O_{jk} is the job opportunities within industry *k* in zone *j* (proximity count); B_j is the binary value equal to 1 if area *j* is in the assumed threshold and 0 otherwise; threshold values are 15-, 30-, and 45-minute travel times within FFS and congested speed; and *k* is the industry.

The accessibility proximity coefficient measure and the contour accessibility measure were calculated for FFS and congested speed.

3 Study area: City of Cape Town

The City of Cape Town is used as a case study to investigate the impact of congestion and spatial form on accessibility to job opportunities. The City of Cape Town is the second largest city in South Africa and is situated in the southwestern part of the country (see Figure 3).

The city faces socio-economic challenges, including high levels of inequality and poverty, and has visible disparities in living conditions. The City of Cape Town is known for its spatial divide, with poor communities located on the periphery of the city. It is characterized as a polycentric city, with two main employment areas: the central business district (CBD) and the Bellville northern suburbs area (Krygsman et al. 2016).

Figure 3: Map of South Africa showing the location of the City of Cape Town

Source: authors' construction.

Table 2 presents population, employment, and productivity (gross value added, GVA) statistics for the City of Cape Town for the analysis period from 2014 to 2020.

Table 2: City of Cape Town population and employment statistics

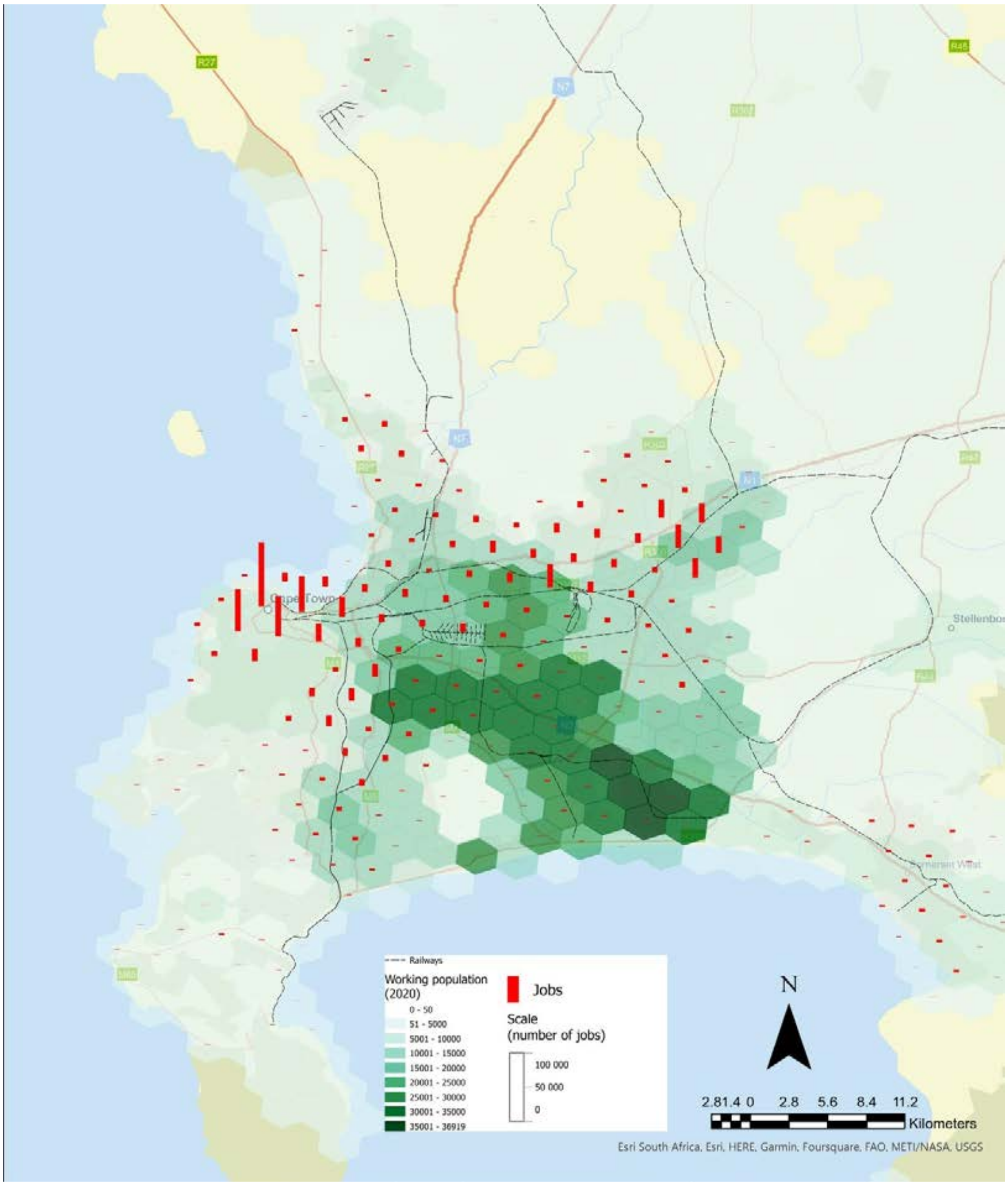
Statistics (City of Cape Town)	2013/14	2019/20	Change (2013/14–2019/20)	% change (2013/14–2019/20)
Population (*N*)	3,948,866	4,484,125	535,259	13.6%
Working-age population (*n*)	2,750,590	3,115,923	365,333	13.3%
Labour force participation rate	66%	68%	2%	2.5%
Employed				
Total (*N*)	1,475,811	1,618,448	142,637	9.7%
Formal (*n*)	1,135,093	1,291,056	155,963	13.7%
Informal (*n*)	340,718	327,392	−13,326	−3.9%
Primary sector [SIC:1–2]	40,375	45,172	4,797	11.9%
Secondary sector [SIC:3–5]	276,338	285,745	9,407	3.4%
Tertiary sector [SIC:6–9, 0]	1,159,098	1,287,531	128,433	11.1%
Unemployed (*n*)	338,710	487,531	148,821	43.9%
Unemployment rate	19%	23%	4%	24.0%
Not economically active (*n*)	936,069	1,009,944	73,875	7.9%
GVA (ZAR million basic prices)	792,218	1,119,833	327,615	41.4%
Gini	0.633	0.618	−0.15	s2.5%

Source: authors' construction using Quantec EasyData, 2023.

Cape Town experienced a consistent increase in the number of people and households over an 18-year period, with a population growth rate of 2% per annum since 2000. It is expected that the population will grow by approximately 375,000 people from 2021 to 2025 (Western Cape Government 2021).[3]

The spatial distribution of the working population (green hexagons) and employment (red bar chart) is indicated in Figure 4 for the 2019/20 tax year. It indicates a spatial mismatch between where the population is situated and where the main employment hubs are located. Comparing Figures 4 and 5, it is also clear that the highest percentage of low-income population is on the outskirts of the city, far from the CBD.

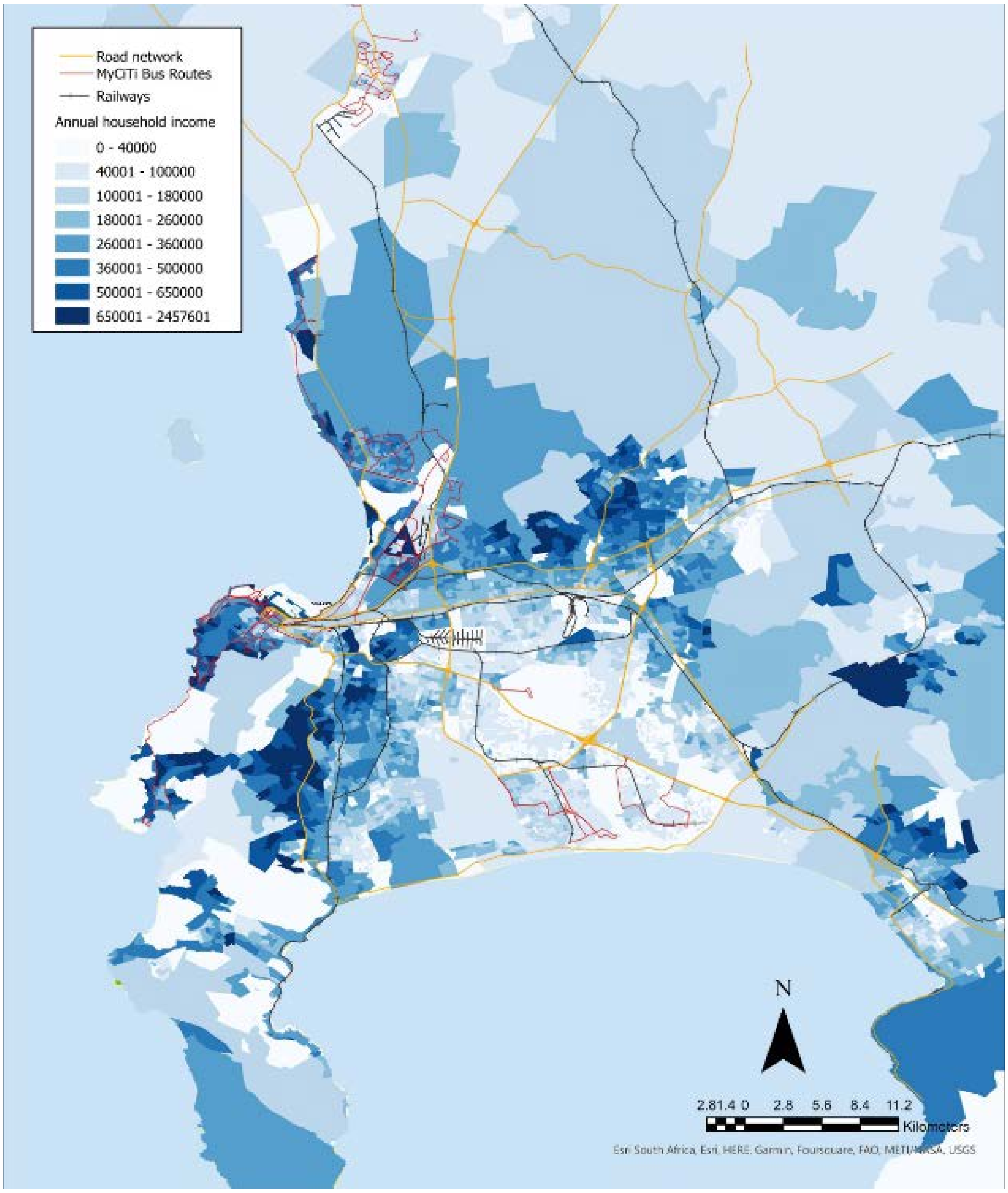
Figure 4: Working population density and job density (2020)



Source: authors' construction using the SARS spatial tax panel.

[3] Includes birth rate and migration.

Figure 5: Annual household income



Source: authors' construction using census 2011 data.

3.1 Employment change

This section focuses on the change in employment across wage groups and the location of different industries in the City of Cape Town. Understanding the change of employment across industries over time provides insight into whether these shifts increase or decrease access to the labour market for different industries.

Table 3 shows the distribution of jobs across four primary industries (manufacturing, retail, services, and community industries) differentiated across different wage bands via the graduated green colour, with the darkest colour being the highest. It shows that retail, services, and community industries employ approximately 75% of all workers in the City of Cape Town, with the lowest-income wage band working predominantly in these industries. The highest-income wage bands are predominantly employed in services and community industries.

Table 3: Distribution of jobs across wage bands and industries (2020)

Wage band (ZAR/year)	Industry						Percentage jobs by wage band
	Manufacturing	Retail	Services	Community	All other industries	All industries	
Jobs (number)							
[1; 3,200)	6,669	47,313	38,892	34,511	19,793	147,178	10
[3,201; 6,400)	37,821	187,244	65,464	34,968	47,737	373,234	26
[6,401; 12,800)	55,593	114,176	75,127	33,326	54,142	332,364	23
[12,801; 25,600)	33,681	50,223	62,385	65,013	37,263	248,565	17
[25,601; 51,200)	17,772	28,462	53,197	91,925	20,992	212,348	15
[51,201; 102,400)	7,196	13,367	28,396	25,993	8,328	83,280	6
[102,401; 1,638,400)	1,665	3,561	11,050	4,958	2,692	23,926	2
All jobs by industry	160,397	444,346	334,511	290,694	190,947	1,420,895	100
Percentage jobs by industry	11	31	24	20	13	100	

Note: Darker green cells indicate a higher concentration of workers working within that industry within the specific wage band.

Source: authors' construction using the SARS spatial tax panel.

Table 4 shows the percentage point change in the distribution of jobs by wage band within the four industries between the 2013/14 and 2019/20 tax years. Across industry types, the proportion of workers did not change by more than 1 percentage point. Differentiating between wage bands shows that there was a shift in the lowest wage bands, moving from manufacturing and retail to services and community industries. The highest-income bands moved to the community industry.

Table 4: Percentage point change in the distribution of jobs across wage bands and industries between 2013/14 and 2019/20

Wage band (ZAR/year)	Industry				
	Manufacturing	Retail	Services	Community	Other
[1; 3,200)	**−1.7%**	**−6.3%**	2.5%	7.4%	**−1.9%**
[3,201; 6,400)	**−2.4%**	5.2%	**−1.1%**	1.5%	**−3.2%**
[6,401; 12,800)	**−1.0%**	1.0%	3.5%	**−1.9%**	**−1.6%**
[12,801; 25,600)	1.6%	2.5%	0.8%	**−6.1%**	1.1%
[25,601; 51,200)	**−0.3%**	**−0.2%**	**−0.1%**	0.2%	0.4%
[51,201; 102,400)	**−1.1%**	**−1.6%**	**−1.1%**	4.5%	**−0.7%**
[102,401; 1,638,400)	0.5%	**−0.3%**	**−3.5%**	4.4%	**−1.1%**
All jobs by industry	**−0.7%**	0.9%	1.0%	0.1%	**−1.3%**

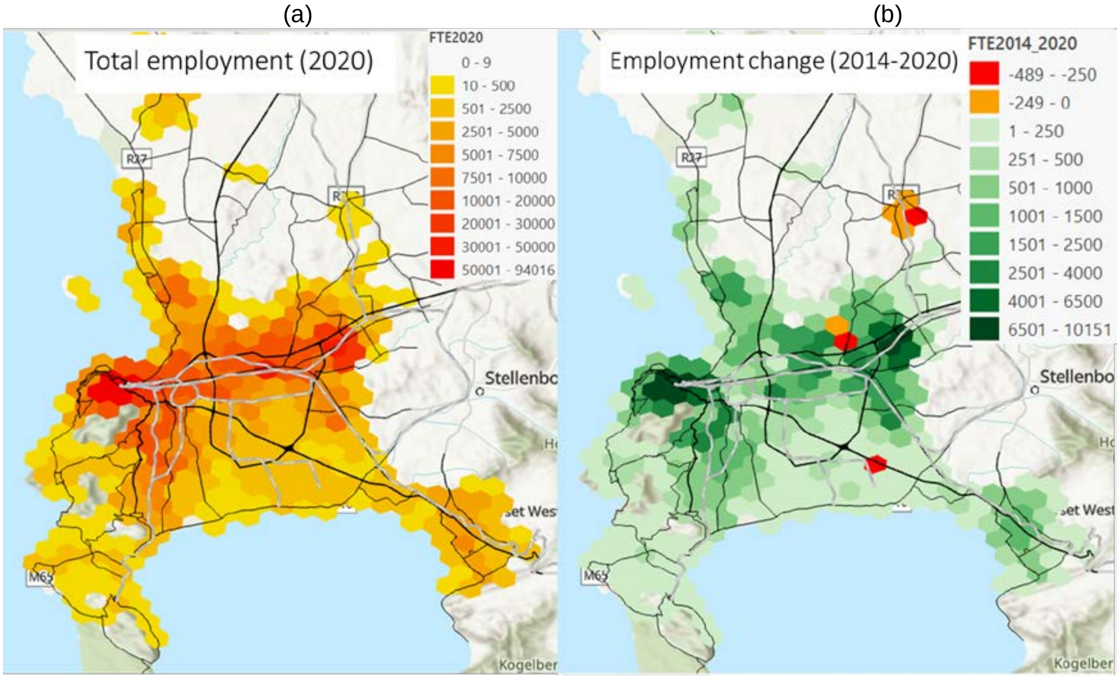
Note: Darker green cells indicate a higher percentage positive change in workers employed within an industry within the specific wage band between 2013/14 and 2019/20. A negative percentage change in employment between 2013/14 and 2019/20 is indicated in bold.

Source: authors' construction using the SARS spatial tax panel.

Figure 6 shows spatially where jobs were located in Cape Town for 2020 and the change in jobs between the 2013/14 and 2019/20 tax years. It shows the trend in location change for all employment. Employment increased in the CBD and in the northern suburbs. This may reflect the emergence of a stronger polycentric urban form for the larger metropolitan area. The increase in jobs towards the northern suburbs is not integrated or aligned with the rail network. Currently, there is no dedicated right-of-way public transport infrastructure connection, such as the bus rapid transit system or rail linking lower-income communities from the Metro South-East Area to the Bellville employment area in the north. As a result, all public transport trips will be via the general road network, adding to traffic volumes.

Figure 6: All industry employment (2020) (a) and total employment change (b) between 2014 and 2020

(a) (b)



Source: authors' construction using the SARS spatial tax panel.

4 Analysis and discussion

To show how individuals are competing for jobs against others in the working-age population in the 5 km^2 hexagon in which they reside, the concept of the job/worker mismatch is used. Although this concept does not give an indication of the job–skills match, it shows the need to travel when the number of workers exceeds the number of jobs within the hexagon.

Table 5 shows the job/worker mismatch by the income quartile for the 2019/20 tax year. On average, in the lowest-income quartile neighbourhoods there are 24,000 workers for every job. In 2019/20, individuals living in the highest-income quartile had 747 jobs, on average, for every individual in the working-age population. This provides some insight into the results of the QLFS, which indicate that 70% of all discouraged job seekers (those individuals who will accept a job if offered to them, but have become too discouraged to search for employment) state the reason for their becoming discouraged as being due to 'no jobs in their area'. This analysis quantifies the impact of job proximity to residential areas and clearly shows the job/worker mismatch faced by lower-income communities.

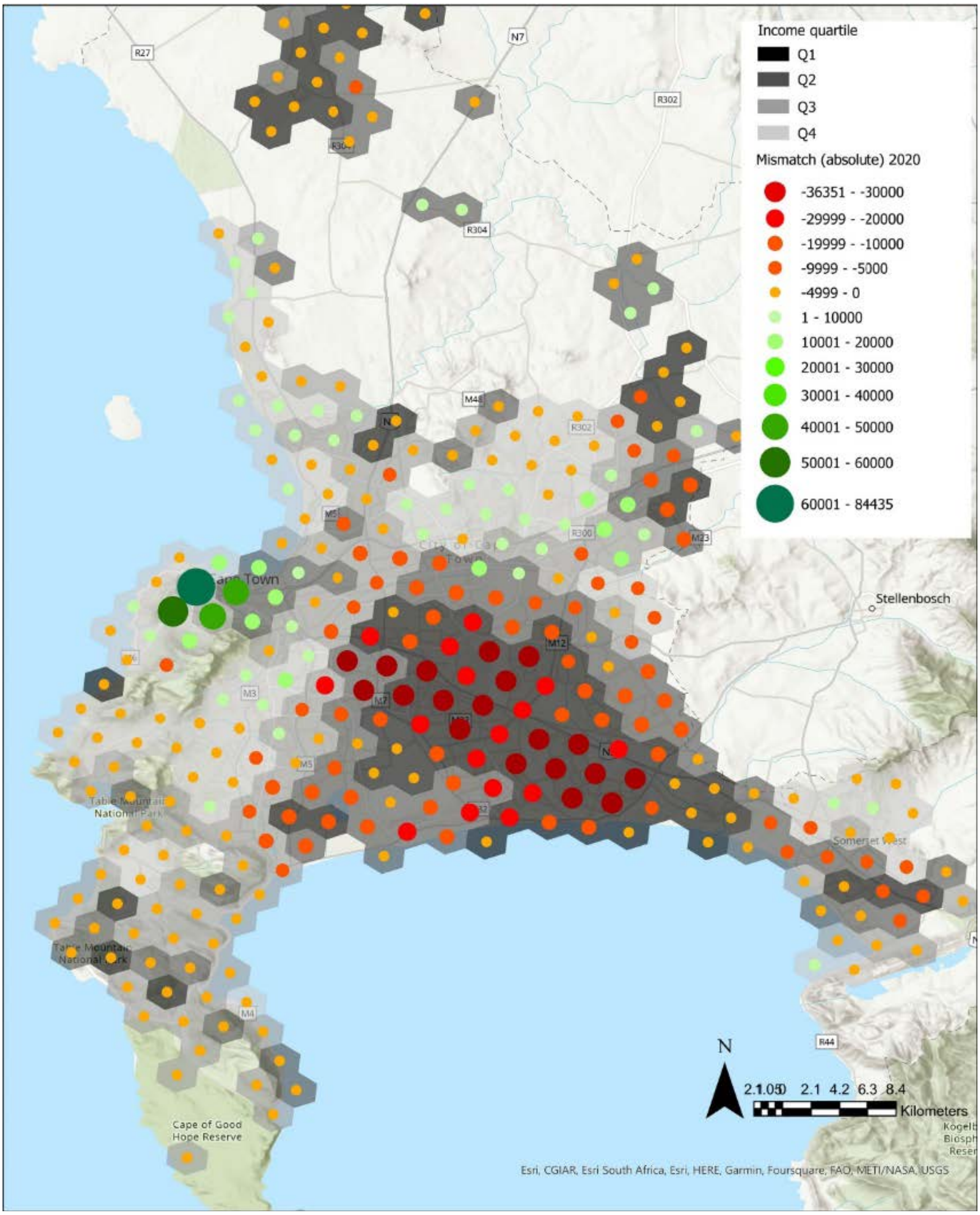
Table 5: Mean job/worker mismatch (2020) by income quartile

Income quartile	Job/worker mismatch				
	Mean	Median	Standard deviation	Minimum	Maximum
Quartile 1	−24,164	−29,442	10,315	−36,351	350
Quartile 2	−12,344	−11,947	13,133	−31,457	44,875
Quartile 3	−2,267	−3,789	16,086	−28,459	84,434
Quartile 4	747	−1,228	9,451	−9,085	53,164
All hexagons	−13,644	−11,947	15,742	−36,351	84,434

Source: authors' construction using the SARS spatial tax panel.

The job/worker mismatch for different income quartile hexagons is illustrated in Figure 7. The size of the circles shows the magnitude of the job/worker mismatch, with orange to dark-red circles indicating a working population surplus, and light to darker green circles indicating a job surplus. This map shows that the population surplus is most prominent in low-income hexagons (dark-grey hexagons) compared with job surpluses, which are more prominent in hexagons considered being high-income areas (light-grey hexagons).

Figure 7: Job/worker mismatch by hexagon within the City of Cape Town for the 2019/20 tax year

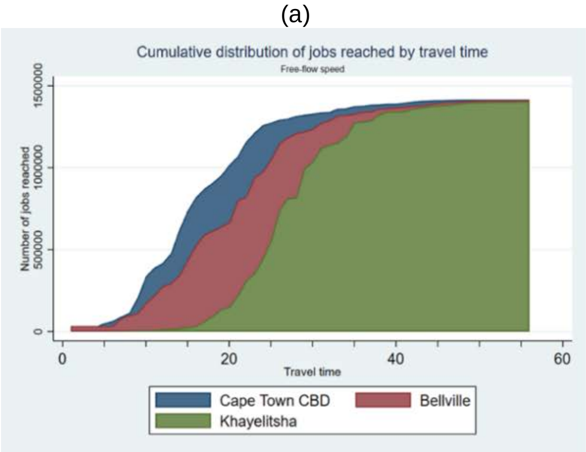


Source: authors' construction using the SARS spatial tax panel.

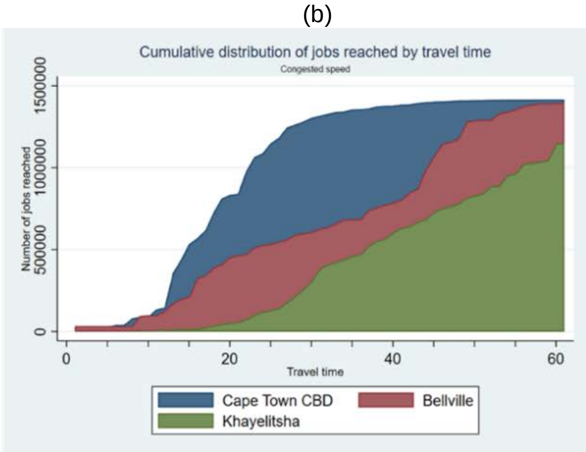
The cumulative distribution function used to reach the number of jobs for three suburbs in the City of Cape Town is shown in Figure 8. Cape Town CBD and Bellville are the two main employment hubs. Khayelitsha is a low-income area in the Metro South-East Area, far from job opportunities. The figure shows that individuals living in the CBD can rapidly get access to employment opportunities within a short travel time. Because of its proximity to employment, this area is also least affected by congestion compared with other areas, such as Bellville and Khayelitsha. The proximity coefficients for 18 suburbs in the City of Cape Town is summarized in Appendix Table D1. It can be used to identify areas with higher or lower accessibility and to prioritize transport and land-use interventions accordingly.

Figure 8: Cumulative distribution function of jobs reached by travel time: (a) free-flow speed; (b) congested speed

(a)



(b)

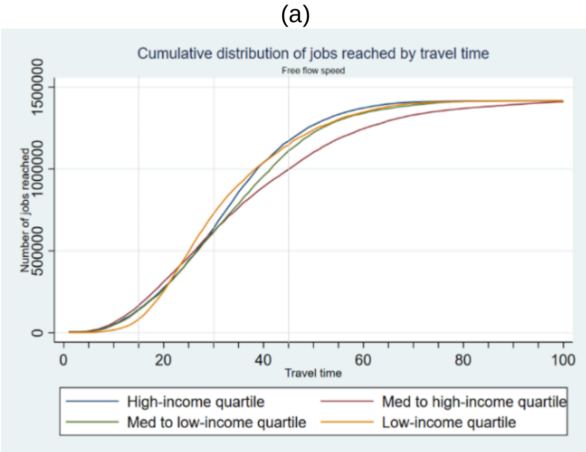


Source: authors' construction using the SARS spatial tax panel data.

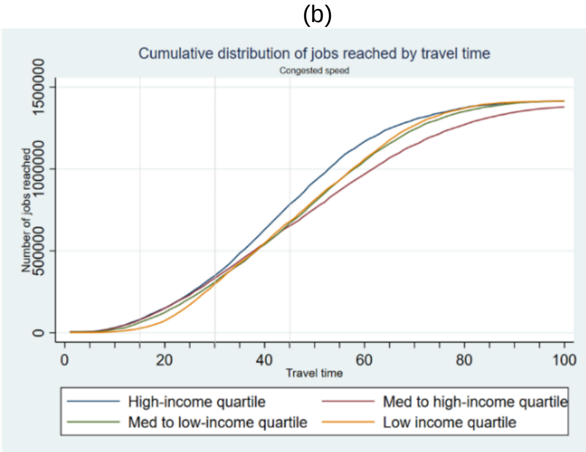
The cumulative distribution functions by income quartile and travel speed are shown in Figure 9 and show the low accessibility of low-income areas (yellow line) within the shorter travel times. By comparison, higher-income areas (blue and red lines) have the advantage of reaching a higher percentage of jobs within the same travel time under both FFS and congested speed. However, for FFS, lower-income quartile areas 'catch up' with higher-income quartile areas from approximately a 20-minute travel time. Under congested speed conditions lower-income quartile areas only 'catch up' to the higher-income quartiles from travel times of 30–35 minutes. Congestion flattens the cumulative distribution function and further increases the unequal distribution of accessibility among different income groups.

Figure 9: Cumulative distribution function of jobs reached by travel time by income quartile: (a) free-flow speed; (b) congested speed

(a)



(b)



Source: authors' construction using the SARS spatial tax panel.

Table 6 shows the mean proximity count, which evaluates accessibility to job opportunities across income groups for FFS and congested speed and supports the observations from Figure 9. Under FFS conditions, lower-income quartile areas have a relatively good proximity coefficient compared to other income quartile areas. However, the lowest-income quartiles are most affected by the impact of congestion, resulting in the mean proximity coefficient for this quartile being lower than the overall average across all income groups.

Table 6: Mean proximity coefficient by income quartile and speed

Income quartile	Mean	Median	Standard deviation	Minimum	Maximum
Free-flow speed					
1	0.54	0.57	0.11	0.02	0.67
2	0.53	0.56	0.14	0.02	0.71
3	0.54	0.60	0.16	0.00	0.71
4	0.51	0.54	0.15	0.08	0.70
All income	0.53	0.57	0.14	0.00	0.71
Congested speed					
1	0.34	0.35	0.10	0.02	0.54
2	0.37	0.36	0.15	0.01	0.70
3	0.41	0.40	0.17	0.00	0.69
4	0.39	0.40	0.15	0.04	0.61
All income	0.37	0.36	0.14	0.00	0.70

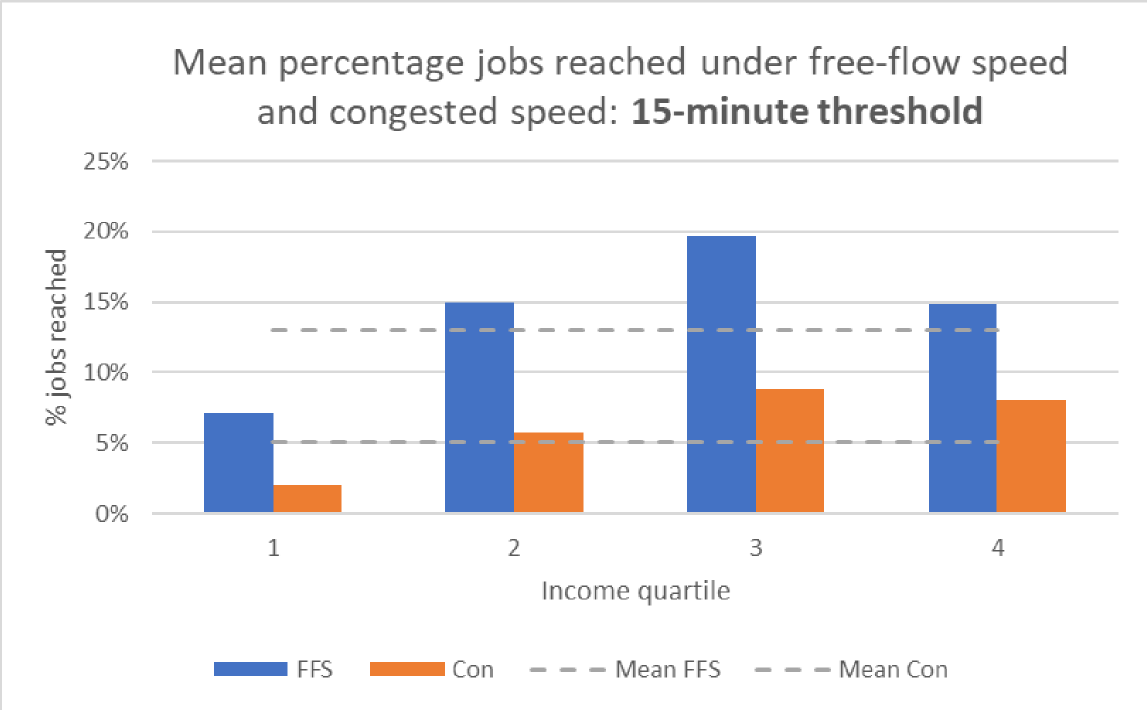
Source: authors' construction using the SARS spatial tax panel.

The contour accessibility measure indicates the percentage of total jobs in the City of Cape Town that can be reached when there is no congestion, or when FFS and congested conditions prevail in the morning peak period within different travel-time thresholds. This accessibility measure is a snapshot of the cumulative distribution function at a 15-, 30-, and 45-minute travel-time threshold as illustrated by the vertical dotted grey lines in Figure 9.

The accessibility results over all industries are indicated in Figures 10–12, differentiating between different travel-time thresholds. The difference between FFS and congested speed is the lowest for the shortest travel-time threshold (15-minute threshold) indicated in Figure 10, which makes intuitive sense. It shows that nearby job opportunities are more easily reached by higher-income quartiles during FFS for this 15-minute threshold. Only an average of 5% of total jobs within the City of Cape Town can be reached within the 15-minute threshold under congested speed conditions.

There is a significant jump in increased accessibility between the 15- and 30-minute thresholds (see Figure 11). Interestingly, it shows that lower-income quartiles have better access to job opportunities (considering all use the private road network) that high-income quartiles under FFS, but the converse is true under congested speed (refer to Figure 11). This indicates that congestion negatively affects lower-income commuters more in terms of access to employment opportunities. On average, commuters can reach 36% fewer opportunities during morning peak travel compared with free-flow speed using a 30-minute travel-time threshold. The maximum difference in accessibility is for the lowest-income group for the 30-minute threshold: 44% fewer jobs are reached for congested speed versus FFS.

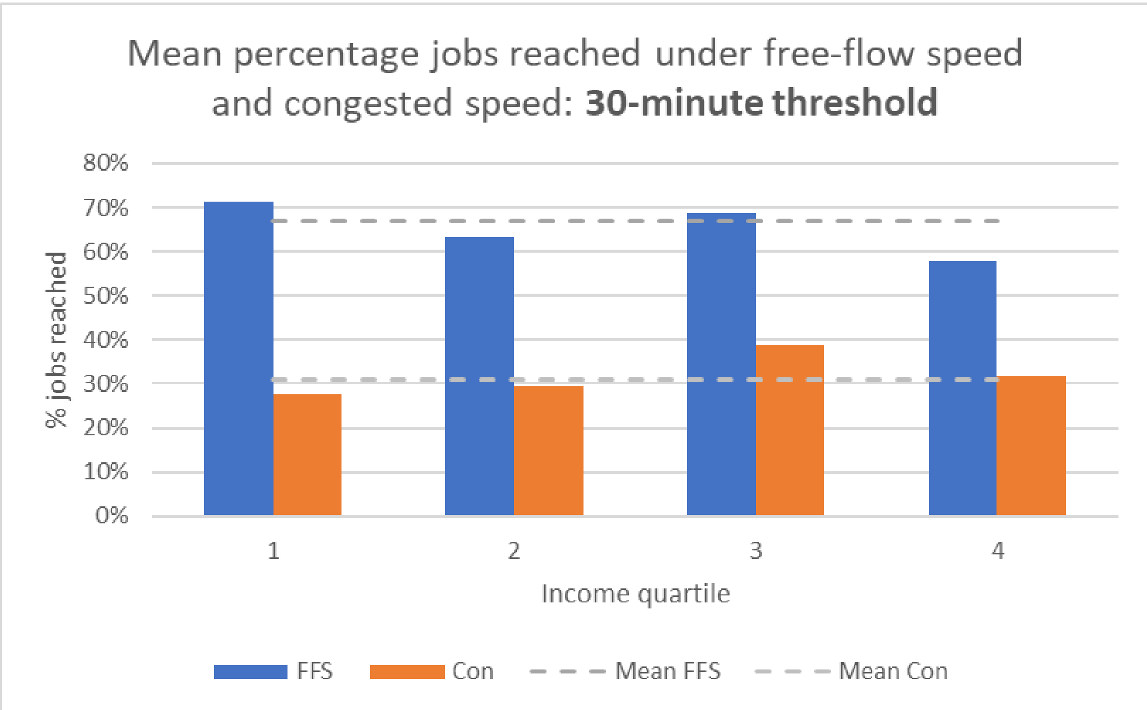
Figure 10: Mean percentage jobs reached under FFS and congested speed: 15-minute threshold



Note: FFS, free-flow speed; Con, congested speed.

Source: authors' construction using the SARS spatial tax panel.

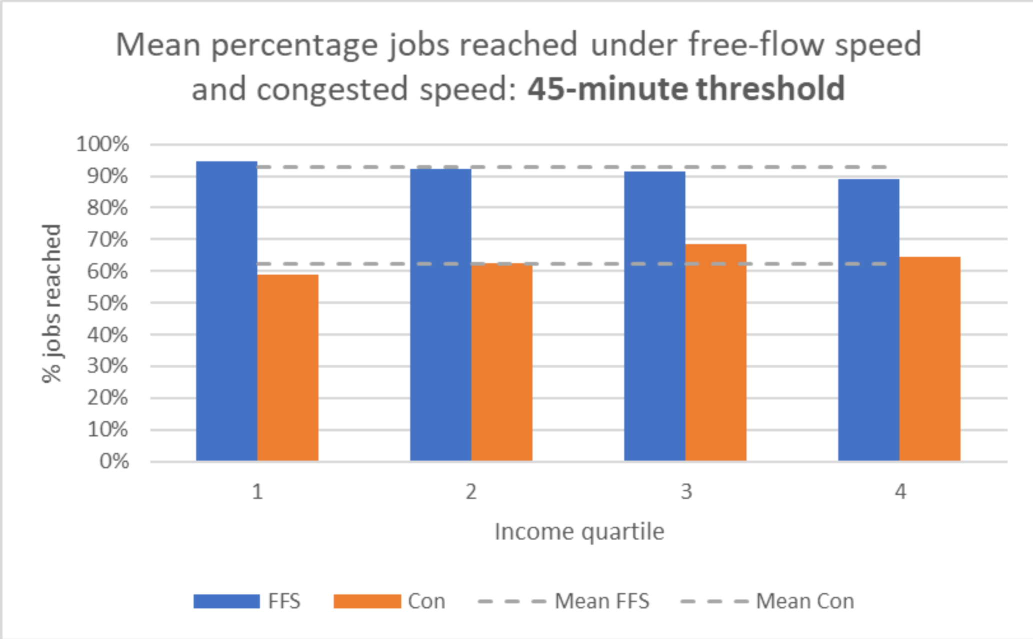
Figure 11: Mean percentage jobs reached under FFS and congested speed: 30-minute threshold



Source: authors' construction using the SARS spatial tax panel.

Figure 12, illustrating accessibility under the 45-minute threshold, shows the same result as Figure 11, whereby the lowest-income quartile is most affected by congestion. On average, only 62% of all jobs can be reached within the City of Cape Town in 45 minutes.

Figure 12: Mean percentage jobs reached under FFS and congested speed: 45-minute threshold



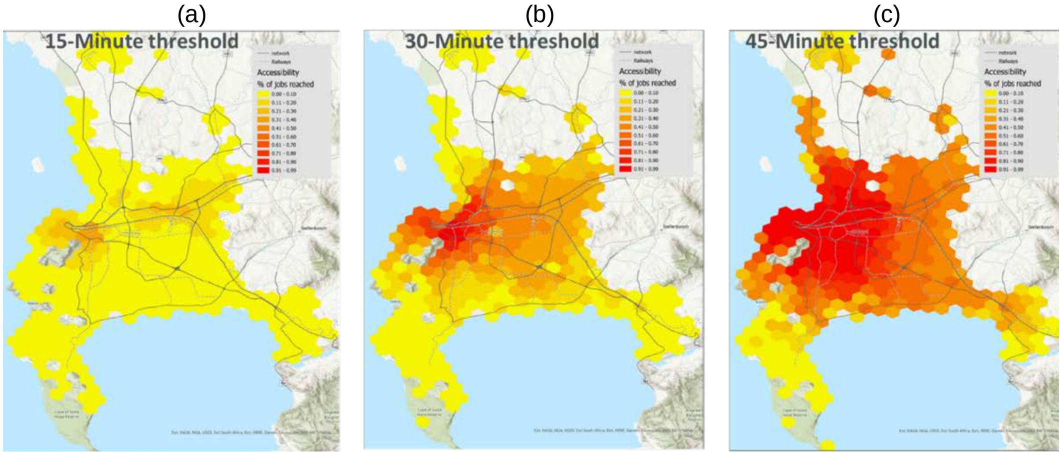
Source: authors' construction using the SARS spatial tax panel.

These figures show the impact of poor transport policy and investment, where most commuters are forced to use road-based transport. It shows that the distribution of accessibility across income groups is equitable under FFS conditions, but because of high levels of congestion, fewer than half of the job opportunities can be reached within 30 minutes, with commuters from the lower-income areas being affected the most by congestion. This links to the study by Mocetti and Roma (2021), showing that congestion not only increases the travel-time loss to commuters but also affects the functioning of the labour and housing market. Figures 10–12 illustrate that congestion affects the vertical equity on accessibility across income groups.

The difference in accessibility between different travel-time thresholds can be spatially viewed in Figure 13, giving an indication of horizontal equity. The 30-minute threshold shows significant improvement in accessibility around the CBD, but lower-income areas in the Metro South-East Area (Khayelitsha and Mitchells Plain) can only reach a maximum of 30% of total jobs under congested travel-time conditions.

Figure 13: Accessibility to job opportunities within different travel-time thresholds within the City of Cape Town in the 2019/20 tax year under congested speed—(a) 15 minutes (b) 30 minutes, and (c) 45 minutes

(a) (b) (c)



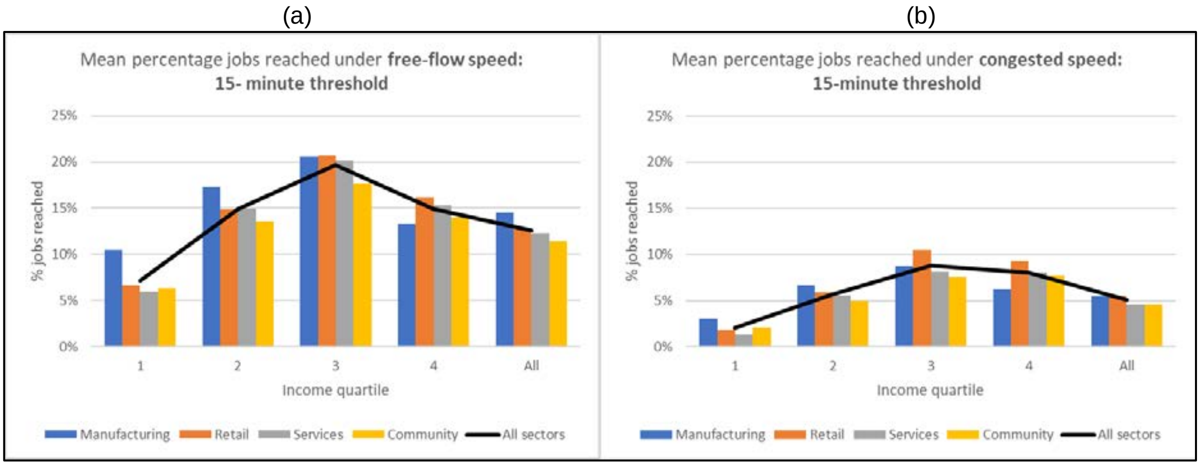
Source: authors' construction using the SARS spatial tax panel.

4.1 Accessibility by industry

Figures 14–16 show accessibility by different industries. These figures highlight the most prominent differences in accessibility between industries, and between FFS and congested speed compared with the average accessibility for all industries and all income groups (black line).

The 15-minute threshold indicates that the difference between the FFS and congested speed accessibility by industry varies between 7% and 9% (Table 7). The second and third income quartiles experience the highest impact on access to opportunities, particularly for manufacturing and services, owing to congestion. Individuals living in the lowest-income quartile hexagon experience below average accessibility across all industries under FFS and congested travel conditions for the retail, services, and community sectors.

Figure 14: Mean percentage jobs that could be reached in 2020 within the 15-minute travel-time threshold for (a) free-flow speed and (b) congested speed by income quartile and industry



Source: authors' construction using the SARS spatial tax panel.

Table 7: Percentage point difference in the percentage jobs that could be reached within the 15-minute travel-time threshold for free-flow and congested speeds by income quartile and industry

15-minute threshold	Income quartile	Manufacturing	Retail	Services	Community	All sectors
Percentage point difference between free-flow and congested speeds	1	−7%	−5%	−5%	−4%	−5%
	2	−1%	−9%	−9%	−9%	−9%
	3	−12%	−10%	−12%	−10%	−11%
	4	−7%	−7%	−7%	−6%	−7%
	All	−9%	−7%	−8%	−7%	−8%

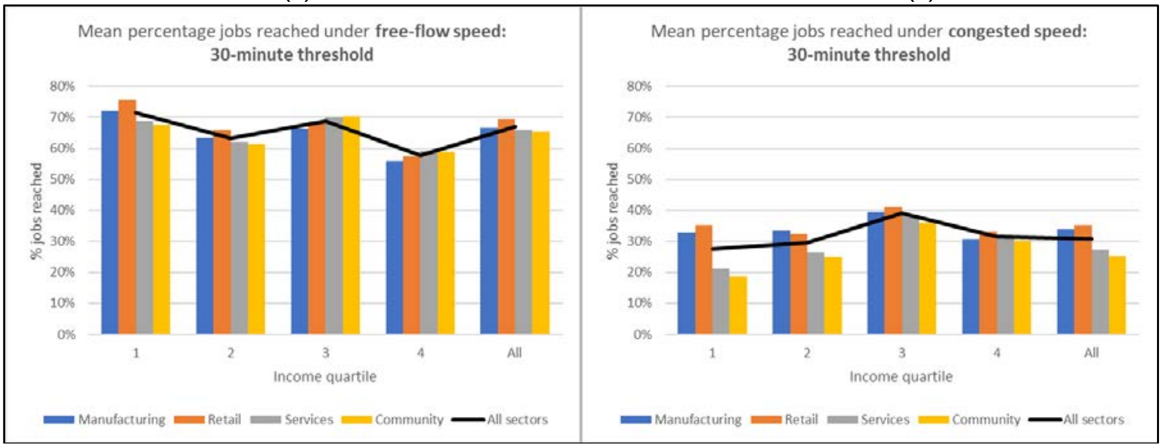
Source: authors' construction using the SARS spatial tax panel.

Accessibility for a 30-minute threshold between industries shows a different pattern to the 15-minute threshold, as individuals living in the lowest-income quartile hexagons have higher access compared with those in the higher-income quartiles under FFS conditions (Figure 15). The lowest-income quartile experiences the highest impact on accessibility to opportunities, particularly for the services and community industries, because of congestion (Table 8). These industries are important for this income quartile because approximately 50%–70% of commuters in this quartile work within these two industries (depending on the wage band).

On average, the retail industry has the highest access by employees in the City of Cape Town, with 35% of these jobs being reachable within a 30-minute commute during the morning peak period.

Figure 15: Mean percentage jobs that could be reached in 2020 within a 30-minute travel-time threshold for (a) free-flow speed and (b) congested speed by income quartile and industry

(a) (b)



Source: authors' construction using the SARS spatial tax panel.

Table 8: Percentage point difference in the percentage jobs that could be reached within a 30-minute travel-time threshold for free-flow and congested speeds by income quartile and industry.

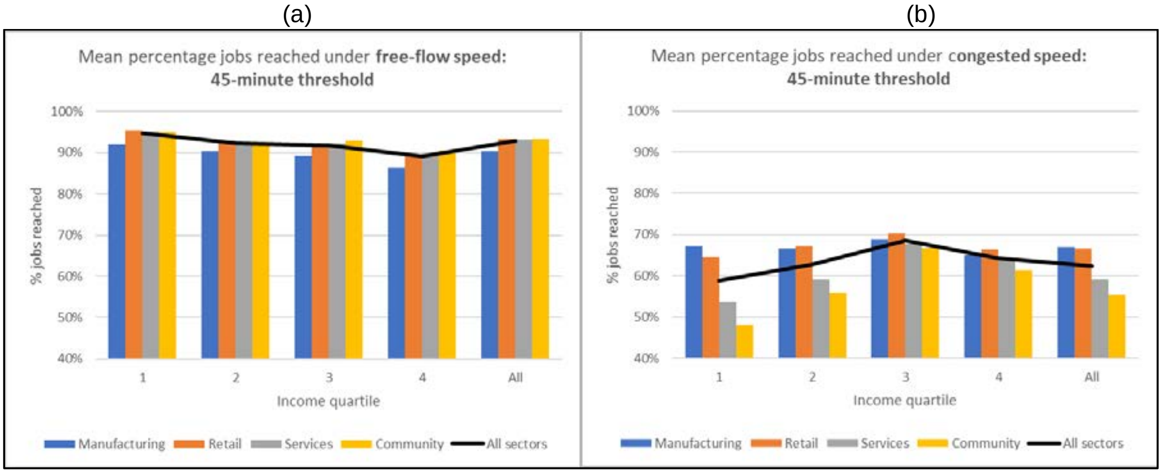
30-minute threshold	Income quartile	Manufacturing	Retail	Services	Community	All sectors
Percentage point difference between free-flow and congested speeds	1	−39%	−40%	−48%	−49%	−44%
	2	−30%	−33%	−36%	−37%	−34%
	3	−27%	−27%	−31%	−34%	−30%
	4	−25%	−24%	−27%	−29%	−26%
	All	−33%	−34%	−39%	−40%	−36%

Source: authors' construction using the SARS spatial tax panel.

For the 45-minute threshold, the difference between the FFS and congested speed accessibility by industry varies between 23% and 38% (Table 9). Access to services and community industries is the most severely affected by congested speed, again, in particular, for the lowest-income quartile. Employees in the manufacturing and retail industries have the highest access in the City of Cape Town, with 67% of jobs reachable within a 45-minute commute during the morning peak period (Figure 16).

Figure 16: Mean percentage jobs that could be reached in 2019/20 within a 45-minute travel-time threshold for (a) free-flow speed and (b) congested speed by income quartile and industry

(a) (b)



Source: authors' construction using the SARS spatial tax panel.

Table 9: Percentage points difference in the percentage jobs that could be reached within a 45-minute travel-time threshold for free-flow and congested speeds by income quartile and industry

Income quartile	Manufacturing	Retail	Services	Community	All sectors
1	−25%	−31%	−41%	−47%	−36%
2	−24%	−26%	−33%	−37%	−30%
3	−20%	−21%	−25%	−26%	−23%
4	−21%	−23%	−26%	−29%	−25%
All	−23%	−27%	−34%	−38%	−30%

Source: authors' construction using the SARS spatial tax panel.

4.2 Accessibility between road-based public transport and private transport

The results from the 2020 National Household Travel Survey in Table 10 show the shift from rail to road-based transport between 2013 and 2020. The table also shows a significant increase in rail, minibus taxi, and bus one-way commuting time to job opportunities within the same period (Van der Merwe and Krygsman 2022).

Table 10: Modal share and one-way travel time (minutes) to work by main mode for 2020 in the City of Cape Town

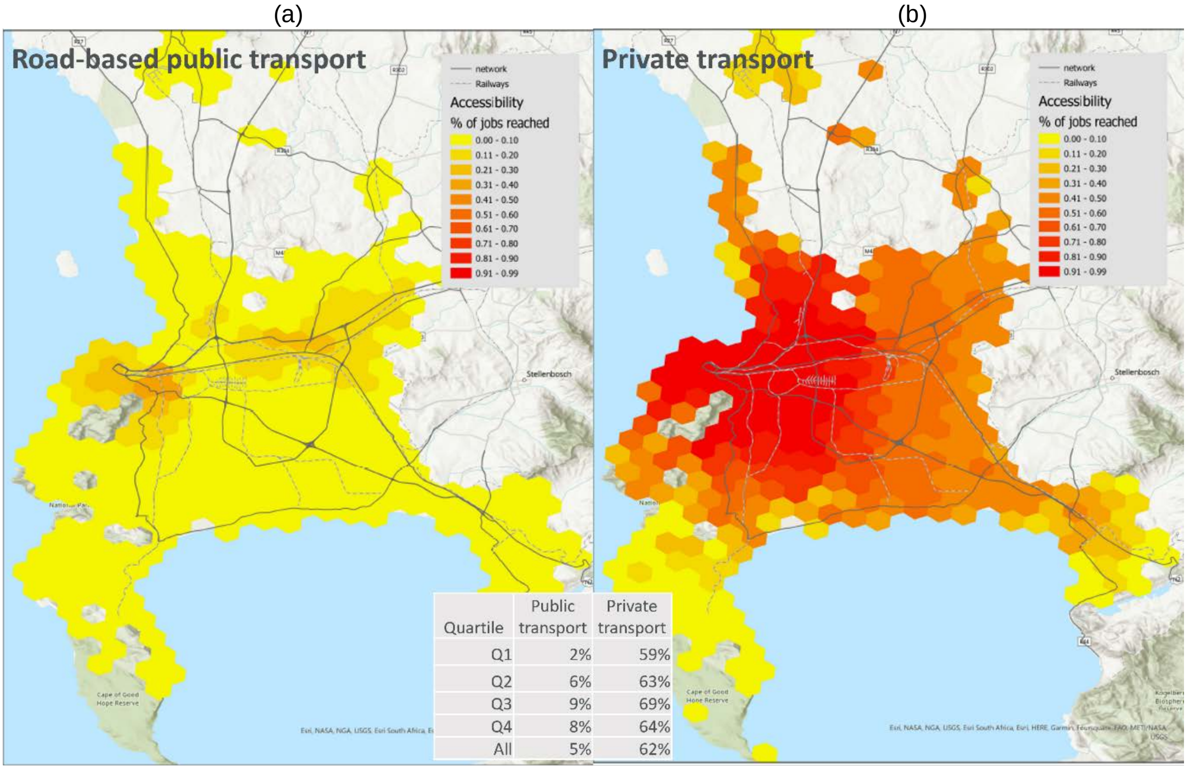
Mode	Mode share		Mean travel time	
	2020 (%)	% change (2013–20)	2020 (minutes)	% change (2013–20)
Rail	3	−15	106	35
Bus	9	0	92	23
Minibus taxi	26	9	73	35
Private—driver	46	6	48	12
Other	16			
All modes	100		59	10

Source: adapted from Van der Merwe and Krygsman (2022) with permission.

The accessibility results in Figures 14–16 refer only to road-based transport accessibility. Public transport takes even longer and will increase the differences in accessibility to employment between the various income groups even further. Considering the additional access, egress, transfer, and waiting times for public transport, a significant percentage of job opportunities cannot be reached within the same travel-time threshold as for private transport.

The average travel-time difference between road-based public transport and private transport derived from Table 10 was used to compare the opportunities that can be reached within a 45-minute travel-time threshold (Figure 17). The figure shows that individuals who are captive to public transport cannot reach more than 10% of all job opportunities within 45 minutes under congested conditions. This corresponds to a study conducted by the World Bank (see Peralta Quiros et al. 2019) showing that only 5% of all job opportunities can be reached by public transport in the City of Cape Town within a 60-minute travel-time threshold.

Figure 17: Comparison of accessibility between the percentage of opportunities that can be reached by (a) road-based public transport and (b) private transport within a 45-minute travel-time threshold



Quartile	Public transport	Private transport
Q1	2%	59%
Q2	6%	63%
Q3	9%	69%
Q4	8%	64%
All	5%	62%

Source: authors' construction using the SARS spatial tax panel.

5 Conclusions

This research makes use of tax administrative data to identify job locations by industry and wage band. Employment data on such a disaggregated level over time has not previously been available in South Africa. The employment data are then combined with road network data obtained from TomTom, which includes information on speeds. The impact of congestion on accessibility to job opportunities is also considered.

In the City of Cape Town, which was used as a case study, the highest population densities are in the Metro South-East Area (Khayelitsha and Mitchells Plain), which is considered as the lowest-income area. Job growth in the city follows a polycentric format along a radial axis tied to the main highways. As commuters living in the low-income area are far from the CBD, they cannot access job opportunities using non-motorized transport. Residents in these low-income areas also do not have access to the high job growth areas through the use of dedicated right-of-way public transport services such as rail and bus rapid transit system, which makes them vulnerable to the impacts of congestion and significantly lowers their job accessibility.

The proximity coefficient accessibility measure, together with the contour accessibility measure, confirms the unequal distribution of accessibility to jobs across space (horizontal spatial inequality). It also shows the significant impact of congestion on accessibility, with only 31% of total jobs reached within a 30-minute travel-time threshold under congested conditions compared with 67% under FFS conditions. Accessibility for the lowest-income group decreased by 44% from FFS to congested conditions, which highlights the disproportional impact of congestion on accessibility to jobs on commuters in lower-income areas compared with high-income areas. This reflects the vertical spatial inequality caused by congestion regarding accessibility to jobs. This study addresses a gap in the research by evaluating the impacts of congestion on accessibility and spatial equity. The disproportional impact of congestion on accessibility to jobs can contribute to higher unemployment among lower-income households, which can lead to further income inequality.

The accessibility results will enable policymakers and planners to identify areas with higher or lower accessibility and prioritize interventions accordingly. The proximity coefficient and contour accessibility measure confirmed the inequitable distribution of accessibility across income groups. These results can be incorporated into policies seeking to reduce the income inequality through land-use and transport interventions. The government can also use these accessibility measures to assess the impact of transport infrastructure investments or changes in land-use patterns on accessibility. By comparing proximity coefficients before and after implementing interventions, policymakers can evaluate the effectiveness of their policies in improving accessibility.

The government can consider the following land-use, transport, and income policy interventions to improve the equitable distribution of accessibility across regions or demographic groups.

- Attract firms to locate closer to low-income areas by providing location subsidies, zoning and bulk infrastructure closer to targeted residential areas. This will decrease the job/worker mismatch and reduce the distance required for lower-income workers to travel to employment.
- Subsidize public transport as a form of income transfer to reduce the generalized cost of transport for lower-income workers, which will result in higher transport affordability and reduce income inequalities.
- Provide better transport links such as dedicated right-of-way for low-income areas on the periphery to main employment hubs. An example of this is to prioritize the Blue Downs rail link proposed in the Integrated Public Transport Network Plan (City of Cape Town 2014), which links the Metro South-East Area to the Bellville employment hub, or reviving the rail network within the entire city. This links to the results indicating the impact of congestion on horizontal and vertical equity. Implementing public transport modes that do not interact with normal traffic will reduce travel time and increase job accessibility to individuals captive to public transport services.
- Release land for affordable housing closer to employment areas. This policy will also improve the job/worker mismatch and reduce urban sprawl that contributes to increased travel and increased congestion.

The methodology and data within this research can be used to test the outcome of these above-mentioned government interventions to improve access to jobs.

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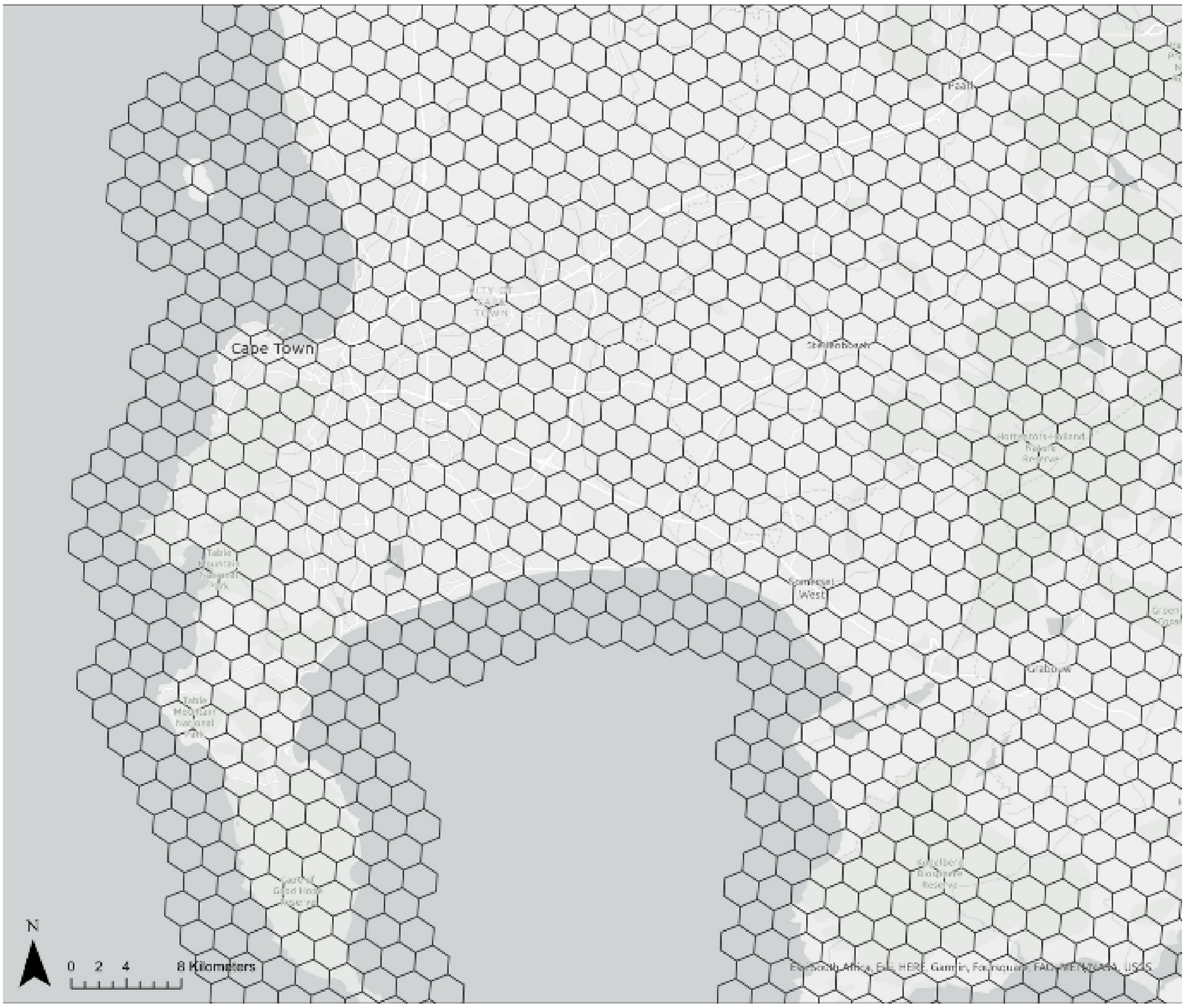
Appendix A: Spatial levels

Figure A1: Hexagon spatial map: Cape Town, South Africa

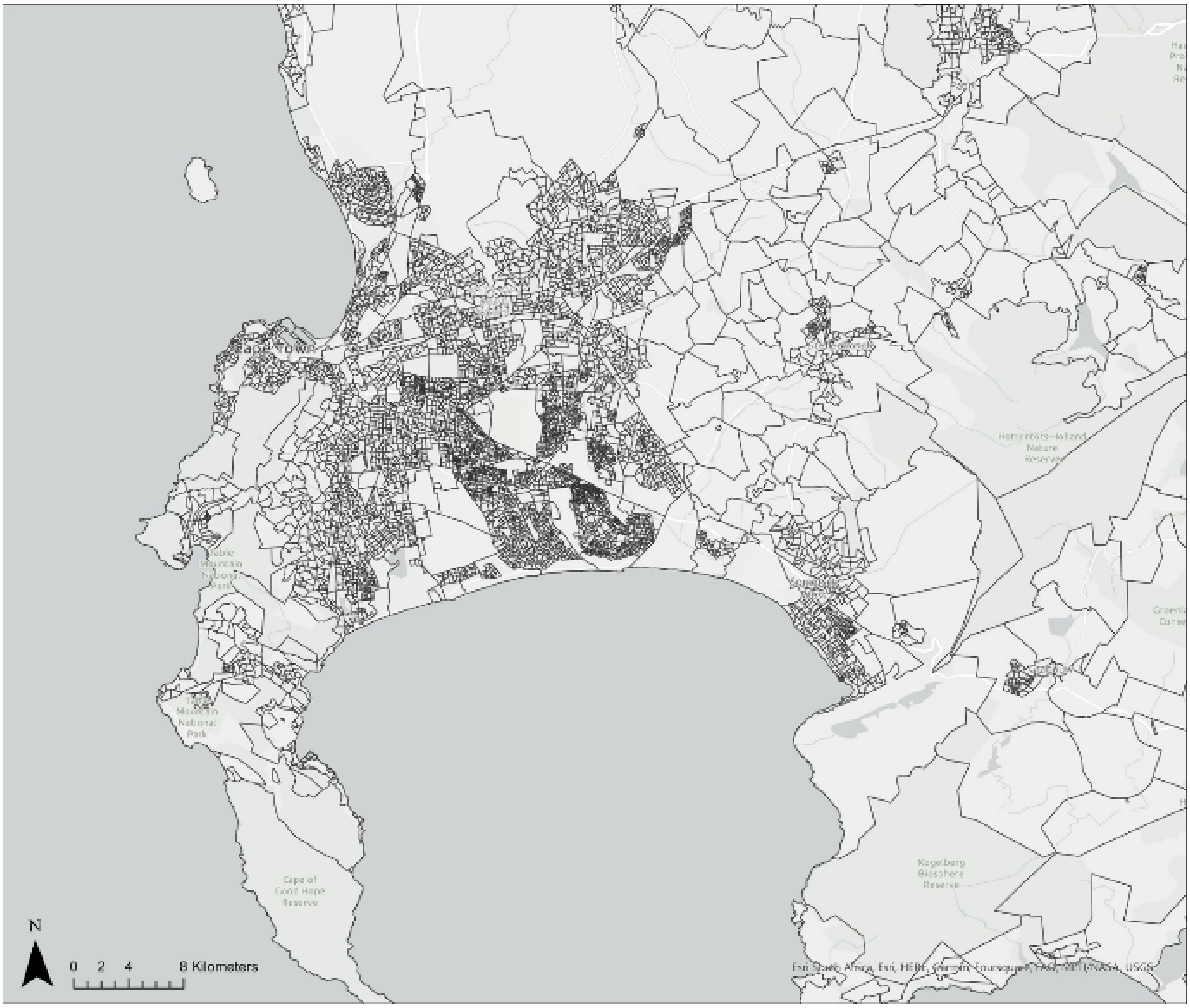


Source: authors' construction.

Figure A2: Mesozone spatial map: Cape Town, South Africa

Source: authors' construction.

Figure A3: Small area layer spatial map: Cape Town, South Africa



Source: authors' construction.

Appendix B: TomTom effective speeds

Table B1: Average effective free-flow speed (FFS) and congested speed by functional road class (FRC) and speed limit derived by TomTom dataset

FRC	Speed limit (km/h)	Average effective FFS (km/h)	Average effective congested speed (km/h)
0: Motorways; freeways; major roads	FRC 0—average	91	72
	60	64	37
	70	74	63
	80	79	63
	100	89	60
	120	96	76
1: Major roads less important than motorways	FRC 1—average	76	59
	60	65	42
	70	61	36
	80	72	53
	100	91	76
	120	93	86
2: Other major roads	FRC 2—average	57	43
	30	41	32
	50	31	14
	60	48	32
	70	52	37
	80	72	59
	90	80	73
	100	83	74
	120	89	82
4: Local connecting roads	FRC 4—average	53	42
	20	47	46
	40	41	37
	45	35	28
	50	40	35
	60	50	39
	65	63	51
	70	55	41
	80	67	51
	90	79	66
	100	85	70
	120	59	44
5: Local roads of high importance	FRC 5—average	44	29
	40	37	30
	45	34	24
	50	82	74
	60	44	28
	65	46	29
	70	46	31
	80	63	46
	90	75	66
	100	59	52
	120	57	42
6: Local roads	FRC 6—average	29	21
	20	31	25

	30	36	31
	35	27	19
	40	31	25
	50	34	25
	60	31	22
	70	45	32
	80	54	47
	90	75	65
7: Local roads of minor importance	FRC 7—average	27	19
	18	21	16
	20	24	16
	30	20	12
	35	41	28
	40	34	26
	50	60	42
	60	52	32
	70	40	29
	80	50	31
	90	53	34
	100	119	74
All FRC average		30	21

Note: the City of Cape Town does not have an FRC 3 in the TomTom data. This can be because of different road classifications by the provincial Western Cape government or the metropolitan municipality.

Source: authors' construction using TomTom dataset.

Appendix C: Dataset description

C1 Combined SARS spatial panel and CSIR population dataset including mismatch and accessibility

The dataset is derived from the South African Revenue Services (SARS) spatial panel dataset including employment data by tax year, industry and wage band. The Council for Scientific and Industrial Research (CSIR) data on hexagon level including working population by tax year is merged, together with the income quartile variable derived from the 2011 census data on small area layer level. The mismatch and accessibility variables were derived from the employment, population, and road network data for each hexagon by tax year and industry. The dataset consists of 330 hexagons in the City of Cape Town and the variables described in Appendix Table B1 ('Major roads less important than motorways').

Table C1: Variable description—combined SARS spatial panel and CSIR population dataset including mismatch and accessibility

Variable	Example	Description
hex7	87ad36004ff ffff	The Uber H3 hexagon identifier
FTE	25	The number of full-time equivalent (FTE) employees
TaxYear	2014	Tax year (range: 2014–20)
RealWageBand	[400, 800]	The inflation-adjusted wage of corresponding FTE employees aggregated into bands
SIC7_1d	1	The one-digit industry classification code (range: 1–11)
Work_Pop	1,000	Working population
quart_Inc_CPT	4	Income quartile number (range: 1–4)
mismatch	−2,378.87	Mismatch in jobs and working population in given tax year
mismatch_Ratio	0.70	Mismatch ratio in jobs and working population in given tax year
A_prox_FFS	0.6	Proximity coefficient under free-flow speed conditions
A_prox_Con	0.4	Proximity coefficient under congested speed conditions
access_Con_15	0.2	Proportion of total jobs that can be reached under congested speed within 15-minute travel time
access_Con_30	0.2	Proportion of total jobs that can be reached under congested speed within 30-minute travel time
access_Con_45	0.2	Proportion of total jobs that can be reached under congested speed within 45-minute travel time
access_Con_60	0.2	Proportion of total jobs that can be reached under congested speed within 60-minute travel time
access_FFS_15	0.2	Proportion of total jobs that can be reached under free-flow speed within 15-minute travel time
access_FFS_30	0.2	Proportion of total jobs that can be reached under free-flow speed within 30-minute travel time
access_FFS_45	0.2	Proportion of total jobs that can be reached under free-flow speed within 45-minute travel time
access_FFS_60	0.2	Proportion of total jobs that can be reached under free-flow speed within 60-minute travel time

Source: authors' construction.

C2 TomTom road network dataset

The dataset is derived from the TomTom network combined with the speed data for each segment. The dataset consists of 300,538 road segments within the City of Cape Town and the variables described in Appendix Table B1 ('Other major roads').

Table C2: Variable description—TomTom road network

Variable	Example	Description
Segment Id	−17100018914699.00	Road segment unique ID
NewSegId	−00005a41-3100-0400-0000-000000000016	New road segment unique ID
Length	83.09	Road segment length (metres)
FRC	6	Functional road classification (range 0–7)
SpeedLimit	35	Maximum speed limit for road segment (km/h)
EFF_FFS	17.1	Effective free-flow speed (km/h)
EFF_Con	12.526667	Effective congested speed (km/h)
Con_FFS	0.732554	Effective congested/free-flow speed ratio

Source: authors' construction.

C3 Hexagon origin–destination (O–D) matrix

The TomTom road network together with the hexagon shape file was used to derive an O–D travel-time matrix between each hexagon. The dataset consists of 108,900 observations and the variables described in Appendix Table B1.

Appendix C3: Variable description—hexagon O–D matrix

Variable	Example	Description
hex7_origin	87ad36004ffffff	The Uber H3 hexagon identifier for origin
hex7_dest	87ad36004fffff2	The Uber H3 hexagon identifier for destination
Con_TT	42	Travel time under congested speed (minutes)
FFS_TT	34	Travel time under free-flow speed (minutes)

Source: authors' construction.

Appendix D: Proximity coefficient by suburb

The results of the proximity coefficient accessibility measure by suburb are shown in Appendix Table D1.

Table D1: Proximity coefficient by suburb under free-flow and congested speed conditions

Suburb	Income quartile	FFS		Congested speed		Ranking change (FFS versus congested speed)
		Mean proximity coefficient (%)	Rank	Mean proximity coefficient (%)	Rank	
Central Cape Town	4	64	1	59	1	
Parow/Bellville	4	64	2	45	4	−
Belgravia/Athlone	2	64	3	51	2	+
Langa/Bishop Lavis	1	62	4	43	5	−
Kraaifontein	3	57	5	33	9	−
Mitchells Plain/Gugulethu	1	55	6	36	8	−
Wynberg	4	55	7	45	3	+
Kuilsrivier	3	53	8	30	12	−
Khayelitsha	1	52	9	30	13	−
Durbanville	4	52	10	38	7	+
Blue Downs	1	49	11	28	14	−
Oostenberg	4	49	12	30	11	+
Grassy Park	2	45	13	32	10	+
Sea Point	4	43	14	41	6	+
Northern Corridor	4	32	15	24	15	
Strand	2	32	16	16	16	
Somerset West	4	25	17	12	17	
Simonstown	4	15	18	8	18	
Overall average		42		29		

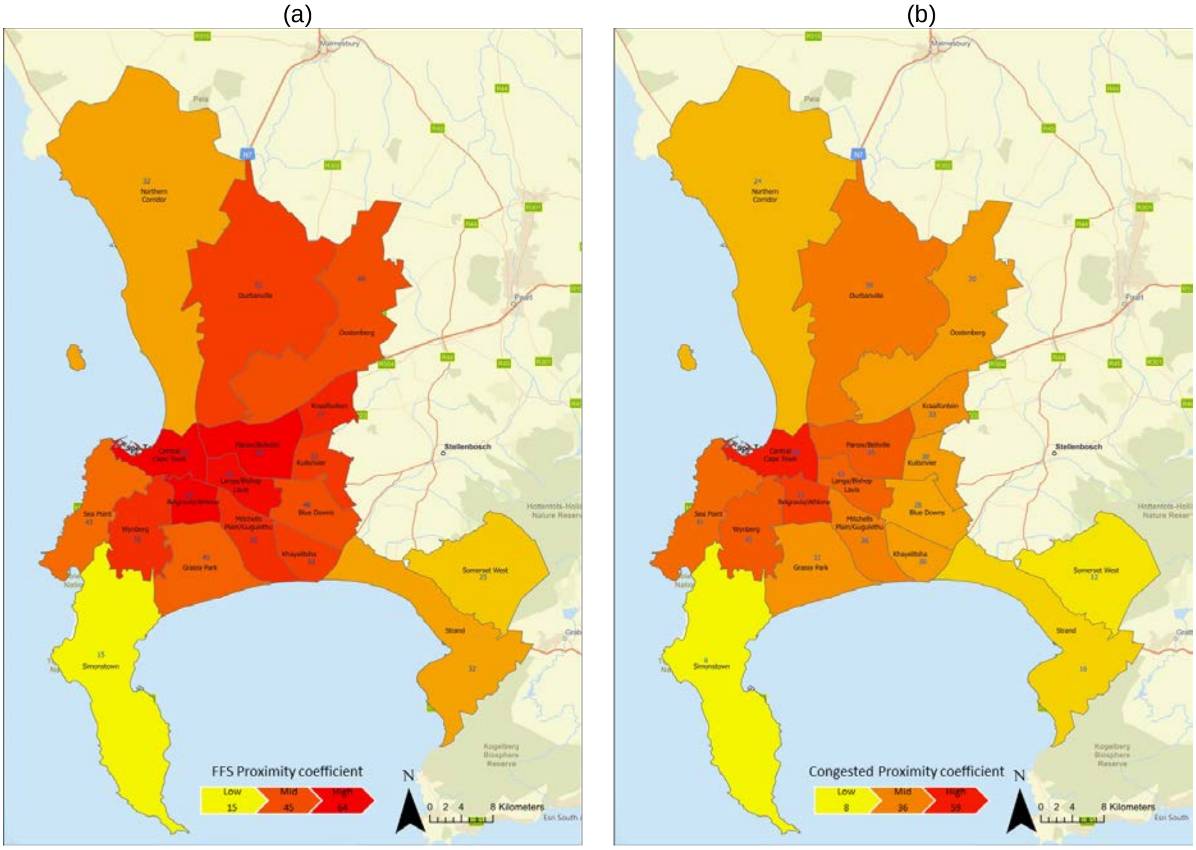
Note: ‘ +’ represents an increase in ranking between FFS and congested speed conditions. ‘−’ represents a reduction in ranking between FFS and congested speed conditions. A blank cell represents no change in ranking.

Source: authors’ construction.

The results of the proximity coefficient are presented spatially in Appendix Figure D1.

Figure D1: Proximity coefficients by suburb: (a) free-flow speed and (b) congested speed conditions

(a) (b)



Source: authors' construction.