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School of Geography, Archaeology and Environmental Science

Title: Assessing Geo-Spatial Opportunities within the City of Cape Town Metro: An Exploratory Spatial Data Analysis

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1. Declaration

I declare that this thesis is my own unaided work. It is submitted for the partial fulfilment of the requirement for the degree Masters of Science in the University of Witwatersrand, Johannesburg. It has not been submitted, before for any degree or examination at any other university.

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Abstract

The dawn of democracy in South Africa more than 25 years ago, brought a contrasting world of the poor (homelands) and rich (first world) together. Over this period, increased poverty among the poor continued to increase, with an inherent lack of economic advantage. The lingering poverty and therefore inequality can be expected to negatively increase the gap in opportunities, geographically. Past research not only highlights the importance of the geography of opportunity in metropolitan areas, but also points to the spatial distribution of such opportunities outside metro areas. This thesis provides a geography of opportunity perspective for the City of Cape Town, using the opportunity index calculated for 55 Main places.

The study uses Exploratory Spatial Data Analysis (ESDA) techniques to geographically map variations in deprivation across the City of Cape Town Metro, identify areas of high and low opportunities. The research found that there is a wide variation in the spread of opportunity between main places across the City, evident from a significantly high standard deviation. The results show that the opportunity index remains high in well off places. Poor areas, which are mainly township establishments, such as Gugulethu and Nyanga, remain in the same clusters in terms of the Morn’s I test quadrant. The study recommends a need to investigate a shift in opportunities due to the emergence of multi centres of economic development in space due to the recent polycentric spatial development of economic hubs within the city. Further that there be improved and timely data collection and sharing at a more granular spatial level.

Dedications

My dedications go out to my family for their unwavering supporting me towards completion of this work. To God the Almighty, for the strength and wisdom bestowed upon me.

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1. INTRODUCTORY CHAPTER

This research provides a version of the City of Cape Towns' exploratory data spatial analysis. Our analysis originates from the Opportunity Nation (2014a) and Wilson and Greenlee (2016) around the development of the concept, geography of opportunity (Galster and Killen, 1995). Geography of opportunity concept implies that people's places of stay affect their available socio-economic opportunities (Rosenbaum, 1995). Geography of opportunity (Lens, 2017) explains the structural composition of neighbourhoods that determines the importance of household outcomes (like job accessibility, quality of school outcomes and crime) and how concentrated these across a given location.

In terms of scope, data and coverage, the study investigates the main places within the City of Cape Town Metro from the latest official available census 2011 data. It uses geographic information systems (GIS) coupled with spatial statistics techniques, to reveal spatial trends related to mismatch and opportunities across the city. The thesis implements a methodology developed by Opportunity Nation (2014b) and used by Wilson and Greenlee (2016), to identify clusters of high and low opportunities. Opportunity is determined using three dimensions, i.e. jobs and the economy; education and community health and civil life. We therefore closely follow the indicator dimension composition used by these two other studies (Opportunity Nation, 2014b, Wilson and Greenlee, 2016). However, given our time limit and data constraints we rely on the only selected and readily available data from official data sources.

1.1 Study Area

The City of Cape Town is located in the province of the Western Cape at the south-western tip of South Africa (Statistics South Africa, 2011). Known as the Mother City, the city is considered South Africa's oldest, with a land cover area of 2 461 km^2. The metro has an irregularly shaped boundary which is constrained by the renowned mountain, Table Mountain (Budlender and Royston, 2016). The mountain intrudes significantly into the Cape Town urban landscape itself.

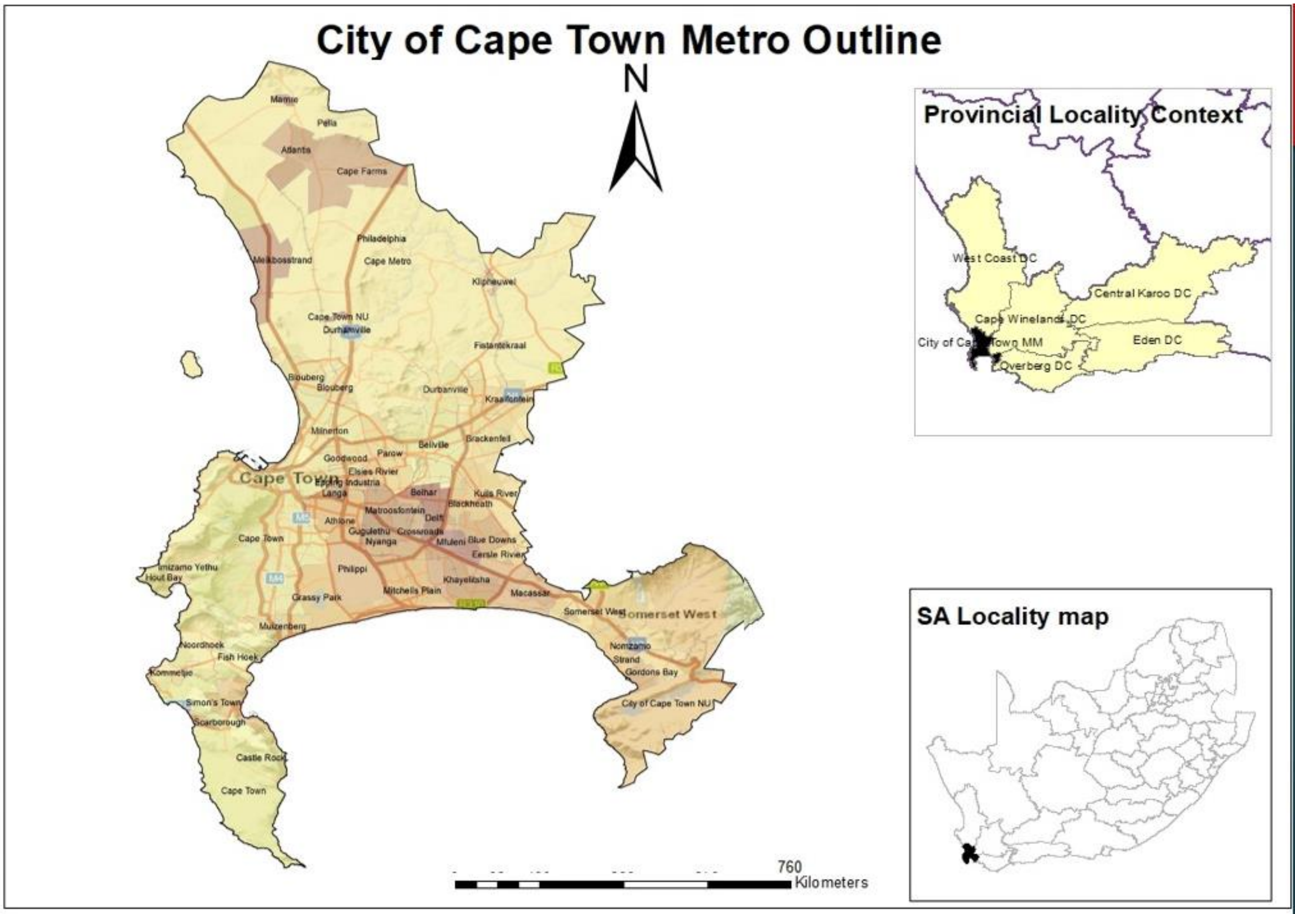

Figure 1: Map of the Study area (City of Cape Town Metro)

From the official 2011 census data, the metro is predominantly urban, with a population of 3.74 million as at 2011 that had increased by 2.94% from 2.89 million in 2001 and population density of 1530 persons/km^2. The total general unemployment in 2011 was 23.9% while that for youth was at 31.9 %. In 2011 the formal housing structure set at 78.4%, making it highly compared to other metros in the country. The city is also renowned as the major economic hub, boosting the second-highest amount of residents compared to other metros in the country (Budlender and Royston, 2016).

1.2 Research Question

Given the persistent levels of inequality in South Africa, does the city of Cape Town metro exhibit a concentrated bias of geographic opportunities in the city centre, or are these opportunities spread out in clusters across the metro?

1.3 Aim

To determine if there is an existence of unequal geographic opportunities among the City of Cape Town's main places, using the Exploratory Spatial Data Analysis (ESDA) techniques.

1.4 Objectives

1. To calculate the composite and multi-dimensional opportunity index for the City of Cape Town metro using official data and administrative records.
2. To investigate whether there are a spatial mismatch and difference in access to, and distribution of opportunities between neighbouring main places.
3. To identify areas most in need and lagging in respect of improvement in progress against deprivation and or opportunities, using spatial statistics tests.

1.5 Hypothesis

The null hypothesis for the study is that there is complete spatial randomness in the distribution of opportunities in the metro. We, therefore, set ourselves to prove or disprove that the spatial clustering of opportunities is a result of a random chance.

1.6 Knowledge Gap

The rationale for our study is to fill the academic gap identified by Wilson and Greenlee (2016) in respect to the geography of opportunity among metros, concerning the City of Cape Town metro. We particularly do an Exploratory Spatial Data Analysis at a disaggregated spatial level, to allowing unearthing of factors that could be influencing observed distribution patterns.

The thesis is broken down into six sections. It begins with an introductory chapter, literature review, methodology, results and analysis, discussion and ends with the conclusion. The first chapter sets out the aim and objectives of the study and is broken down into the following: introduction, the aim, objectives, the research question, hypothesis, rationale and knowledge gap. The second chapter reviews the literature on the origins and applications of the concept of geography of opportunities (Galster and Killen, 1995, Wilson and Greenlee, 2016 and the Opportunity Nation, 2014b) by key authors. The chapter touches on the concept of spatial mismatch, how this relates to the geography of opportunity, its implementation, internationally and in South African literature. The third chapter provides the methodology deployed in our study and its theoretical construct. It further carries the description of the data used in the study and statistical test used. The fourth chapter presents the results and analysis of the study, while the fifth and last chapter provides the conclusion, discussion and recommendations with suggested future work.

2. LITERATURE REVIEW

2.1 Background

South Africa may be an upper-middle-income country, however, it is still facing high levels of income poverty (Budlender and Royston, 2016) and the biggest inequality (Leibbrandt, Finn and Woolard, 2013). Such high unemployment levels are known to lead to increased income poverty, which was recorded at 53% (Stats SA, 2015). The picture is even direr, where some authors (Budlender et al, 2015) estimating poverty level to be around 63%. This makes it virtually impossible for the country to make progress in reversing the poverty situation post-1994. South Africa, like other young democracies, is struggling to find a good balance between economic development and job creation, and concurrently, deal with the eradication of injustices of the past spatial segregation.

The South Africa of today may look different from that of 1994, however many people are still trapped in poverty with persistent inequality. The President's report on performance monitoring acknowledges that since 1994 a substantial amount of funds spent (Abrahams, 2016), without such spend always leading to the achievement of desired services. The government might have spent substantial financial resources, without these leading to the eradication of poverty and inequality, due to the lack of appropriate targeting approach or instruments. We do our ESDA using GeoDa Software analysis techniques to reflect on what has been the factors influencing some of the observed spatial mismatches in opportunities across the metros landscape.

Financially, after two decades of democracy, South Africa's national budget has grown to more than R1.3 trillion. About 9 per cent of this budget goes to local government (Mboweni, 2019), where the metro receives its share. Besides this share, the metro, like others in the country, raises most of its revenue from its residence, especially through rates and taxes. Such funding allows it to address poverty in a much more direct and substantive manner. Given their location in the intergovernmental continuum, metros as local governments, provide basic services, which in return create local job opportunities during the capital phase of their implementation.

Therefore creating opportunities at this level, is a short in the arm for the country, as metros contribute significantly to the creation of less impoverished communities.

There is evidence of eradication of poverty through the provision of non-monetary government basic services, in some parts of the country, compared to where there has never been any investment at all (Leibbrandt, Finn, and Woolard, 2013). Literature (Leibbrandt, Finn, and Woolard, 2013) also points to entrenched poverty, where there are multiple dimensions of deprivation. Such entrenched deprivation is known to require targeted and strategic mediation strategies and instruments by the State. Without geographic targeting of these deprivation using geographic and statistical techniques, these efforts may not be easily targeted.

The impact of apartheid spatial planning led to the current observed spatial mismatch within cities, wherein the economically active population lives far from areas of job opportunities. This problem is not exclusively a South African problem, globally, studies show that geography of opportunity and spatial mismatch, exist in other cities as well. Below we explore the literature on the concept of opportunity and spatial mismatch in other parts of the world.

2.2 Geography of Opportunities and the Opportunity Index

The concept of opportunity concerning our study is described by the advocacy group, Opportunity Nation (2014a), "as the range of circumstances that open the doors for people to increase their economic mobility and improve their life chances" (Opportunity Nation (2014a.p4). The advocacy group believes that an individual's chance of upward social mobility, is affected by intrinsic factors such as race, ethnic group and individual's parents access to some form of level of education. Secondly the individual's attributes (e.g. level of intelligence) and thirdly the presence of decent jobs and low levels of crime in their neighbourhoods. These underlying reasons are critical to explaining the opportunity index, and its focus on societal issues that are beyond the control of individuals.

From its conception, the geography of opportunity was considered as "geography of metropolitan opportunity" (Galster and Killen, 1995), to describe the "structure of socioeconomic opportunities facing various societal groupings living in metropolitan areas" (Galster and Killen, 1995, p8). Galster and Killen (1995) explained the conceptual framework of opportunity as having two dimensions, namely, process and prospects. "The process dimension is explaining how the markets, institutions and service delivery systems utilise and modify the innate and acquired behaviour of participants. The process dimension, on the other hand, deals with the prospective socioeconomic outcomes that people believe will occur if they make particular decisions regarding education or work prospects" (Galster and Killen, 1995, p9). There are spatial variations within the metros in the operation of markets, institutions and social systems (Galster and Killen, 1995). Spatial variation contributes to the ability of an individual's upward mobility in society, influenced by personal first-hand experiences and second-hand information about the opportunity structure (Galster and Killen, 1995).

Galster and Killen (1995) in their study of the geography of metropolitan opportunity, provides a set of research questions amongst which Wilson and Greenlee (2016) sought to explore. These include identification of a gap that exists in understanding the importance of geography outside of the metropolitan areas, especially the spatial and temporal variation. The latter paper further extends the use of exploratory spatial data analysis in the investigation of opportunity from a multidimensional perspective. The paper highlights some of the frameworks for measuring opportunity to calculate a multidimensional opportunity index. Wilson and Greenlee (2016), acknowledges that their paper stems from the work by "the advocacy organisation, Opportunity Nation (2014a). The Opportunity Nation advocacy group is said to have brought a coalition between government and non-governmental organisations (Wilson and Greenlee, 2016, p.626), to focus on extending the opportunity for the facilitating social mobility and strengthening of communities across the United States.

In its definition, Opportunity Index is regarded as an annual composite measure of key economic, educational and civic indicators, launched in September 2011 (Opportunity Nation, 2014a). These indicators used are explained in the methodology section of this thesis and are grouped into three dimensions as described by Opportunity Nation (2014b) and Wilson and Greenlee (2016). These dimensions are Economic and jobs access, 2.) Education and 3.)

Community Health and Civil Life. The original dimensions, Economic and Jobs compose of the following indicators unemployment, poverty, household income, Gini coefficient, Banking institutions (per 10,000 residents) and household spending of less than 30% on housing. The second dimension Education, includes pre-school enrolment, high school dropout and post-matric attainment. The third dimension Community Health and Civil life includes youth economic and academic inclusion, the existence of primary health care providers in an area and Grocery stores and produce vendors. Collectively these indicator sets make up the Opportunity Index, which the US provided a snapshot of what opportunity looks within its states and counties. Galster and Killen (1995) provide some of the reasons why public policy needs to understand not only which opportunities are important for certain sections of the community like the youth, but what institutional mechanisms need to be placed for these to be taken advantage of. Geography of opportunity deals with the idea that the "attributes of neighbourhoods and the experiences provided by neighbourhoods have profound effects on their capabilities and their ideas about what they can accomplish" (Rosenbaum et al 2002. p81). The concept deals with how the spatial distribution of opportunities differs between the inner parts of the metro and the peri-urban area of the CoCT (Wilson and Greenlee, 2016). For this research, just like Wilson and Greenlee (2016), we take the meaning of the word "opportunity" to be synonymous with and implying access to opportunities such as jobs or job creation as was also proposed by Rosenbaum et al (2002). We can, therefore, conclude that literature agrees to Opportunity Index as being a range of circumstances that increase the chances of an individual's economic mobility, enabling them to improve their chances of leading a successful life (Wilson and Greenlee, 2016).

We, therefore seek to understand both which opportunities are important and need to be prioritised. For our study, we analyse a combination of numerous indicators including age, gender, race, level of education and the geography type (urban or rural) and how they influence accessibility to job opportunities.

2.3 Spatial Mismatch Concept

Sociologists (Grover 2019, Kain 1968; Wilson, 1987; Grover, 2019) have long been arguing that spatial mismatch, or costs for workers associated with the distance from home to work, determine the extensive margin of labour supply of urban areas in developed countries. “The historic policy of confining particular groups to limited space, as in ghettoization and segregation, and the unfair allocation of public resources between areas, must be reversed to ensure that the needs of the poor are addressed first rather than last.” (National Planning Commission, 2012:277). Sugie and Lens (2017) suggest that even though location matters in finding work, the one most important other factors to consider and include in testing spatial mismatch is the ability to travel to areas that are rich with jobs. Low skilled job seekers, the poor and unemployed reside in disconnected areas far from the well-endowed job opportunities within suburban areas (Laurent et al 2007, Gobillon and Selod 2007, Gobillon and Selod 2014). In its most basic form, the concept of Spatial mismatch theory is that “unemployment rates are higher for people living in areas which do not have appropriate jobs opportunities closer to them, such distance between jobs opportunities and residence of skilled people makes it harder for people to attain employment (Budlender and Royston, 2016).

From a South African perspective, for instance, recent housing policies perpetuate the prevalence of the apartheid city structure and not disrupting it, thus entrenching the spatial mismatch. This Budlender and Royston (2016), argue that it is a result of the government policy of prioritising quantity of houses over strategic locations such as places of employment. The impact of the apartheid spatial policy is reflected in people being removed from their places of work to peri-urban areas and townships, where there is no proper basic services, nor good education, and employment. Thus creating a negative impact on the possibility they have to access opportunities and creating a spatial mismatch. It has been thoroughly argued (Turok, 2012, Gotz & Todes 2014 and Wray et al, 2015) that jobs and economic opportunity are concentrated around city centres, but most of urban poor and unemployed live in dense urban peripheries.

2.4 Geography of Opportunities and Spatial Mismatch

Unlike the concept of geography of opportunity, the spatial mismatches explained by Rosbape and Selod (2006) deals with the existence of lack of connection between where people live and work. On the geography of opportunity deals with the presence of opportunities or lack thereof, among neighbourhoods as a result of spatial mismatch. Therefore the impact of a negative spatial mismatch is the creation of increased socio-economic difference in opportunities among neighbourhoods.

2.4.1 Spatial Mismatch and Geography of Opportunities in other parts of the world

In studies worldwide like those on firm relocations in the Glasgow conurbation by Houston (2001), the argument made is that skills, job search and people's network of contact adversely reinforce spatial mismatch. Sugie and Lens (2017) emphasize spatial mismatch or the "concentration of low-skilled, non-white job seekers within central cities and the prevalence of relevant job opportunities in outlying areas" as the biggest factor affecting former prisoners in finding employment, soon after being re-introduced back to the society.

Gibillion and Selod (2007) believe that residential isolation and distanced or bad access to jobs leads to unemployment in urban areas. They emphasize the point in their latter studies (Gibillion and Selod, 2014) that the problem of spatial mismatch (neighbourhood segregation) heightens the impact high unemployment (due to their remoteness from job opportunities) and therefore poverty. Zenou (2013) adds that spatial mismatch not only physically disconnects people and their places of work, but tends to create a slant along with ethnic groups. Structurally the impact can go as far as resulting in people commuting long expensive journeys, which in turn hinder jobseeker's mobility. As such it can, therefore, be rgued that "distance from job opportunities may also discourage job search (due to travelling costs) or even deteriorate its efficiency" (Zenou 2013, 74). Furthermore, patial mismatch due to, residential segregation, has been found to aggravate unemployment as a result of low-quality people's network of contact (Gobillon, Selod, and Zenou, 2007). Some of the influences of spatial mismatch and skewed opportunities are straddled across racial lines. According to Selod and Zenou, (2006) finding employment in South Africa for instance, amongst the black population, depends on people's network of contact as well as the distance to jobs, with location choices, which is mainly driven along racial lines.

2.4.2 Spatial Mismatch Cases in South Africa

Bhorat and Kanbur (2006) compiled a series of work done in the area of tracking outcomes and government around poverty in post-apartheid South Africa. Rosbape and Selod (2006), indicates that the apartheid spatial planning policies created spatial segregation. Rosbape and Selod (2006) indicate that in South Africa. Rosbape and Selod (2006) conclude that there are important spatial factors such as, distance from job opportunities, the rural background and the length of stay in the current dwelling that exacerbated unemployment. In terms of provisioning socio-economic conditions, the City of Cape Town is no different from the other cities in South Africa. Its demographic composition includes different racial mixes and more importantly to our study (Budlender and Royston, 2016), the impact of apartheid spatial regime still lingers on, wherein we can expect worsening of the spatial mismatch among main places.

To exemplify the point above, according to Grover (2019), the further a worker stays from their workplace (i.e. an opportunity) the higher the spatial mismatch. In South Africa, Rospabe and Selod (2006) argue that apartheid system ensured that only the privileged section of the society especially whites lived in the city centre closer to job opportunities, while most of the underprivileged, especially blacks, were pushed to the periphery with limited opportunities within their neighbourhoods. Such policies created structural challenges wherein the layout of the city negatively affect the chances of job seekers to find jobs close to where they live. Both spatial mismatch and lack of opportunities within neighbourhoods have a negative influence on how poverty could be dealt with. Arguably, the spatial segregation of the past regime in South Africa has entrenched impoverishment and unemployment.

In respect to the City of Cape Town, in particular, Budlender and Royston (2016) identify spatial mismatch across the majority of South Africa's metropolitan main places, especially in Johannesburg-Ekurhuleni-Tshwane sub-region in Gauteng. They, however, could not conclusively ascertain the same for the City of Cape Town and Nelson Mandela. For those metros' where spatial mismatch exists, especially in the City of Johannesburg and Tshwane, distance from jobs correlated with higher unemployment rates. Rospabe and Selod (2006) found out that employment probabilities were negatively influenced by job distance in terms of commuting time. They conclude that there is evidence suggesting a spatial mismatch in

Cape Town but do not quantify the significance of the effect in widening the opportunity gap amongst the neighbourhoods.

According to Budlender and Royston (2016) within the City of Cape Town metro, there is skewed high unemployment and low job intensity in areas such as Mitchells Plein, Khayelitsha, Nyanga, and Atlantis. Areas with lower unemployment include the city centre, Blouberg, Durbanville, Goodwood, and Bellville. Budlender and Royston's (2016) concern is that the geographic mountain and coastal relief, especially Table mountain straddling across the city, causes a divide. Such a land feature, they argue, affects the commuting patterns (if measured using a straight line assumption, not detectable when using the job proximity model). This is truer for when people, in reality, would travel a significantly longer distance, as the city centre is isolated from the rest of the main places. Budlender and Royston (2016) conceded that even though spatial mismatch might exist in the City of Cape Town (Turok, 2001; Rospabe & Selod, 2006; Rospabe, S. and Selod, H., 2006; Sinclair-Smith & Turok, 2012), proximity to jobs as a factor is weakened by the irregular physical geography of the metro.

The next section of this literature looks into some of the application areas where other forms of indicators were used to measure opportunities and spatial mismatch in different forms to measure improvements in people’s lives.

2.5 Spatial Mismatch and Performance Indicators

Various types of indicators have been used across the literature to track and measure progress in reducing spatial mismatch within and between regions. Performance indicators are typically a means to measure economic opportunity progress, which in their nature reduce spatial mismatch. The best way to measure government service delivery is to use regional economic development indicators (Xiangjian et al, 2011). Arguably regional development indicators are in themselves a type of indicators to measure spatial mismatch between regions, because they assess progress against a set of set policy outcomes, to be achieved. Boyne (2003), also argue for the use of performance indicators in tracking government policy targets. In India, citizens were concerned that the state was spending proportionally more funds but giving low value for money (Gupta, 2010), as such they adopted the use of outcome-based performance indicators to improve service delivery. These policy targets typically include access to services such as water, sanitation and health care. All of which are indirectly measurable and a means to detect spatial mismatch within neighbourhoods. The link or association between spatial mismatch and performance indicators is therefore that spatial mismatch can be measured using performance indicators.

In South Africa, the use of performance indicators has been integrated into the monitoring of service delivery across government. The Constitution of the Republic of South Africa entitles all citizens of South Africa to have access to the basic services, which are measurable through indicators. National Planning Commission, (2013), argues that Government, through the national development plan aims to ensure that citizens have access to services enlisted below. The use of approaches such as the opportunity index contributes to the discourse on tracking progress using indicators. In a more recent policy direction, the government has through the Department of Monitoring and Evaluation (2014), announced 12 outcomes to be focused on. Even though these were revised in 2014 to 109 to 14, they have recently been reduced to only 7 for the 2019 to 2024 MTSF. The initial 2014, 12 outcome areas include;

(1) Improved quality of education.
(2) Long and Healthy Life for all South Africans.
(3) All people in South Africa are and feel safe.
(4) Decent employment through inclusive economic growth.
(5) Skilled and capable workforce to support an inclusive growth path.
(6) An efficient, competitive and responsive economic infrastructure network.
(7) Vibrant, equitable and sustainable rural communities and food security for all.
(8) Sustainable human settlements and improved quality of household life.
(9) Responsive, accountable, effective and efficient local government system.
(10) Environmental assessment and natural resources that are well protected and continually enhanced.
(11) Create a better South Africa and contribute to a better South Africa and World.
(12) An efficient, effective and development-oriented public service and an empowered, fair and inclusive citizenship.

In their entirety, these outcomes speak to service delivery in various government areas that directly and indirectly influence the standard of people's lives, for the achievement of the National Development Plan goals of 2030. In its intent to deliver on these outcomes it becomes important for the government to accurately target people's needs. This would require an understanding and measure of where progress has been made in terms of people's standard of living and the extent of access they have to public services and community infrastructure. Each of these outcomes comprises of measurable outputs with targets and indicators. The South African case is one of several, where commitments to reduce poverty and create improved living conditions are policy imperative. This also clearly shows a commitment to poverty and spatial mismatch eradication for improved living conditions and efficient service delivery. Research such as ours could further shed insights on better and advanced specialised technique on improving on these government initiatives.

2.6 Why Measure Spatial Mismatch and Opportunities using a combined index

According to Hicks and Streeten (2002), the measurement of economic opportunity has moved from using a single measure indicator like income, to a multi-focal one, that uses a combination of various indicators. Such a single measure like the use of income alone would miss out on capturing the other forms deprivation, such as access to housing, water, sanitation, and electricity. In dealing with geography of opportunities, Salazar, Pallares-Barbera and Vera, (2020), agree that income alone is an inadequate measure to understanding hierarchical cluster analysis to deal with complex policies targeting. This complex policy targets (Porter, Stan, and Green, 2014), include a need to account for the measurement of social and economic progress and not just income alone.

Furthermore, the use of multiple indicators clustered into dimensions enables the incorporation of statistically non-comparable forms of data. The other advantage in the composite and ranking approach we are using is the production of estimates of precision maps that allows for guiding decision and policymakers to target deserving regions. As a combined index, the opportunity index is an index (Mazziotta and Pareto (2013) created from a grouping of indicators, which are standardised to provide a statistical overall measure of a region. These indices have proven to be a good measure of overall spatial mismatch over time. As described by Nardo et al (2005), a composite index, much like the opportunity index, works by initially taking raw statistics, ranking them from high to lowest scores and creating quintile that allows for a cross-sectional comparison between variables of different dimensions. An example of a well-known composite index measurement is that by Mo Ibrahim as discussed below.

Mo Ibrahim (2011) developed the African Governance index (Figure 2). According to Mo Ibrahim (2011), the Ibrahim Index of African Governance (IIAG) is an annually published composite index that provides a statistical measure of governance performance in African countries. The index combines various indicators, standardising statistical measures of governance performance into a uniform scale before they are transformed and grouped in sub-categories and finally into key categories that averaged into a final composite score. Unlike the Opportunity index, the IIAG governance framework is a much bigger index and comprises of four dimensions namely: Safety & Rule of Law, Participation & Human Rights, and Sustainable Economic Opportunity, and Human Development. These categories are made up of 14 sub-categories, consisting of 94 indicators' (Mo Ibrahim, 2013. P6). According to Mo Ibrahim (2013), before the implementation of the IIAG, the raw data used is pooled for at least two periods e.g. 2000 and 2012, with the latter not being allowed to be more than three years old. Where there is missing data, such raw data values are estimated with outliers subjected to statistical treatment to remove their influence.

The IIAG follows fairly similar steps to the calculation of the Opportunity Index, which can be briefly summarised, briefly as follows: The initial step in the IIAG is the collation of raw data from 32 sources. Such data is then standardised to make it meaningfully combined. Like the opportunity index, the data for each indicator are "transformed by the method of Min-Max normalisation which puts the data on a standardised 0–100 range, where 100 is the best possible score." (Mo Ibrahim, 2013. P6). Thereafter the data is subjected to a simple aggregation to combine the normalised indicators into sub-categories, which are in turn categorised into the overall IIAG.

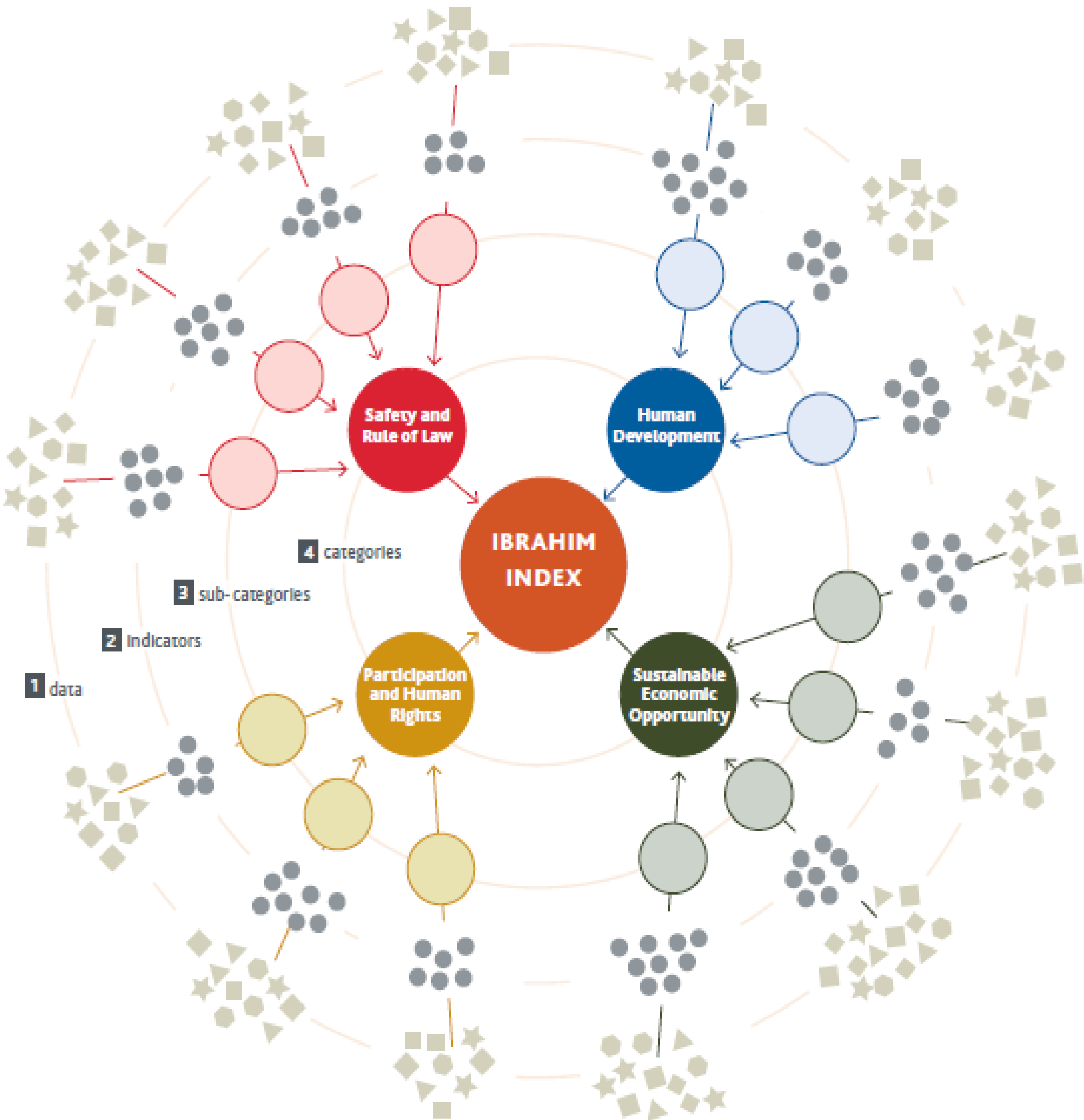

Figure 2: The Ibrahim Index on African Governance

Source: Ibrahim (2013)

As a composition index, an opportunity index is a valuable geographic targeting measure of government policy intervention. This is because composite indices have proven to be a good technique for targeting programs to the disadvantaged communities. Opportunity index is a typical geographic targeting method that ranks regions (Baker and Grosh 1994) according to their deprivation status, assigning high scores to the poorest groups, making them stand out from those areas that a not deprived. Therefore an opportunity index provides an advantage of being simple in application, assigning priority to regions based on existing aggregate data and not requiring new or complicated administrative mechanisms of selecting policy target beneficiaries.

The next section deals with the methodological approach to the thesis. The section provides, procedures and steps we took in implementing the opportunity index. For our thesis, we used the Main place dataset for the City of Cape Town Metro. This allowed us to reflect the difference in opportunity access across the City of Cape Town using mainly demographic data of the last Census 2011. In terms of dimensions of the index, we used similar categories as that by Wilson and Greenlee i.e.: 1.) Economic and jobs access, 2.) Education and 3.) Community Health and Civil Life.

3. METHODOLOGY

Our study takes a multi-indicator approach to measure opportunity as discussed in the literature review section. Our choice of this framework is from our conclusion that a single indicator dimension of deprivation would not adequately capture various elements often experienced by communities. The approach of using multiple indexes and their dimensions contributes to the policymaking discourse, to allow changing of the weight, depending on the interest at hand. In this case, the choice of a dimension of our index, except for the Economy and Jobs, captures the extent to which government has made investments in local areas.

While generally, an opportunity index provides a measure of the extent to which people have experienced an increase or decrease in opportunities, it may not be a good measure of providing the underlying causes or reasons for such observed changes. Similar to Wilson and Greenlee (2016), for this purpose, we add the use spatial statistical techniques, the spatial autocorrelation technique Moran's I, to unearth the underlying reasons for the observed outcome of our resultant opportunity index. The importance of the use of this spatial statistical measure for our study is to determine if there is any influence of neighbouring sub-places in urban developed clusters compared to those further off to economic opportunities, some studies elsewhere have already given thought to the influence of emerging main towns as new centres of employment under the polycentric theory, for which we do not consider for our study due to the time limit and feasibility.

The spatial autocorrelation is a form of an Exploratory Spatial Data Analysis (ESDA) technique to reveal spatial patterns and structures (Anselin and Getis, 2010), allowing for the researcher to develop hypotheses and choose models from. Among the initial applications of the ESDA, Eldridge and Hillier (1998) tested whether spatial statistical analysis techniques like ESDA offer more information compared to classical visual analysis of point and polygons data. Spatial autocorrelation describes the degree to which two observations (in space), are similar to each other (Hijmans and Ghosh, 2019). Spatial autocorrelation determines whether an observed variable, at a particular location, is significantly dependant on the value of that variable in a neighbouring region (Thompson, Saveyn, Declercq, Meert, Guida, Eads, Robles, and Britto, 2018 and Fu, Jiang, Zhou and Zhao, 2014). Though there are numerous spatial autocorrelation measures, Moran's I (Porter, Stern, and Green, 2014), is a much simpler method that computes values ranging from -1 to 1 reflect negative correlations and positive correlations respectively. Moran's I as a statistical technique to measure spatial autocorrelation estimates statistical randomness or clustering, denoted by the values between 0 for complete randomness and 1 for complete clustering. According to Fu et al (2014), Moran's I used together with geostatistics and GIS, are useful to study spatial patterns thus become a very popular method in spatial-cluster analysis. The following are data used for our analysis.

3.1. Data used in the Study

Table 1: Dimensions, Data, and sources

Dimension	Indicator	Data Source
Local Economy and Jobs	Unemployment Rate (%)	Statistcs South Africa Census (2011)
	Poverty Rate (%)	Statistics South Africa, General Household Survey (2011)
	Median Household Income (R)	Statistcs South Africa Census (2011), Living Conditions Survey
	Access to Rental Housing (%)	Stats SA Income and Expenditure Survey 2011
	Total Population (%)	Statistics South Africa, Midyear Population Estimates (2011)
Education	Pre-School enrolment (%)	Stats SA, Educational Enrolment and Achievement, 2016
	High School Droput rate (%)	Statistcs South Africa Census (2011), Educational Enrolment and Achievement, 2016
	Post Matric attainment (%)	Statistcs South Africa Census (2011), Educational Enrolment and Achievement, 2016
Community Health and Civil Life	Youth economic and academic inclusion (%)	Statistcs South Africa Census (2011)
	Access to Clinics per 100,000 (proxy for Primary Health Care Providers)	Statistics South Africa, Community Survey (2011)
	Access to Retail produce and Vendors (Spar and Pick Pay Outlets) (per 10,000)	Spar and Pick n Pay 2015, Integrated Annual Report

As per Table 1, our data for the opportunity index was sourced from Stats SA, supplemented other sources such as records from departments such as the Basic Education and Higher Education. Other data were sourced retailers such as the pick 'n pay group and spar annual reports.

The following Dimensions and their data were included in our database raw table to create a combined index for the three dimensions we developed.

3.1.1. Dimension 1: Jobs and Local Economy.

Jobs and the local economic opportunity dimension was chosen because it captures the importance of jobs and employment. Together with, the poverty rate these sets of indices indicate the economic wellbeing of households.

The first variable directly related to the measure of poverty is the extent of unemployment across main places, to capture the extent of access to job opportunities. A focus on the provision of decent jobs needs to be underscored by the provision of basic employment. In this case, a need to first create more jobs for all those qualifying in terms of employment age, as it is crucial for the economically active to have access to job opportunities in dealing with poverty within households. Secondly, poverty headcount is a classic measure of deprivation, literature shows that economists usually prefer income, for example, according to Foster, Greer, and Thorbecke (1984) the Foster-Greer-Thorbecke (FGT) family of poverty measures introduced in 1984 is highly regarded because it meets all the axioms desirable in income-based poverty measures. For this variable, we chose the rate of the population that is below the income line, strictly measuring absolute poverty headcount. The variable poverty headcount measures the extent of poverty. The index is developed using poverty headcount, which provides an estimate of the number of poor population within an area. The third variable under this dimension is the Median household income, to measure the variability in levels of income across the metro.

The unemployment rate is taken from StatsSA's Labour force Survey last quarter of 2019 calculations and reflects for us, the importance of jobs and labour force attachment. Median household income and the poverty rate come also comes from StatsSA calculated from the 2016 Community survey and the Income and expenditure survey. These complementary indicators provide insight into the economic wellbeing of residents. Our calculations of the poverty profiles were pre-calculated for us by StatsSA, does eliminate any possibility of introducing errors especially dealing with it at a lower spatial level.

3.1.2. Dimension 2: Education

The second dimension, Education, covers the percentage of pre-school enrolment, high school dropout rates, and post-matric attainment rates. It provides us with an understanding of the learner's household economic background influence on their throughput. Indicators in this dimension capture the importance of learning at key stages of the life cycle (Wilson and Greenlee, 2016). The benefits of access to education have a very positive spillover effect on both the individual being educated and the society in general. For purposes of our analysis, the following education-related indicators are used in our study;1) Early Childhood Development (ECD) attendance rate; 2) Percentage of 16 to 19-year-old not at school and; 3) graduate throughput for adults above 25 years and over.

Like the Opportunity Nation and Wilson and Greenlee, our Education dimension consists of three straight forward indicators that capture the importance of learning at key stages of the life cycle. Each of these measures are taken from the StatsSA’s educational enrolment and achievement of 2016. Our preschool enrolment data was prepared similarly to the Opportunity Nation (2014b). It represents the preschool enrolment as the percentage of 3 and 4-year-olds enrolled in school, the high school dropout rate is the number of residents ages 16–19 who are not enrolled in school and not high school graduates divided by the population aged 16–19 sourced from the mid-year population estimates at the main place level. The same applies to the post-secondary educational attainment, which reflects the percentage of residents aged 25 or older with an associate’s degree or higher. Unlike the Opportunity Nation (2014b) who used the percentage of high school who graduate in 4 years as an indicator, we used the percentage matric learners drop out due to data limitations we substituted the dropout rate as defined above in our analysis.

3.1.3. Dimension 3: Community Health and Civil Life.

Similar to the Opportunity Nation (2014b), with the third dimension our, Community Health and Civic Life dimension consists of three indicators, with the first coming from the 2011 Census from Stats SA, while the second and third are taken from Stats SA Community Survey and the retail data from the respective retailers themselves.

We followed to the letter the selection and calculation used by Opportunity Nation on the Youth economic and academic inclusion. Specifically that of using the percentage of residents aged 16–19 who are not in school and who are not working as measured in the 2011 Census. The number of primary care providers per 100,000 residents is included as a proxy for access to healthcare is taken from the annual community survey itself. The number of grocery stores and produce vendors per 10,000 residents is a well-established indicator of the availability of healthy food and also derived from the Spar and Pick n Pay retailers themselves. The violent crime rate data was not included, as it is not freely available at the time of finalising the data collection process.

To assess and measure of living conditions, access to formal housing, basic health care and shopping were used. Such access will increase the time available for job-seeking efforts by individuals.

Youth Economic and Academic Inclusion: This indicator is calculated using Census data on the percentage of residents aged 16–19 who are not in school and who are not working. Access to Retail facilities and Vendors: While the opportunity nation used to access to retail and banking, we opted to use retail outlets data as a proxy. For feasibility the number of Spars and Pick and Pay Stores per 10,000 population is used because data on the number of banks was not readily available. Access to Primary Health facilities is a proxy for access to healthcare. For the latter, we used the number of clinics per 100,000 population per ward aggregated to the main places.

3.2. Data Quality Assessment and Limitations

In total, we got 10 of the 12 variables included in the paper by Wilson and Greenlee (2016) with all the 3 dimensions represented. The two left out variables that could not be accessed in time are Gini-coefficient and banking institutions. The variable total population was used to assist in calculating ratios of various population groups. We arguably covered more 83% (or 10 out of 12) of the data used in the original opportunity index, by Opportunity Nation (2014b).

In general, unlike the opportunity Nation, we could not get hold of all the enlisted data variables they used due to time constraints in completing the thesis, as that some of the data like those of banks would come at a cost. While the opportunity nation had six indicators associated with the Jobs and Local Economy dimension, we have five four of which are matching as we added the percentage of population per area. Data that could not be accessed in time is that for banking and Gini-Coefficient, due to cost and response time from the suppliers. Unlike the Opportunity nation and explained above, we did not get access to the number of banking institutions data and therefore our index does not account for personal assets and capital and investment at the community level. Our study also included the number of homeowners and renters spending 30 % or less of their income on housing to capture a standard indicator of housing access. While the Opportunity Nation included high-speed internet access as an indicator within the Jobs and Local Economy dimension, this data was unavailable in the General Household survey at the required main place level.

Because our data is limited to a single period, we do not perform a comparative analysis over time. This is mainly due to the non-availability of data from Stats SA on two consecutive censuses and the boundary re-demarcation of boundaries. For feasibility and time constraints, we exclude temporal analysis and restrict our study to regional analysis.

A further limitation of our study is not assigning weights to different dimensions as indicated by Moreira, Simões and Crespo (2012). The idea of weights is important, where a particular individual or government may want to express the importance of certain indices, for specific policy purposes.

3.3. Data analysis procedures

In implementing the Opportunity Index approach developed by the Opportunity Nation (2014b), and following similar steps as per Wilson & Greenlee (2016), we included the following;

- Normalising the indicator variables
- Averaging the rescaled indicator scores within each of the three dimensions and

- Finally calculating an overall composite index by averaging the three dimensions scores.

The opportunity dimensions are created from a grouping of indices, which are standardized to provide a statistical overall measure of a region. The composite index works by initially taking raw statistical data, ranking it from high to lowest and creating quintile or groups with ranks from bad to worse socioeconomic conditions. This exercise transforms the raw statistics into the number scale from 1 to 100, which we automatically recalled to 1 to 10 for ease of working with the data and interpretation.

3.3.1. Steps Used In Mapping Our Composite Opportunity Index

3.3.1.1. Step 1: Normalising and rescaling the indices

1. Most of the data come from Statistics South Africa's census Super Cross[1], as the package contains verified, aligned and geo-coded data. Other data is obtained through specific queries to Stats SA.
2. Data from each dimension and various indicators were separately extracted, and relinked into a single database, using the Main place unique identifiers.
3. Once all the data was joined into a single data file, each variable type from the three dimensions was aggregated to the City of Cape Town's main places. This produced a percentage share contribution from each Main place.
4. We then use the resultant percentages to rank all the Main places for every variable into 5 quintiles breaking the data at every 20 percentile point, in Arc Map or GeoDa.

It is important to note that during standardisation or normalisation process, high values in some cases may imply worse off conditions, while in some cases it may imply good socio-economic conditions e.g. Areas with a high rate of access to clinics are better compared to areas of the high poverty rate. Therefore, the normalisation process ensures that we can deal with unevenness in the data. We adopted the data normalisation approach, (Opportunity Nation 2014b, Wilson and Greenlee, 2016) as it is an easier method to express areas of priority and or those most in need and vice versa. The equation for normalisation from equation (1) refers,

A Statistics South Africa's Census viewing application distributed with census data.

wherein the rescaled value is a product of the observed minus the minimum value over the maximum value minus the minimum value, normalised to a 100.

$$Value_{\text{Rescaled}} = \left(\frac{Value_{Observed} - Value_{Minimum}}{Value_{Maximum} - Value_{Minimum}}\right) \times 100 \quad \text{……………………………………….. (1)}$$

The 'relationship between the indicators and opportunity is not always positive' as explained by (Wilson and Greenlee, 2016, p628). We, therefore, implemented equation 2, which deals with such cases in a negative relationship. The only difference being that we subtract 1, from the rescaling ratio before multiplying by the value of 100. This equation (2) helps in ensuring that the rescaled indicators value points in the same direction.

$$Value_{Rescaled} = \left(1\text{-}\left(\frac{Value_{Observed} - Value_{Minimum}}{Value_{Maximum} - Value_{Minimum}}\right)\right) \text{x}100 \quad \text{……………………………. (2)}$$

3.3.1.2. Step 2: Averaging the rescaled indicator scores for each dimension

Each of the resultant score is broken down at every 10 percentile grouping count of incidents of data occurrences. Therefore, the 10 ranks are 1) 1-10 percentile until 90-100 percentile, with higher values indicating poor opportunities. Every one of the indicators within the three dimensions would be an aggregated set of scores from their indicators.

3.3.1.3. Step 3: Computing an overall Composite Index

The next step was to compute the final composite index. This was done by aggregating overall scores of the 3 dimensions from the resultant aggregated percentage of step 2 into a single final index, i.e. adding the three resulting percentage scores and dividing them by three.

For mapping purposes, the data file is firstly joined with the shapefile to create the output map of the index. The same file was then used to create graphs of analysis in GeoDa including preparation of the Moran's I plot.

Once all the data was properly ranked, each variable within a dimension could be independently aggregated or joined to present scores to express them as a combined dimensions index. The combined index is important to use during the running of the Moran's I plot regression.

3.3.2. Creation of the Spatial Weight Matrix

We performed the spatial weight matrix using GeoDA software, and in particular, used the contiguity weight. The study is undertaken in the City of Cape Town metro which has 55 main places. This is lower than what Wilson and Greenlee (2014) study worked with of just above 3000 observations, because they were applying the index at a lower spatial scale, with more detailed and readily available data. This is because we are working mainly with polygon-to-polygon data as opposed to points or line data, which according to Balu and Devi (2011) recognises the neighbouring polygons. This assisted in measuring the number of neighbours within our study area. The option for contiguity weight assumes a Manhattan Block Distance. The concept expressed in an equation takes into account "two points i and j in a two-dimensional space. Wherein the variable i is described with the coordinates (xi, xj) and j with the coordinates (yi, yj). For this purpose, we adopted the K Nearest neighbour, expressed by Wilson and Greenlee (2016) with the row-standardized, first-order contiguity matrix in equation (3). The expression "spatial weight *wij* indicates the influence of main place *j* on the main place *i* with polygons sharing an edge or vertex (queen contiguity) coded 1 and all others coded 0. Row standardization accounts for variation in the number of neighbouring units by constraining the sum of all weights to 1" (Wilson and Greenlee, 2016.p629). Apply this to your study, i.e. "county" refers to "the main place.

$$W_{ij} = \begin{cases} 1 & \textit{if counties i and j are contiguous} \\ 0 & \textit{otherwise} \end{cases}$$

$$\sum_{j=1}^{n} w_{ij} = 1, \quad i = 1, \ldots, n \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

The matrix is given the value of 1, if centroid j is one of the k $nearest$ $neighbours$ and the value of 0, if centroid j is not one of the neighbours.

3.3.3. Moran's I test and a measure of Autocorrelation.

Hypothesis testing

The null hypothesis for the study is that there is complete spatial randomness in the distribution of opportunities among the deprived or well-off main places across the City of Cape Town Metro. We test the null hypothesis with the Moran's' I spatial statistical technique.

Global Moran's I

Global Moran's I test the extent of linear association between the value of a parameter at one location and the spatially weighted average value of the same parameter at neighbouring locations.

The Global Moran's I is useful to test our hypothesis, by providing us with a scatter plot and a matrix output that has a range of -1 to 1 for negative spatial autocorrelation, positive spatial autocorrelation, respectively. As per Wilson and Greenlee (2016) we would be therefore able to tell whether observations near one another have more similar attributes or the opposite condition wherein if we get values closer to zero, that would be interpreted as there is a little visible pattern.

Theoretically and as per the equation (4) by Waller and Gotway (2004) the Global Moran's I measure an association, wherein, ''the comparison between area *i* and *j* defined as the product of the corresponding dissimilarity between Yi and Yj with the general mean'' (Waller and Gotway 2004, p.227; Wilson and Greenlee 2016, p629). The equation generally tests the notion of the first law of geography conceptualised by Tobler in 1970.

$$I = \left(\frac{n}{\sum_i \sum_j w_{ij}}\right)\left(\frac{\sum_i \sum_j w_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_i (Y_i - \bar{Y})^2}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

The Local Moran's I

Even though there are other forms of autocorrelation measurements because our attribute data is continuous over space, we use the Local Moran's I. The local Moran's I test was developed using the Moran's Scatter plot to test whether there is clustering, random or dispersion of main places by various indicators at a finer scale. Because the Global Moran's I s not meant to "test spatial relationships at finer scales, we are able through the Local Moran's, to identify and visualize spatial clusters, spatial outliers, and other areas of ''local instability'' (Wilson 2016, p630; Anselin 1995). Equation expression (5), has the same variables as those of Global Moran's I under equation (4) above, except that the variable Q_Y denotes the standard deviation of Y.

$$I_{Local} = \frac{(Y_i - \bar{Y})}{\sigma_Y} \sum_j w_{ij} (Y_j - \bar{Y}) \quad \text{.. (5)}$$

The observed I_{Local} statistic is calculated for each unit and its neighbours according to the relationships specified in the spatial weights matrix. This includes standard deviate (z-score) comparing the observed value of the statistic to the reference distribution (Anselin 1995; Bivand et al. 2014; Wilson and Greenlee 2016). Because of the large number of observations generated, "the significance test normal and standard deviate values 1.96<z>1.96 are considered statistically significant at the 0.05 level, with plots of high–high (HH), low– low (LL), high–low (HL) and low–high (LH) as a resultant association. A spatial cluster can take the form of a group of observations with high opportunity index values or a group of observations that all exhibit low opportunity index values" (Wilson and Greenlee, 2016; Anselin 1996).

4. RESULTS AND ANALYSIS

This section of the report, examines the spatial distribution, patterns and an exploratory analysis derived using the opportunity index approach at the main place level to reveal how the geography of opportunity compares across the city of Cape Town Metro. We present an analysis of the chosen indicators without a theoretical in-depth analysis of their impact as a whole, but more a geospatial presentation across the City of Cape Town.

4.1. Results and critical Analysis

Our database contained 55 main place polygons or observations. From the results of running the spatial weight matrix, the average number of main place neighbours (adjacent polygons) is 4.04, the maximum number of neighbours is 16, while the lowest is 0, when taking into account Robin Island, which has no neighbours. The most frequent number of neighbours a main place has across the metro is 5. Because a spatial weight matrix reflects the intensity of the geographic relationship between observations (Getis and Aldstadt, 2004.), we can conclude that most of the main places under observation have an adequate number of neighbours around them (at the frequency of 5) to allow for drawing of patterns from their spatial interaction. For purposes of construction the neighbourhood analysis we did not exclude less populous main places (e.g. nature reserves). Therefore some of the observed resultant values on the descriptive analysis table may appear as 0 % of 100% unemployment on the minimum. These were therefore carefully interpreted and not included as part of the calculation of the final analysis.

Table 2 presents descriptive statistics for all indicator variables used in the calculations of each of the three dimensions of opportunity, and the index itself. On average, main places scored lower on the Jobs and Local Economy and education dimensions compared to the Community Health and Civil Life dimension and the overall opportunity index. The standard deviation of the opportunity is an overall 8.2, which reflects variations in the spatial equilibrium within the city of Cape Town metro. This reflects the lack of convergence of opportunity across geographic locations. The range for the education dimension is lowest at 41.9, compared to the 86.2 for the Community Health and Civil life. This shows that there is more spatial mismatch in the Community Health and Civil life compared to the education dimension.

Table 2: Descriptive Statistics of the Opportunity Index

Dimension	Indicator	Minimum	Maximum	Mean	STD	Range
Jobs and Economy	Unemployment Index (%)	0.0	100.0	24.3	22.7	100.0
	Median Median HH Income	892.5	3369.0	1803.5	570.3	2476.5
	Poverty index (%)	0.0	100.0	37.6	23.9	100.0
Dimension Education	Preschool Index	0.0	100.0	62.2	26.2	100.0
	Dropout Rate	0.1	0.8	0.3	0.2	0.8
	Education Attainment	0.0	0.3	0.1	0.1	0.3
Dimension Community Health and Civic Life	Youth Unemployed Index	0.0	100.0	39.7	22.9	100.0
	Clinics per 100K pop	0.0	43.0	4.9	8.7	43.0
	Retials per 10K Pop	0.0	27.0	2.4	5.3	27.0
Opportunity	Dimension Jobs and Economy	11.5	57.1	32.3	11.3	45.6
	Dimension Education	32.0	73.9	47.6	12.4	41.9
	Dimension Community Health and	9.5	95.7	73.2	15.6	86.2
	Combined/Opportunity Index	22.6	61.7	50.9	8.2	39.1

In addition to the descriptive analysis from table 2, we looked into the interaction between the dependent variable, combined index, with the individual variables enlisted in table 1. That make up the three data dimensions in the previous chapter. These are captured by table 3, which represents the output of the Ordinary Least Square Regression of these variables. With R-Square of 0.761, this means that the proportion of the variation in the outcome value of the combined index is 76.1 % of the time explained our variables. The adjusted R-square is very close to the R-squared at 71.34, meaning that the results of our sample compared to the full data set is indifferent.

Table 3: Regression summary of output: Ordinary least squares estimation

```
>>03/22/20 22:56:10
REGRESSION
----------
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  ct_mp_socecon1_new
Dependent Variable  :  Combi__Idx  Number of Observations:   55
Mean dependent var  :     51.6142  Number of Variables   :   10
S.D. dependent var  :     7.46916  Degrees of Freedom    :   45

R-squared           :    0.761238  F-statistic           :     15.9414
Adjusted R-squared  :    0.713486  Prob(F-statistic)     :2.63447e-011
Sum squared residual:     732.606  Log likelihood        :    -149.247
Sigma-square        :     16.2801  Akaike info criterion :     318.493
S.E. of regression  :     4.03487  Schwarz criterion     :     338.567
Sigma-square ML     :     13.3201
S.E of regression ML:     3.64967

-----------------------------------------------------------------------------
       Variable      Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------------
          CONSTANT       42.4307        3.20077        13.2564     0.00000
           Poverty      0.267004       0.125023        2.13564     0.03819
        Median_Inc    0.00348992     0.00131766        2.64857     0.01111
        Unemp_ment   0.000885173    0.000571746        1.54819     0.12858
              ECDs   -0.00681568     0.00858769      -0.793657     0.43156
        Dropo_Rate      -6.82422          5.398       -1.26421     0.21266
        Educa_ment      -8.55775        8.75652        -0.9773     0.33365
        Unemp_outh    0.00226266      0.0061755       0.366392     0.71579
        Clini__pop     -0.180245       0.125843       -1.43229     0.15897
        Retia__pop     -0.674345        0.22398       -3.01073     0.00426
-----------------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   31.808885
TEST ON NORMALITY OF ERRORS
TEST                  DF           VALUE             PROB
Jarque-Bera            2             0.8067          0.66807

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF           VALUE             PROB
Breusch-Pagan test     9             9.1760          0.42119
Koenker-Bassett test   9            11.5197          0.24176

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : Queen
   (row-standardized weights)
TEST                           MI/DF        VALUE          PROB
Moran's I (error)              0.0587         1.1187         0.26328
Lagrange Multiplier (lag)        1            1.4114         0.23482
Robust LM (lag)                  1            2.3913         0.12202
Lagrange Multiplier (error)      1            0.3169         0.57348
Robust LM (error)                1            1.2967         0.25482
Lagrange Multiplier (SARMA)      2            2.7081         0.25819
============================== END OF REPORT ================================
```

In terms of co-efficient of interaction, the estimates of the marginal impact of individual variables show that the most significant and positive influence of the variables to the observed change in the combined index is that by poverty at 0.26 at less 10% confidence level. Youth unemployment, Median Income and global unemployment, though expected to have a direct relation to poverty have a much lesser impact at 0.002, 0.00348, and 0.00088 respective to the combined index. The education attainment and dropout rate show a significant but inverse relation impact on the combined index change at -8.5 and -6.8 respectively. Retails, clinics and ECD attendance, all have a negative interaction, though at a lower significance level.

4.2. Analysis of the Global Moran's I

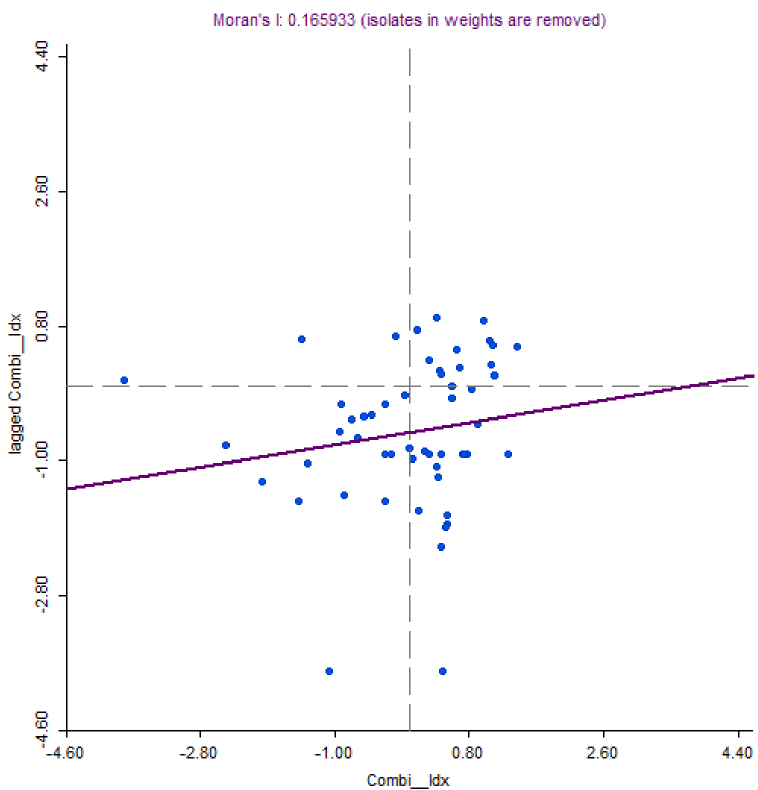

Figure 3: Moran's I plot for Combined (Main places) Index

At 95% confidence interval, the slope of the regression line in the Moran's I scatter plot, is positive and statistically significant at a value of 0.166 (Figure 3), confirmed by the local indicators of spatial association (LISA) regression results in Table 3. The overall pattern of spatial dependence reflected by this Global Moran's I at 0.166, therefore, reflects a positive and significant presence of global spatial autocorrelation.

We, therefore, accept the null hypothesis at the 10% level probability that there is a 5% of spatial clustering or dispersion of opportunities amongst main places in the city of Cape Town.

Next, we look into the Local Moran's I and unpack the dimensions of the Combined Index to try and understand the observed output from the global Moran's I.

4.3. Analysis of the Local Moran's I

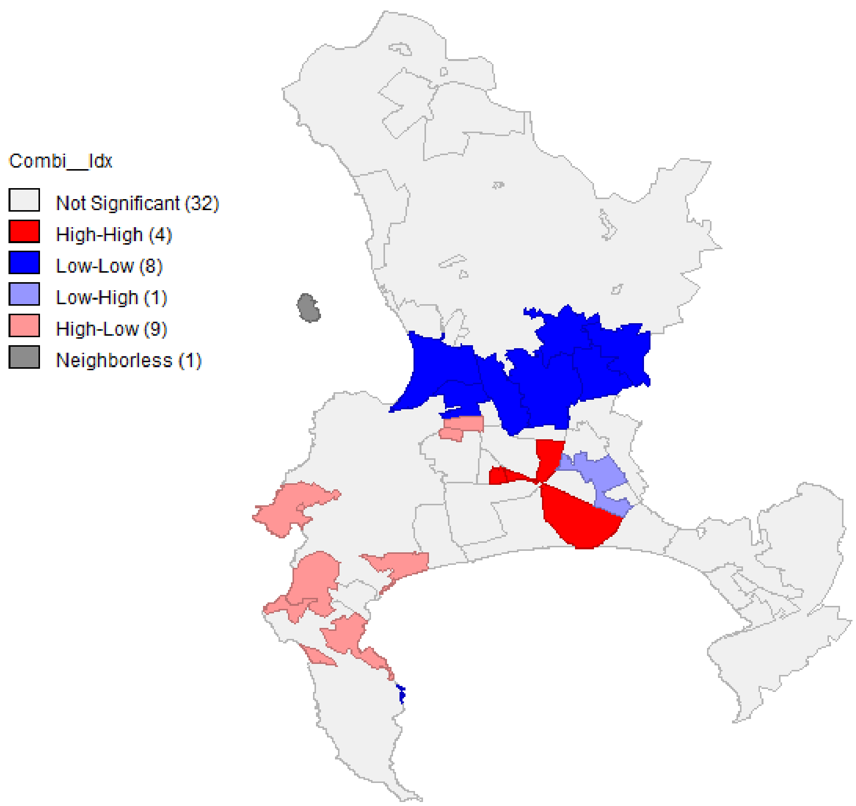

Figure 4: Local Moran's I cluster map of the City of Cape Town Metro Combined Index

After identifying the pattern of the Global Moran's I, we implemented the Local Moran's I to test whether the specific main places are correlated (positively or negatively) with their neighbours. A quadrant-by-quadrant grouping of the main places in Figure 4 and 5 show the following clustering of main places;

Quadrant I: High-High [4 main places]

Four out of the 55 main places i.e. Delft, Nyanga, Crossroads and Khayelitsha are located in the first quadrant of the Moran's I scatter plot. These main places show high levels of spatial clustering, with two of them Nyanga and Delft (reflected in the descriptive analysis above), forming part of the most deprived areas.

Quadrant II: Low-High [1 Main place]

There is only one main place, namely Blue Downs, in this Quadrant. The Main place reflects a combined index score of 50.2, made of an aggregate score of 36.4 % for the Jobs and 31.2 % Economy Dimension, for the Education dimension and 82.2 % for the Community Health and civic life. The Blue Downs combined index score is below the mean of 51.6 on the deprivation index.

Quadrant III: Low-Low [8 Main places]

Eight of the 55 main places i.e. Bellville, Brackenfell, Castle Rock, Durbanville, Goodwood, Kraaifontein, Milnerton, and Parow. All these main places (except for Milnerton and Parow) are also reflected as part of our 10 socio-economically better places in our deprivation index (see Table 3), which includes Kraaifontein and Blouberg in addition to those in this quadrant.

Quadrant IV [9 Main places]

The following nine main places form part of the 4th quadrant, Epping Industria, Langa, Houtbay, Imizamo-Yetho, Muizenburg, Noordhoek, Simon's Town, Kommetjie, and Scarborough

4.4. Unpacking the observed results through the analysis of the Dimensions

This part of the analysis provides a summary of the observed relationships and interaction between variables used for the opportunity index. This is summarized into the three dimensions of Jobs and the Economy, Education and Community Health and Civic life.

The results of the Local Moran's I from the three dimensions used in the study are discussed below.

4.4.1. Jobs and Economy Dimensions Results

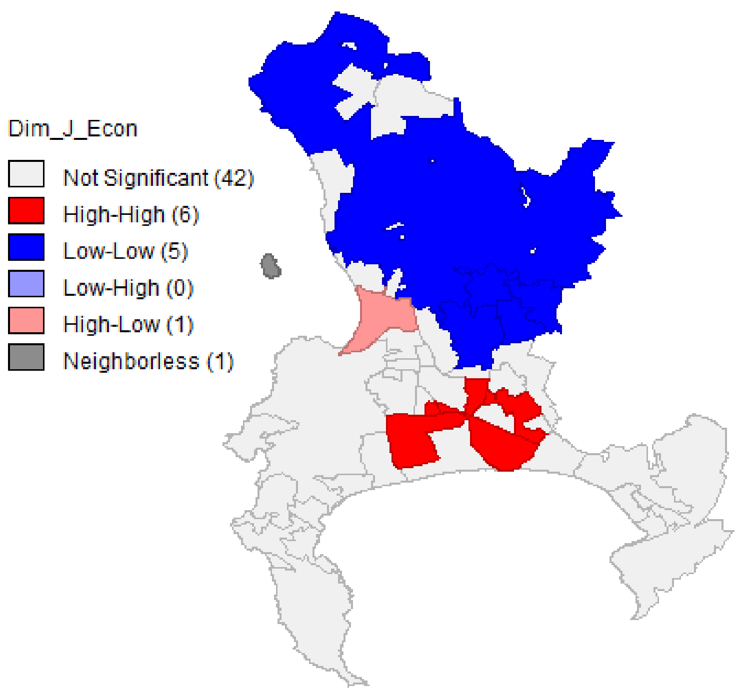

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Figure 5: Local Moran's I cluster map of aggregated Poverty, Median income and Unemployment

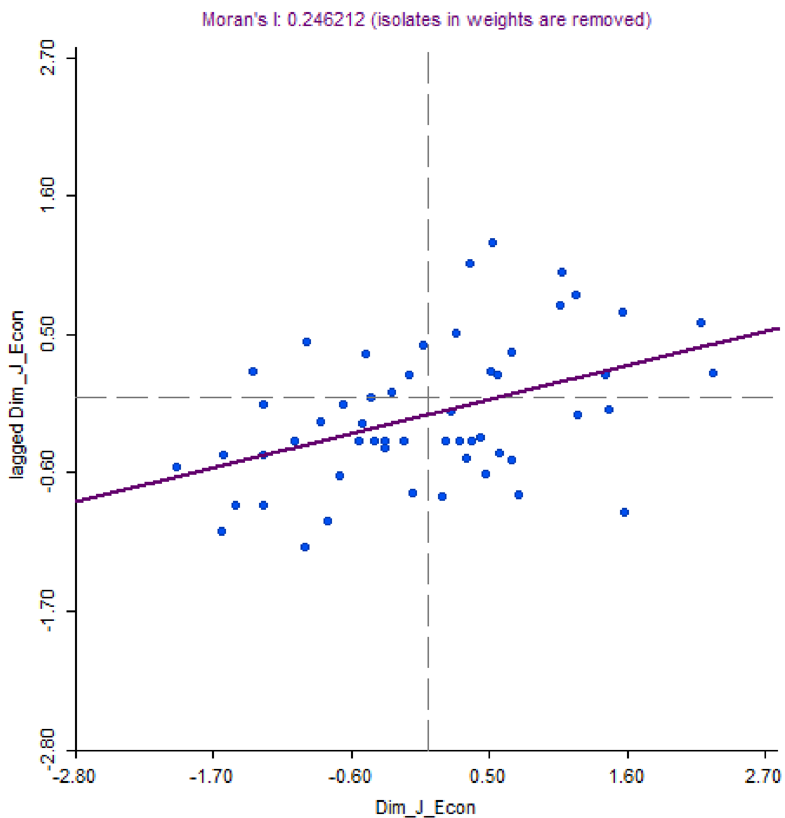

Figure 6: Local Moran's I plot of aggregated Poverty, Median income and Unemployment

Firstly, the Jobs and Economy Dimension has a Moran's value slope of 0.246 (see figure 6). This reading is the highest amongst the three dimensions. It is followed by the dimension of Community Health and Civic life then education respectively, with values of 0.12 and 0.044. This order of significance shows that the most influence from our global Moran's I is the jobs and economic dimensions. The results of the regression analysis (see Table 3), shows that for every observed change in the final opportunity index, poverty, a variable under the first dimension, changes 0.26 (coefficient) fold at a significance level of less than 5 %, or probability rate of only 0.03. The second variable of influence, though at a significantly lower level is that of median income, show a 0.0034 coefficient change at a probability of less than 5 %.

4.4.2. Education Dimensions Results

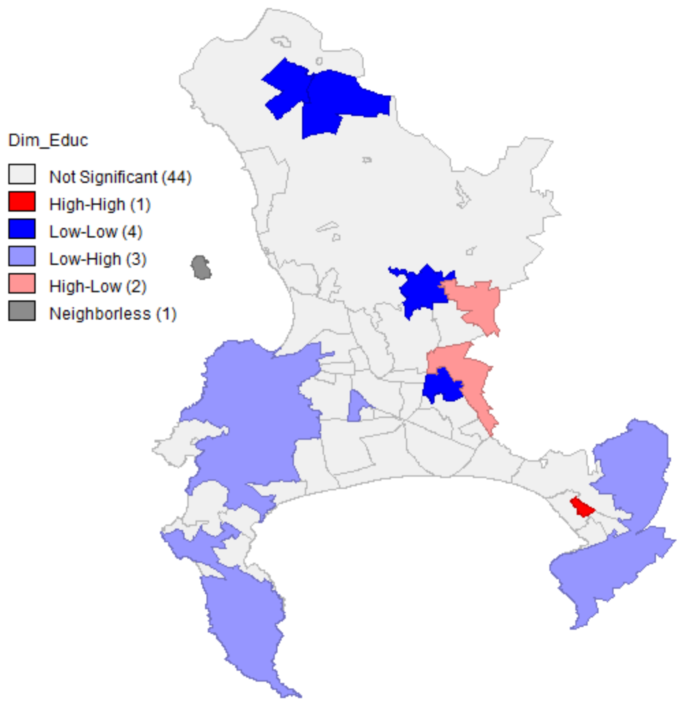

Figure 7: Local Moran's cluster map of aggregated secondary dropout rate, ECDs and Education Attainment

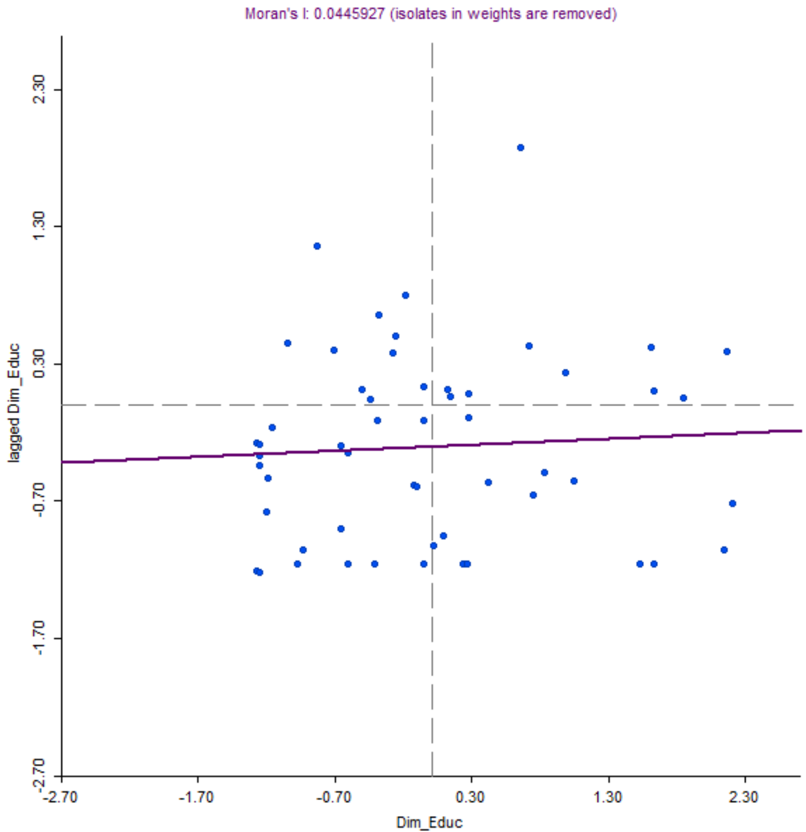

Figure 8: Local Moran's I plot of aggregated secondary dropout rate, ECDs, and Education Attainment

The second Education Dimension Global Moran's I plot has a scatter plot value and slope of 0.0044 (see figure 8). This reading is the weakest among the three dimensions. This low comparative reading shows that the education dimensions have a very low influence on the observed random distribution of the main places with high-high clustering. The results of the regression analysis (Table 3), show that all the variables (ECD, secondary school dropout rate and Education attainment) under this dimension have a negative correlation with the final opportunity index. Inversely this means the disadvantage scores in these areas on main education are very low. In other words, there are better outcomes related to the education dimension, as a result of a high number of children attending preschools, low dropout rates at secondary and high throughput at the post-matric level. However, these have not translated into the increased job and economic opportunities in these areas. In some instances, many areas in the Low-High category contain nature reserves and therefore have lower population density, and therefore most likely leading to the observed poor correlation.

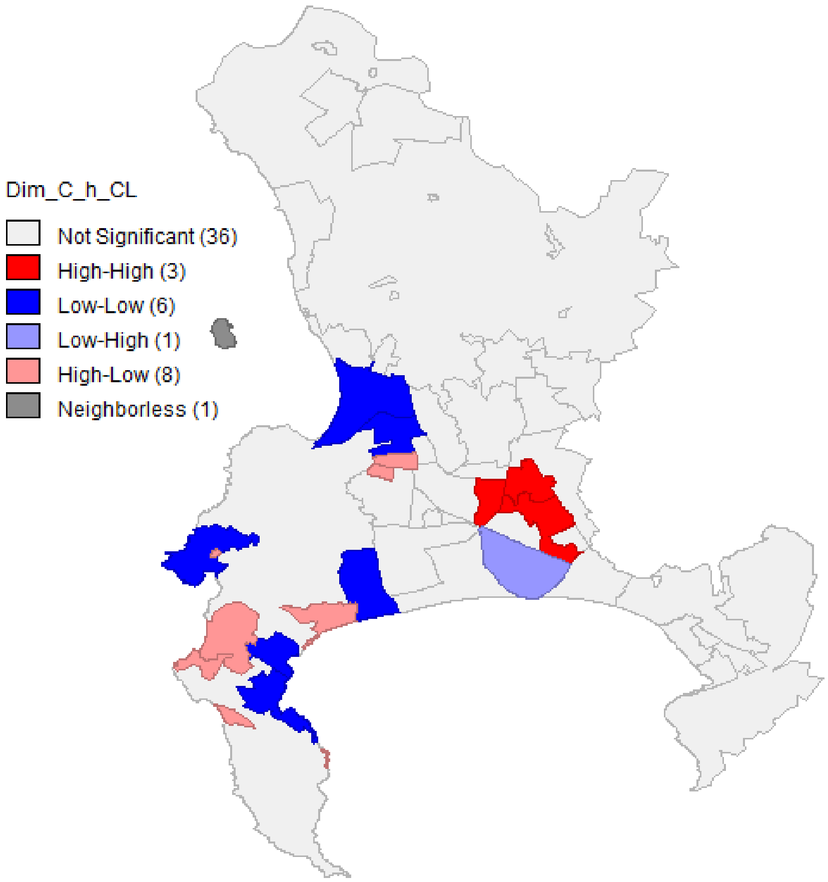

Figure 9: Local Moran's I cluster map of aggregated Clinics, Unemployed youth, Spars and Pick-n-Pays

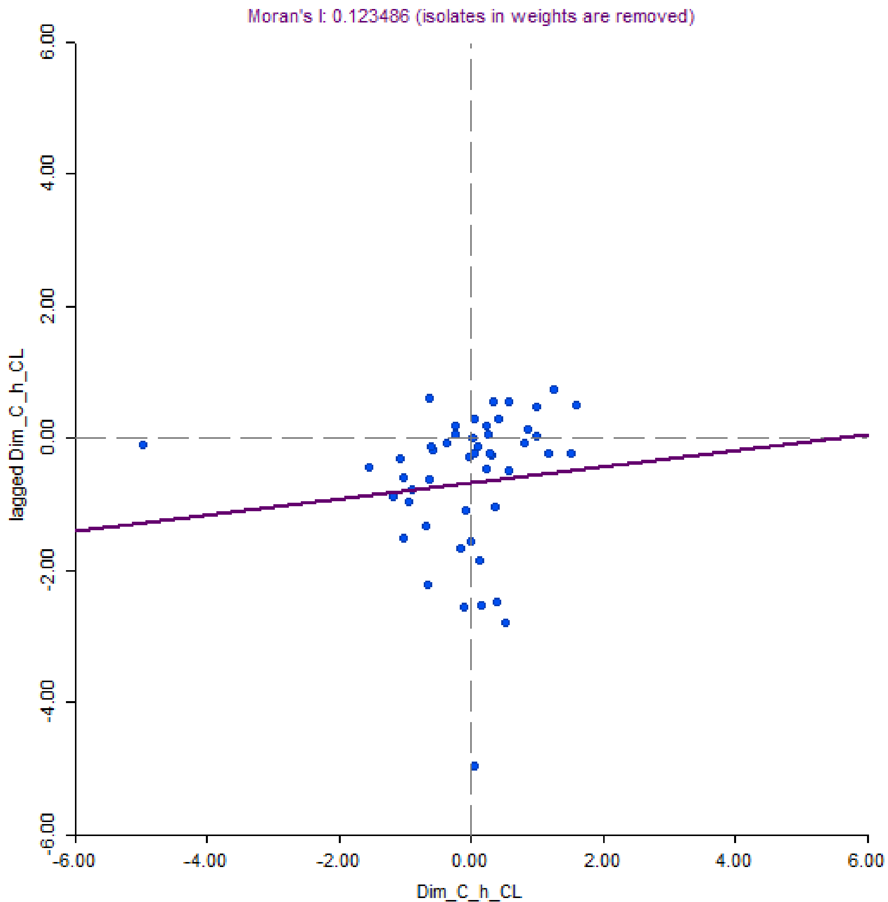

Figure 10: Local Moran's I plot of aggregated Clinics, Unemployed youth, Spars and Pick-n-Pays

The third Dimension of Community Health and Civic Life has a Moran's I scatter plot value and slope of 0.12 (see figure 6). This reading is the second-highest among the three dimensions. From the results of the regression analysis in Table 3, unemployment among the youth contributes positively towards the increased areas of the combined index score. The cluster map of the study area shows that 6 of the areas form part of the low-low areas.

4.5. Using the deprivation Index approach to explain the resultant Moran's I

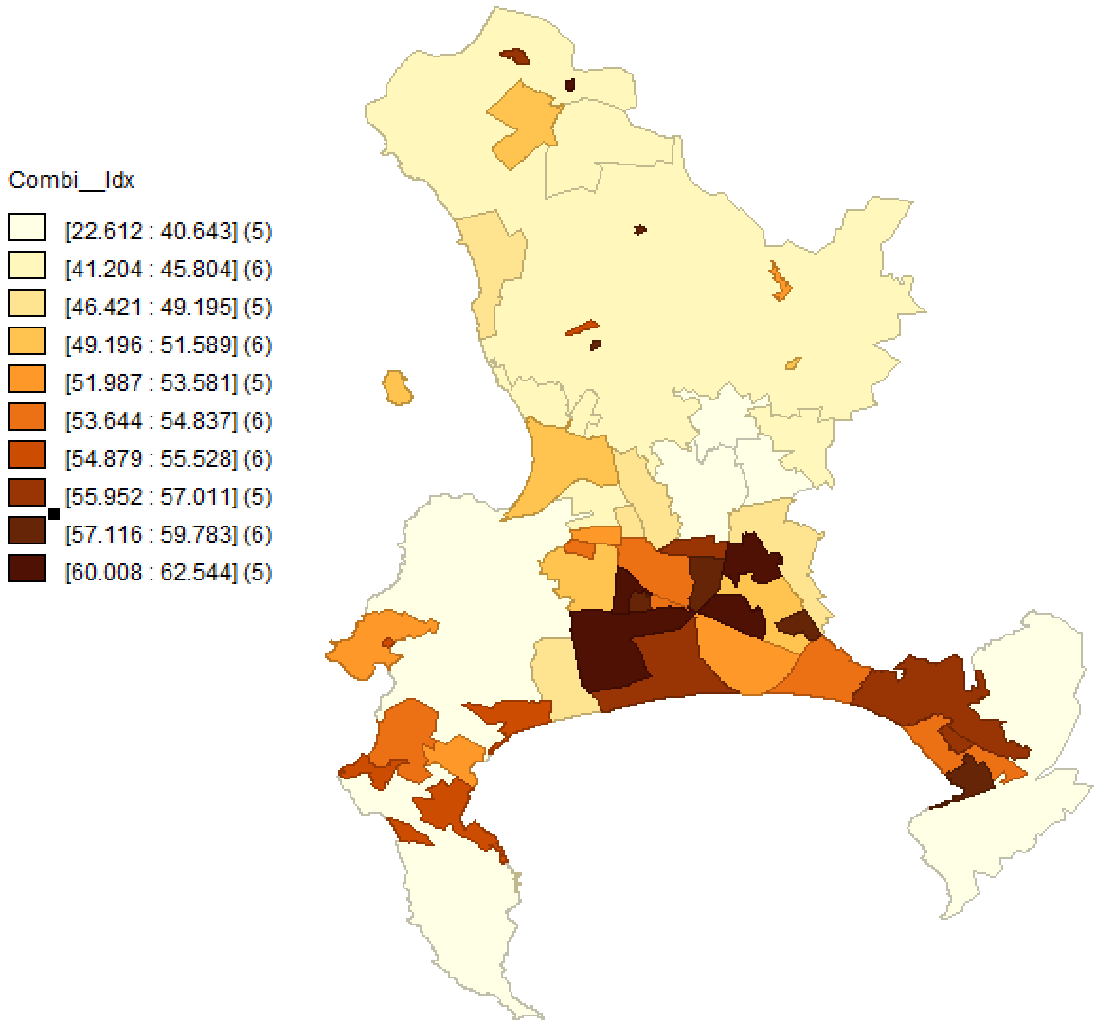

Figure 11: Composite Lack of Opportunity Index in the City of Cape Town

Table 1 reflects all the variables used for each of the three composite maps developed for the periods 2011. Using the opportunity index, a place will be regarded as deprived (or having a low opportunity) if it has high levels of the following indicators; poverty, unemployment, 16 to 19-year-olds dropout rate, unemployed youth, at the same time has low values for; median income, early childhood development, post-secondary education attainment, clinics access per 100 thousand population and retails per 10 thousand population. Figure 11 and Table 4, present a list of the socio-economically good and poorest main places, using a combined index of the three opportunity dimensions we developed. The table presents an aggregation of scores similar to what was developed and adopted in the Opportunity Methodology by Opportunity Nation, 2014a and Wilson and Greenlee, 2016 respectively.

From our deprivation index table, the highest scores per dimension are Gugulethu at 57.1% for the dimension on Jobs and the economy, Philippi and Delft respectively score 66.9% and 95.7 % dimensions education and civic life. In respect of the main places have better socio-economic conditions, the following areas have the lowest scores per dimension, Bellville 11.5% for the Jobs and Economy, Brackenfell 32.2 for the education dimension and City Centre 9.5 for the Civic Life dimension.

	Main Place Name	Total Population	Poverty HeadCount	Median Median HH Income	Unemployment	Preschools and Early Learning Centres	Dropout Rate	Education Attainment	Unemployed Youth	Clinics per 100K pop	Retials per 10K Pop	Dimension Jobs and Economy	Dim Education	Dimension Community Health and Civic Live	Combined Index
10 worst main places	Mfuleni	78,759	8.0	2,084	11,801	141	32%	0.0	1,107	2.0	0.0	49.4	50.7	87.6	62.5
	Pella	86,538	3.6	1,287	10,218	192	20%	0.0	1,188	1.0	0.0	29.3	65.7	90.1	61.7
	Philippi	70,920	5.3	1,703	9,243	200	26%	0.1	890	6.0	1.0	35.3	66.9	78.7	60.3
	Gugulethu	58,875	24.6	1,167	10,173	183	25%	0.1	819	5.0	1.0	57.1	45.1	78.0	60.1
	Blackheath	87,448	1.6	3,369	11,010	189	31%	0.1	1,239	1.0	0.0	56.0	32.9	91.1	60.0
	Delft	96,278	2.4	1,944	14,070	168	27%	0.0	1,626	4.0	1.0	44.3	39.4	95.7	59.8
	Nyanga	58,837	7.2	1,556	10,436	182	26%	0.1	785	3.0	0.0	38.3	59.1	80.0	59.2
	Gordons Bay	88,612	10.4	2,625	6,672	81	18%	0.0	876	1.0	1.0	49.6	44.0	82.3	58.6
	Eerste Rivier	83,904	7.0	2,588	8,450	185	20%	0.2	1,002	1.0	0.0	47.9	40.0	86.2	58.0
	Philadelphia	79,144	1.8	2,061	5,244	60	17%	0.1	600	0.0	0.0	27.0	67.0	78.5	57.5
	Cape Farms	52,590	0.9	2,574	3,849	186	83%	0.0	450	0.0	0.0	29.8	32.2	75.4	45.8
10 better off main places	Kraaifontein	64,784	5.4	1,751	3,510	288	30%	0.1	414	12.0	2.0	24.3	47.6	62.8	44.9
	Cape Metro	51,008	2.2	2,541	2,846	219	62%	0.3	270	0.0	0.0	29.2	33.4	71.6	44.7
	Blouberg	77,889	1.3	2,799	4,542	81	34%	0.2	414	1.0	6.0	34.8	32.3	66.4	44.5
	Castle Rock	63,766	7.2	1,190	3,306	81	10%	0.1	450	0.0	0.0	18.9	36.1	75.4	43.5
	Goodwood	59,770	1.9	1,549	2,859	218	32%	0.1	308	4.0	3.0	15.4	42.6	65.6	41.2
	City of CT NU	23,120	10.4	1,236	339	69	31%	0.0	35	0.0	0.0	18.0	37.3	66.7	40.6
	Durbanville	64,506	10.4	1,418	1,302	162	14%	0.2	165	2.0	7.0	22.4	39.4	59.2	40.3
	Brackenfell	60,967	2.5	1,529	2,556	276	25%	0.1	282	1.0	7.0	15.3	32.2	62.4	36.6
	Bellville	59,903	1.5	1,346	2,565	249	27%	0.2	270	11.0	7.0	11.5	33.0	54.4	33.0
	Cape Town	62,145	5.4	1,625	4,016	183	34%	0.1	486	43.0	27.0	23.7	34.6	9.5	22.6

Table 4: A comparative Index of the most deprived and least deprived Main places for the City of Cape Town Metro

Without going outside of the data used in the study to find the explanations of the observed trends, this section of the analysis explores possible underlying causes from the observed results using various exploratory spatial data analysis (ESDA) techniques. The section provides a summary of the extent of variation in the combination of indicators across the main places of the City of Cape Town.

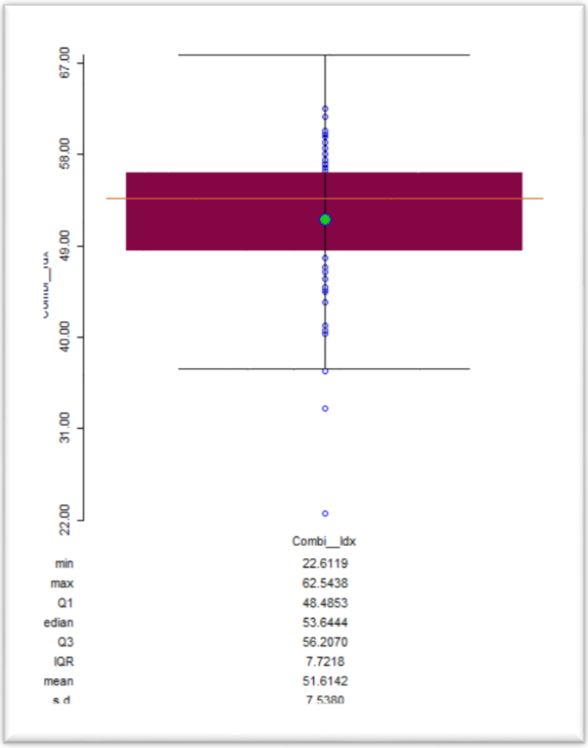

Figure 12: Box and Whisker Plot of the Combined Opportunity Index

The box and Whisker plot and Table 4 of the main places, shows that with the poorest opportunity is Mfuleni at 62.5% lack of opportunities. This is followed by Pella at 61.7% and Philippi, Gugulethu, Blackheath at 60% each, while Delft and Nyanga are just below 60% deprivation each. Gordon's Bay, Eerste Rivier, Philadelphia and Cape Farms have made the remainder of the 10 poorest, with each scoring above 45.8 per cent on the index. The main place with a better opportunities (minimum on the box and whisker plot) is the City of Cape Town at 22.6% or 77.4% (i.e. 100%-22.6%) access to opportunities compared to the rest of the main places in the metro. Bellville and Brackenfell follow at 33% and 36.6% each respectively.

Durbanville, Goodwood, Castle Rock, Blouberg, and Kraaifontein make up the remainder of the best top 10 main places, scoring above 44.9 per cent on the index.

The interquartile range for the combined index is 7.72 basis points. The City Centre of Cape Town, Bellville and Brackenfell are outliers on the box and whisker plot falling outside of the normal distribution range and far from the mean of 51.6 (for the main place of Atlantis) compared to the rest of the other main places. The data is not normally distributed around the mean due to the existence of these outliers, confirmed by a significant standard deviation of 7.5. This is made of an aggregated dimension score of 49.4% from Jobs and the Economy, 49.4 % from Education and 87.6% from Community Health.

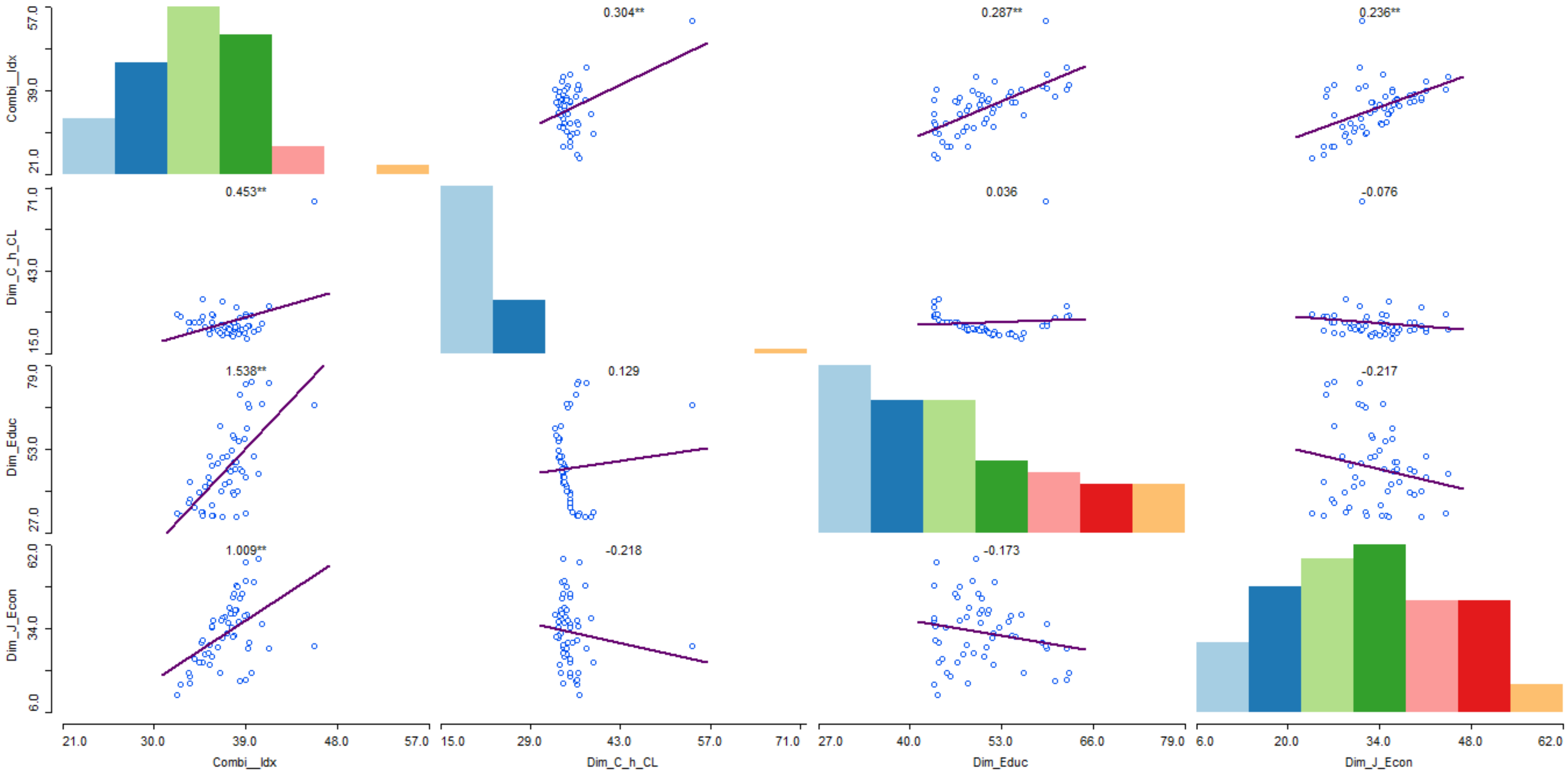

Figure 13: Scatter Plot Matrix of the three Dimensions influence on the Combined Index

The matrix scatters plot for the three dimensions used for building the opportunity index is reflected in figure 13. The following variables show both a positive and strong correlation between the dimensions and the opportunity index, confirming the discussion earlier on the influence of dimension to the final index. The highest influence of the dimensions is the Community Health and Civic Life at 30.4% at a 10 per cent significance level, followed by the education dimension at only 28.7%, while the third dimension on Jobs and the Economy shows and impact of only 23.6 %.

Table 5: Household Rental per Metro

Source: Stats SA Household expenditure Survey (2011)

2015			
Metro name	**Number of households renting**	**% of households renting**	**% of rental expenditure on total expenditure**
City of Cape Town Metropolitan	371,153.00	33	16.6
City of Johannesburg Metropolitan	643,737.00	40.8	12.3
City of Tshwane Metropolitan	333,142.00	35.7	10.1
Ekurhuleni Metropolitan	384,915.00	33.5	9.5
Nelson Mandela	63,140.00	23.3	13.7
SA Metros	**1,796,087.00**	**33.26**	**12.44**

2015			
Metro name	**Share of households renting**	**% deviation from mean households renting**	**% deviation from mean of rental expenditure**
City of Cape Town Metropolitan	21%	-0.26	4.16
City of Johannesburg Metropolitan	36%	7.54	-0.14
City of Tshwane Metropolitan	19%	2.44	-2.34
Ekurhuleni Metropolitan	21%	0.24	-2.94
Nelson Mandela	4%	-9.96	1.26
SA Metros	**100%**	**0%**	**0%**

One of the indicators used by Wilson and Greenlee (2016), (for which we could not access data at the main place level) is that of the percentage of households spending 30% or less on rental as a proxy for housing affordability. This they included as part of the dimension on jobs and the local economy. Given the limited time and feasibility, we were able to access higher-level data to allow comparison to other metros in the country on these statistics.

To this end, an analysis of the six main metros shows that they are home to 1, 7 million rental households, making up 33.26 % of the total number of households on aggregate. The metro with the highest percentage of rentals is the City of Johannesburg at 40%, followed by the City of Tshwane, with the lowest rentals in the Nelson Mandela Metro at 23%. The City of Cape Town, together with Ekurhuleni has the third-highest rental rate at 33% each. In terms of the share of rental across metros, due to its higher amount of rental households, the City of Johannesburg retains the highest share of 36%, while the City of Cape Town, the share is 21% of the analyst metros. Compare to the average rental of all households, the City of Cape Town and Nelson Mandela have both lower than average at each -0.26 and -9.96 percentage point deviation from the mean.

The City of Cape Town has a higher percentage deviation of expenditure compared to the average of 4.16 percentage points of the overall metros. Given the limited data and therefore intimate insights into the dynamics of the observed statistics, we cannot conclusively link affordability to spend on rental. For instance just because people are renting does not mean they can’t afford, i.e. rental does not equate to affordability. The property high cost in the city of Cape Town may result in the percentage spent on rental being, therefore resulting in the number of those renting being less than those in Johannesburg.

5. DISCUSION

We had initially set the null hypothesis for the study to prove that there is complete spatial randomness in the distribution of opportunities among main places across the City of Cape Town Metro. Given the score of 0.166 for the Moran's I, we cannot reject this hypothesis and conclude that, even though there is not complete clustering, the pattern is positive and statistically significant.

From our analysis and result, we can confidently and therefore, conclude that there is spatial autocorrelation, though positive, but not strong among main places in terms of the Opportunity index. This means the adversity of socio-economic conditions between poor and richer main-places may not be as wide, as indicated by the positive slope of the Moran's I. However, the results may be masking the variation that exists between households at a lower geographical level.

The profile of the most deprived main places is consistently for those households living further away from the City of Cape Town centre. These deprived main places have lower income levels, less or no form of education and high poverty headcounts. One of the aspects not reflected on, in the thesis is the impact of "urban systems experiencing a transition from a monocentric to a polycentric organization as they grow and expand" (Louf and Barthelemy, 2013. p 198702-1).

Therefore the positive but less significant observed Moran's I results could be a reflection of the impact that the emergence of new small towns into centres of economic opportunity is having in the overall creation of diversity away from the City of Cape Town as the only monocentric place of opportunities.

6. CONCLUSION

We, therefore, conclude that this paper has helped to identify trends of opportunity distribution among main places in the City of Cape Town. The observed trends are just but a tip of the "iceberg" as the full database report of progress for all the main places exists and can be further refined to track another service for which there has been consistently recording over this period. We have discovered through the local Moran's I that there is insignificant clustering of poor within poorer main places much as there is a clustering of the richer ones together.

Through the There is a wider variation in the spread of opportunity between main places across the City of Cape Town, evident from a significantly high standard deviation. Our results show that opportunity index remains highest in more urbanised main places (like the city centre), while that traditionally poorer main places, with mainly township establishments (such as Gugulethu and Nyanga), are not much different from one another, but differ markedly with those that are more urbanise, concerning the spatial clustering of high opportunity counties.

We recommend a need for an investigation into a shift in opportunities due to the emergence of multi centres of economic development in space due to the polycentric spatial development of economic hubs within the city. Further that there be improved data collection and sharing of timely comparable data time series at a more granular spatial level. For instance, due to the irregular geographic physical space layout of the City of Cape Town, there would be a need to even go spatially further to a more micro level to distil patterns of clustering that may not be apparent at the Main Place level.

The limitations on readily and more recently available data from main sources such as Stats SA, especially at more granular spatial level, needs to be worked on and improved upon, to allow for up to international par analysis. The need also applies to the privately-held data around banking and retail services, to allow for future work in contributing to a more advanced analysis on spatial mismatch.

Given the influence of emerging towns as a possible new economic centre, future research may need to be directed into the influence of such polycentric development on the geography of opportunities. A case in point is that in Gauteng where there is rapid development in Midrand, which could be having a pulling effect on both Johannesburg and Tshwane as the traditional centres of opportunities. Further research could be on the development of mobile applications that would facilitate the ease of use of databases generated from the Opportunity Index.

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