Mapping transit-oriented economic and social impacts of Gauteng's post-Apartheid spatiality: an analysis of precarious workers associated with the Casual Worker's Advice Office

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A research report submitted in fulfilment of the requirements for the degree of

Master of Science in GIS and Remote Sensing

in the

School of Geography, Archaeology and Environmental Studies

Faculty of Science

University of the Witwatersrand

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Declaration

I, Graeme Dor, student number 814809, declare this research report is my own work submitted in fulfilment of the requirements for Masters of Science in Geographic Information Systems (GIS) and Remote Sensing (coursework and research report), and has not been submitted before for any degree or examination. I further declare that I have committed no plagiarism, with ideas from people and scholarly work properly referenced in line with the reference guide of the Faculty of Science at the University of the Witwatersrand.

Signed:________________ Dated:__14/07/2022_____

Acknowledgements

I would like to thank the Casual Workers Advice Office (CWAO) and Ighsaan Schroeder for providing the tools to conduct this research report, in offering valuable insights into the complex milieu of precarious workers together with the data and platforms required to perform the analyses presented herein.

I would also like to thank each supervisor for providing support and guidance throughout the turbulent process brought about by unforeseen circumstances. To Dr Stefania Merlo who provided the support necessary to develop the framework of the paper. To Dr Iqra Atif who stepped in and offered valuable insight and advice to complete the research report. To Samkelisiwe Khanyile who provided continued support and guidance throughout the entire period.

Abstract

Precarious forms of employment have become a prominent feature of the labour process, with varying factors contributing to workers' level of precariousness, informed by inherent social, economic, and spatial dynamics. The influence of social and economic dynamics is well researched and understood, yet the influence of spatial dynamics is largely unexplored. The aim of this research was to explore the spatial attributes and factors that define precariousness, in the context of the post-Apartheid Gauteng region, through a case-based study of the Casual Workers Advice Office (CWAO). Founded in 2011, and based in Germiston, Gauteng, South Africa, the CWAO represents precarious workers, predominantly labour broker workers, providing labour rights-related advice and support to workers spread across the Gauteng City-Region (GCR). Formed out of the recognition that a growing section of the working class is being subjected to new and precarious forms of employment, the CWAO provided an ideal case scenario to assess the influence of Gauteng's unique post-Apartheid spatiality on precarious workers. To assess this, advanced geostatistical and GIS-based analytical techniques were employed using an exploratory spatial data analysis (ESDA) approach. This necessitated analysis of three datasets composing data from the CWAO, in worker membership details and an accompanying survey, and from the Gauteng City-Region Observatory's (GCRO) Quality of Life (QoL) 2017/2018 survey. These datasets enabled the identification of spatial patterns, the creation of a spatial regression model and a job accessibility index, which demonstrated the presence and complexity of spatial dynamics associated with the distribution of precarious workers across the GCR. First, the location of CWAO associated workers' residence and associated workplace was mapped, with findings showing no significant difference in the distance that these workers reside from work compared to respondents from the GCRO QoL survey A geographically weighted regression (GWR) model was then applied given its ability to generate individual regression coefficients as a continuous function across space, providing a valuable measure of spatial heterogeneity. A percentage change increase in model performance of 20% was achieved when compared to a non-spatial regression model, highlighting the effect of spatial heterogeneity across the study area and the importance of adopting spatially weighted variables in predicting employment status, the selected measure of precariousness. In addition, the creation of a job accessibility index, derived from location data in residence and workplace coordinates of precarious workers associated with the CWAO, alongside a net wage after commute (NWAC) layer developed from the GCRO QoL survey highlighted spatially dynamic job accessibility scores across the GCR. Increased job accessibility for areas located centrally within the GCR, corresponding to the economic hub, was contrasted by a less distinct spatial pattern in a NWAC layer, a component of the accessibility index. Nevertheless, the product of the accessibility index displayed a statistically significant association, at a 5% level of significance, with employment status. Overall, the results outlined the complexity of Gauteng's unique spatiality and the necessity for developing multi-dimensional analyses to better understand the underlying spatial dynamics associated with precarious workers. Defining the spatial conditions that influence workers' level of precariousness provides the opportunity to implement practical solutions in advice, advocacy work, and organizing strategies to ensure workers' needs are addressed. The analyses performed in this study have laid the foundation for facilitating future research on the spatial dynamics of precarious workers.

Key words: Precarious workers; Casual Workers Advice Office (CWAO); Gauteng; GIS; exploratory spatial data analysis (ESDA); Geographically Weighted Regression (GWR); Job accessibility index.

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List of Acronyms

AIC	Akaike's Information Criterion
BRT	Bus Rapid Transit
CI	Confidence Interval
COVID-19	Corona Virus Disease 2019
CWAO	Casual Workers Advice Office
ESDA	Exploratory Spatial Data Analysis
GCR	Gauteng City-Region
GCRO	Gauteng City-Region Observatory
QoL	Quality of Life
GIS	Geographic Information Systems
GLR	Generalized Linear Regression
GMPI	Gauteng Multi-dimensional Poverty Index
GWR	Geographically Weighted Regression
IDW	Inverse Distance Weighted
NIDS	National Income Dynamic Study
PoR	Place of Residence
PoW	Place of Work
PPE	Personal Protective Equipment
RDP	Reconstruction and Development Programme
SANLC	South African National Land Cover

Chapter 1: Introduction

1.1. Background

South African cities have been shaped by segregation policies such as the Group Areas Act (Act No.41 of 1950) enacted under the apartheid government (Christopher, 2001; Pieterse, 2009; Kerr, 2015). A characteristic trait of Apartheid spatial planning was the peripheralization of race-discriminated groups, wherein Johannesburg and the broader Gauteng City-Region (GCR), this was predominantly black people (Fair et al., 1957; Kerr, 2015). As Webster (1985) explains, a predominant feature of Apartheid was the ever-increasing reliance on the exploitation of cheap black labour, which in Johannesburg was in part tied to the discovery of gold, seeing the overnight development of labour camps situated close to mining areas to limit transportation (Khanyile, 2016). The Group Areas Act was repealed in 1991 (Mabin, 1992), yet whilst the act was abolished, it has manifested itself into societal and spatial structures, creating an inseparable class-race dynamic that has persisted with worsening urban sprawl and intra-class divisions (Pieterse, 2009).

An important feature of the spatial patterns of the GCR is its perpetuating economic and social impact on much of the working class, i.e., low-income black workers, specifically through the challenges posed by transport and resultant measures of accessibility. The worsening intra-class divisions that Pieterse (2009) alludes to define the precarious nature that much of the working class is being subjected to.

1.2. Research Problem Statement

Prior studies focusing on the relationship between transport and socio-economic groups in a South African context are varied, yet are commonly racial (e.g., Culwick et al., 2015) or class-centric, or in case studies focused on both factors (e.g., Kerr, 2015; Ngarachu et al., 2015) analyse relatively broad socio-economic indictors. Related studies beyond South Africa are also varied, yet lack racial and class components that are comparable and translatable to South Africa's unique geographic and historic context. This study develops the research on the relationship between transport and socio-economic classes by addressing a particular case study of precarious workers[1] across Gauteng associated with the Casual Workers Advice Office (CWAO), which will centre on intra-class comparisons associated with increasingly pressing issues facing the working class.

Post-Apartheid cities characterised by persisting and worsening urban sprawl and intra-class divisions have been succinctly described as neo-Apartheid spatialities (Pieterse, 2009). The term 'spatiality' encapsulates the nature of Gauteng's post-Apartheid make-up and is emphasized by Thrift's (2003) definition of space and spatiality, in which he defines spatiality as an encompassing of an eclectic subject that includes aspects of patterning of social and economic life and natural and built environments.

[1] A "precarious worker" describes an individual in non-standard or temporary employment, often characterised by lower wages, unstable employment and unsafe working conditions.

Aside from inherent spatial patterns, the persistence of socio-economic disparities can also be attributed to the inadequacy of post-Apartheid legislation resulting from neoliberal policy (Kerr, 2015). As Maharaj (2020) noted, the eradication of race-based legislation has not resulted in any significant spatial reforms, and this has been demonstrated in spatial statistical analyses (Wray et al., 2014, Kerr 2015). Pieterse (2009) illustrates how even well-aimed initiatives such as the Reconstruction and Development Programme (RDP) have had unforeseen consequences, reinforcing spatial divides. However, of most prominence may be the influence of labour legislation, which has too failed to eradicate persisting socio-economic disparities, particularly the exploitation of cheap black labour (Theron, 2014; Webster and Englert, 2020). Instead, the labour market has seen a reshaping and enforcement of new and precarious forms of employment (Webster and van Holdt, 2005). Temporary employment service workers, better known as labour broker workers, are one such example and are characterised by the precarious nature of their employment (Webster and van Holdt, 2008). Labour brokering is a form of temporary or casual employment in which the labour broker is deemed the 'fictional' employer, essentially an agenda pushed by corporates to bypass labour laws meant to protect workers' rights (Harvey, 2011).

The CWAO, based in Germiston, Johannesburg, South Africa, represents precarious workers, predominantly labour broker workers, providing labour rights-related advice and support to workers spread across the GCR. The organization was founded in 2011, formed out of the recognition that a growing section of the working class is being subjected to new and precarious forms of employment, in which the traditional labour movement appears unwilling or incapable of organizing. The precarious nature of work is, however, highly faceted and influenced by a multitude of variables. Beyond those already outlined are spatial measures of job distribution and job accessibility, which Maharaj (2020) highlighted as remaining much the same with specific reference to the exaggerated distance between low-income households and potential places of work. The CWAO, operating within Gauteng's unique spatiality, thus formed an ideal case study to better comprehend the influence of socio-economic factors, specifically transit-oriented, on precarious workers, within the context of the particularly pertinent COVID-19 pandemic. Of specific importance is the element of transport and how the legacies of Apartheid spatial planning continue to influence the distribution, movement, and accessibility to work opportunities for precarious workers.

This research project, incorporating spatial statistical analytical methods in addressing intersectional dynamics of Gauteng's unique spatiality on precarious workers, provides a novel approach to research focused on precarious workers and the associated precarious forms of employment. Precarious forms of employment, although not new, have become increasingly prevalent and produce mass labour pools of precarious workers (Webster and Englert, 2020). The stratification of precarious workers, by form of employment, is not documented from a spatial-analytical perspective, neither locally nor globally. Gauteng's unique post-Apartheid spatiality is believed to inform on external factors that contribute to individuals' employment type, as a measure of precariousness. Access to information provided by the CWAO and collaboration on developing a membership survey provided an opportunity to address this critical gap in research about precarious workers. The novelty of this research and case-specific study necessitated an exploratory spatial data analysis (ESDA) approach, for which the capabilities of Geographic Information Systems (GIS) provided the basis for advanced spatial statistical analysis.

1.3. Aim and Objectives

1.3.1. *Aim*

The overarching aim of this project was to assess the economic and social impact of transit-oriented factors on precarious workers in post-Apartheid Gauteng using GIS-based techniques.

1.3.2. *Objectives*

The specific objectives of this research were:

- To map the spatial distribution, i.e., place of work in relation to place of residence, of precarious workers associated with the CWAO;
- To carry out a multi-focal GIS-based survey analysis of the factors, work- transport- and COVID-19-related, influencing vulnerability of precarious workers;
- To create a job accessibility index using membership and survey details of precarious workers associated with the CWAO;
- To assess the relationship of spatial and non-spatial factors to better understand what constitutes vulnerability of precarious workers.

1.4. Research Questions

- Is there a spatial pattern in the relationship of precarious workers' place of residence to their place of work across the GCR?
- What influences the vulnerability of precarious workers?
- What is the relationship between the spatiality of Gauteng and the factors that influence the vulnerability of precarious workers?
- How can significant spatial and non-spatial factors inform what constitutes vulnerability of precarious workers?

1.5. Research Rationale

The economic and social impact of transit-oriented factors is a direct concern for workers and poses a fundamental feature in informing, primarily, advocacy work and organizing strategies, which include collective bargaining and the scheduling of meetings to discuss such issues (I Schroeder 2020, personal communication, 20 May). The CWAO, along with the workers, provided an ideal study to assess the case-specific distribution of precarious workers across the GCR, and the influence of transit-oriented factors on precarious workers within the COVID-19 pandemic milieu. In doing so, the study will provide new perspectives on the increasing and varying challenges faced across the spectrum of the working class. This will create the foundation for further hypothesis testing, an important outcome of ESDA, and comparative studies of broader socio-economic classes to better understand precarious work dynamics.

Chapter 2: Literature Review

2.1. Post-Apartheid Gauteng: Historic and Geographic Significance

2.1.1. Historic significance

The legacy of 'apartheid spatial planning' is well documented, defined by the reorganization of urban space through increasingly discriminatory urban practices and policies that have distinctly differentiated South African cities from other colonial and non-colonial cities (Maylam, 1990; van der Merwe, 1993; Berrisford, 2011).South African cities, in particular Johannesburg, have been shaped by the segregation policies, specifically through the Group Areas Act (Act No.41 of 1950), enacted under the apartheid government (Christopher, 2001; Pieterse, 2009; Kerr, 2015). The racial segregation policies and forced removals during Apartheid has meant that a large proportion of, specifically, black South Africans were and still are often far from economic centres, on the periphery of the main metropolitan areas and the Gauteng City-Region (GCR) more broadly (Kerr, 2015; Ngarachu et al., 2015). Maharaj (2020) argues that the eradication of race-based discriminatory legislation has not resulted in any significant spatial reforms, saying that neoliberal policies have actually reinforced racial and class segregation. These remarkable continuities from the Apartheid era in the persistence and, sometimes, the exacerbation of socio-spatial inequalities (Bremner, 2000; Maharaj, 2020), has been described by Pieterse (2009) as a neo-Apartheid spatiality, simply a morphed post-Apartheid geography with worsening urban sprawl and intra-class divisions.

Emphasizing Pieterse’s (2009) argument of a neo-Apartheid spatiality, Maharaj (2020) describes how South Africa’s historical spatial measures such as job distribution and job accessibility measures remain much the same, indicating a perpetuating and expanding rather than changing urban geography. Maharaj (2020) further explains how the commonalities of racial and class segregation have perpetuated into post-Apartheid planning. Even the implementation of well-aimed initiatives such as the public housing programme, a constituent of the RDP (see Pieterse, 2009), has been shown to have unforeseen negative consequences, exacerbating spatial inequality.

An important feature of the job accessibility measures that Maharaj (2020) explains as remaining much the same is the exaggerated distance between low-income households and potential places of work, i.e., job accessibility for the majority of workers comprising the working class. This perpetuating feature is a concept known as a spatial mismatch, and is the product of the racial segregation policies of the Group Areas Act, and highlights the intractable link between class and race, particularly regarding the working class, in the South African context (Zenou, 2009; Kerr, 2015; Fransen et al., 2018). As Maharaj (2020) alludes, the majority of workers at the bottom of the socio-economic ladder has continued to comprise of black people, above 90% according to the National Income Dynamic Study (NIDS) results from 2015.

2.1.2. Geographic significance

Since the conceptualisation of ‘accessibility’ in the 1950s, transportation, and accessibility-related research have contributed to the understanding of transport dynamics and the associated socio-economic and spatial constraints of movement in urban spaces (Hansen, 1959). Similarly, measures for addressing job accessibility have increased in quantity and complexity, thus enabling comprehensive interpretations of spatial and social interactions related to urban transport and land-use systems (Cheng and Bertolini, 2013).

Accessibility, more generally, can be described as “the potential of opportunities for interaction” (Hansen, 1959, 73). It is a measurement that characterises the spatial relationship between distributing activities or points in space. Understanding the spatial relationship necessitates analysis of travel impedance, which is primarily influenced by transport and land-use characteristics, both spatial and non-spatial (Liu and Zhu, 2004; Cheng and Bertolini, 2013; Miller, 2018). Liu and Zhu (2014) highlight the importance of travel cost, time, and distance in determining accessibility. However, these factors also necessitate its form and the scale for which the outputs of accessibility are produced.

GIS and spatial analyses for the study of accessibility as a function of spatial and transport planning, is comprehensively covered in the literature regarding mainly developed cities (Makri and Folkesson, 1999; Geurs and van Eck, 2001; Liu and Zhu, 2004), where these studies have helped establish general accessibility measures, such as job accessibility, which have become widely used. However, generalized accessibility measures and studies have not proven applicable in many developing contexts, because of fewer studies conducted and differing social, economic, and spatial dynamics. Gauteng’s unique spatiality through inherited socio-economic inequities defines the inapplicability of standardized measures that do not account for spatially varying intricacies.

Maharaj (2020) describes accessibility in contemporary Gauteng to be very similar to the Apartheid period spatial planning, characterised by long travelling distances to places of work for black workers and fueled in part by the need for large scale, low-cost housing and in part by the ideological veneer of separate ‘group areas.’ However, contrary to popular belief, there is no significant difference in the average straight-line distance that workers reside from their place of work for different races in the GCR. Culwick et al. (2015) demonstrated this using the Gauteng City-Region Observatory’s (GCRO) Quality of Life (QoL) III 2013 Survey, the findings showing that the average Euclidean (straight-line) distance to work was the same for African and white populations, approximately 14 kilometers (km). Yet, it was shown that a more significant percentage of the white population travel shorter distances to work (<25km), but so too, a more significant share of the white population were shown to travel further distances (>25km), explaining the equalizing of the averages. Motivation for why white respondents travel shorter distances is because they reside closer to the core of the province, which is where the bulk of economic opportunities is located (Figure 2.1). Conversely, access to private vehicles and gated housing estates were considered significant explanatory factors for motivating the greater share of white respondents shown to travel further distances. Simpson et al. (2012) show that most trips made to work by the white population are made by private car, up to 85% for travel between the City of Tshwane and the City of Johannesburg. And although the inter-municipality journey is relatively low, this may be another contributing factor. These dynamics translated into clear spatial patterning, highlighting the condensed spatial distribution of white respondents compared to black respondents (Figure 2.1).

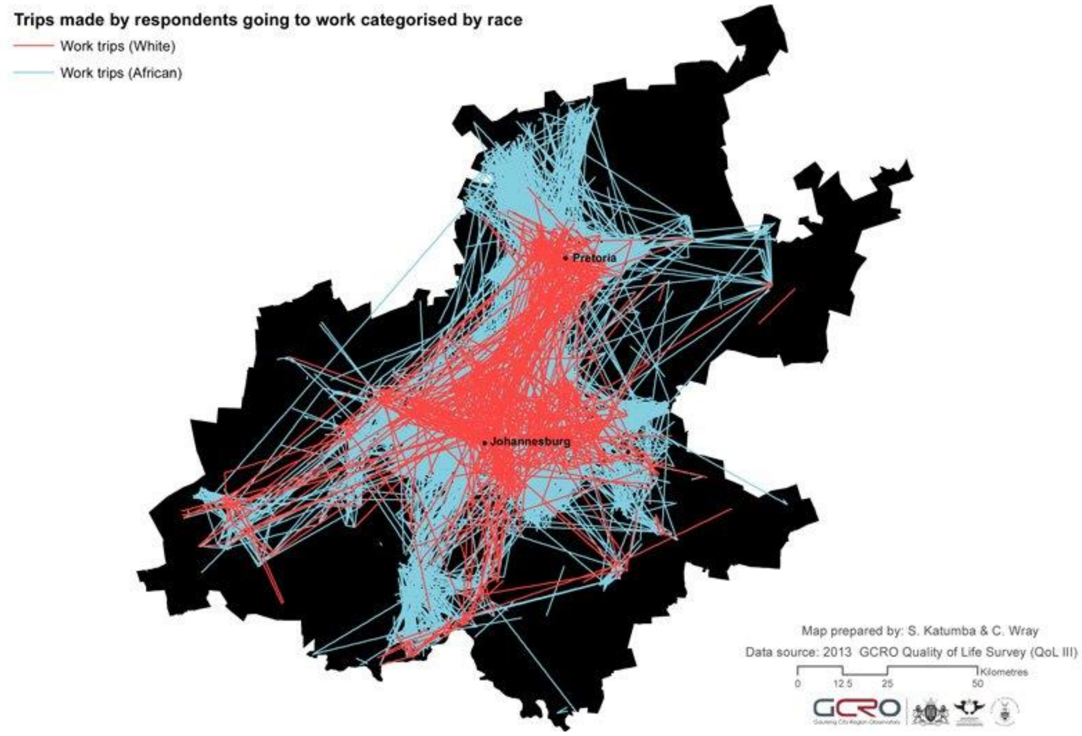


Figure 2.1 – Trips made by respondents going to work categorised by race, created using the GCRO QoL III survey (Culwick et al., 2015)

Culwick et al. (2015) demonstrate that, given the similarity in average travel distances between populations, there was still a significant racial divide in the average duration of travel and travel times. The travel duration to work for African respondents was 56 minutes, 14 minutes more than the white population average, whilst African respondents were also shown to start their journeys to work earlier, 25% starting their journey before 6 am compared to 5% for white respondents. This has also been covered by Kerr (2015), who draws analysis from the 2003 and 2013 National Travel Surveys. However, Kerr's article *Tax(i)ing the poor? Commuting costs in South African Cities* plays on modes of travel and the disparities in the proportion of household income spent on commuting for different socio-economic classes. Kerr's (2005) research suggests that despite the inextricable link between class and race in the South African context, it is precisely class disparities where real contrasts emerge.

2.2. Workers' Transport and Associated Work Conditions

2.2.1. Characterising workers' working conditions

Low-income earning individuals bear the greatest burdens of society's social and spatial structure, thus the coming into prominence of the term 'precariousness.' Standing (2011), in his book - *The Precariat*, describes how the precarious nature of the lowest economic tier of society, specifically workers in vulnerable forms of employment and the unemployed, constitute what he considers a new social class, i.e., the 'precariat'. His argument, although focused on the classification of a new class, a discussion beyond the scope of this study, is founded on the impact that globalization and the neoliberal structures governing society have on the working class. It also highlights the emergence of intra-class divisions, alluded to by Pieterse's (2009) description of a neo-Apartheid spatiality. Interestingly, both accounts describe the transitioning and even reshaping of society as not only a continuation of the past but a creation of new and more severe forms of inequality.

The state of the working class and the conditions they are subject to necessitates an understanding and differentiation of the phrases and terms 'precarious forms of employment', the 'precarious nature of work', 'precariousness', and 'vulnerability'. Given their similar connotations yet varied uses in the literature on the subject, it is best to define what each means in this research. The implications of the global pandemic (COVID-19) on the working class in South Africa is important in this research, and is thus used for illustration.

First, precarious forms of employment refer specifically to work classified more broadly as 'casual employment', within which 'labour broker workers' are categorised. The precarious nature of work can be considered less specific than the form of employment because it refers to the work and work relationships that make it precarious. The facilitation of a 5-stage lockdown system to control the spread of the COVID-19 pandemic in South Africa provides a perfect example of both these concepts, where many workers without formal employment, who were not working in essential services, were the first to lose employment (Arndt et al., 2020). The consequential effects of increasing unemployment resulting from successive 'lockdowns' has been exposed in the looting events which affected numerous parts of Gauteng (Tatsvarei, 2021). The impact of the virus is highlighting the precarious state of the working class at varying levels of precariousness and vulnerability.

Precariousness thus refers to the state of the worker and is a spectrum inclusive of specifically low-income workers across all forms of employment, including permanent work which is becoming increasingly more susceptible to unethical practice. Vulnerability can refer to external conditions facing workers that ultimately affects their quality of livelihood and influence the precarious state of the worker. Essential service workers were the first call of duty, placing themselves at the highest risk of contracting the virus through continual exposure and the inability to 'social distance', particularly in transport and at the workplace, essentially contributing to their vulnerability as workers on the frontline. It is South Africa's low-income earning individuals that comprise the majority of workers in the industries providing essential service and the main industries permitted to reopen under Stage 4 of the initial phased-lockdown approach, particularly manufacturing and mining. The situation in South Africa is especially pertinent given that using public forms of transport form an essential mode of travel for the vast majority of low-income earning individuals. Aropet (2017) and Jennings (2015) demonstrate that the Minibus taxi accounts for the bulk mode of commuting for lower-income individuals, and has the highest occupant density for its dimensions.

2.2.2. **Transport and its influence in worker-conditions**

“*Transport forms an essential part of workers’ lives, and thus constitutes a critical component in understanding workers’ conditions to better support and provide advice to them*” (I Schroeder 2019, pers. comm., 13 May).

In conversation with Ighsaan Schroeder (2019, pers. comm., 13 May), the Founder of the CWAO, there were several insights into the role transport plays in workers’ lives. First, he highlighted that a shorter travelling distance between home and work is advantageous to the worker, as shorter distances are also related to a reduced risk of endangering their employment, lower travelling costs, and the consumption of time that could be better spent (I Schroeder 2019, pers. comm., 13 May). This is, however, not a possibility for most workers, based on the spatiality of the GCR. A compounding problem posed by spatial mismatch is the high unemployment levels, which reduce workers’ job location choice as many workers are desperate for any form of employment and take jobs that require them to travel long distances between home and the workplace. Kerr (2015) demonstrates how this has placed a significant cost burden on already poor and vulnerable workers. Using an econometric approach and statistical analysis of national transport surveys, he finds that as much as 24% of an individual’s wage is spent on transport, affecting in particular individuals in the lower deciles of the income bracket. Conversely, a mere 7% of wages were reported to be spent on transportation for the upper deciles. Schroeder (2019, pers. comm., 13 May) describes how it is not uncommon for workers to travel daily from Pretoria to Isando (near OR Tambo International Airport, Ekurhuleni municipality) or from Sebokeng (near Orange Farm, Emfuleni municipality) to Wadeville (Germiston, Ekurhuleni municipality) and back, with travel costs constituting as much as 30% of the worker’s weekly wage.

Further, working days have increasingly extended to 2 or 3 shifts per day and to Saturdays, Sundays, and public holidays, a common theme experienced by labour brokers and casual workers (Theron, 2014; Englert and Webster, 2020). The reduced availability of transport at non-peak hours and on non-peak days obliges workers to spend more time travelling or to make costlier alternative travel arrangements, such as collectively hiring mini buses. As Schroeder (2019, pers. comm., 13 May) explains, a worker travelling to work at 1 pm to start work at 2 pm is likely to find transport less readily available than at 6 in the morning, whilst the same applies when that worker finishes work at 10 in the evening, compared to finishing at 5 pm. This has not been explicitly covered in the literature about transport accessibility and availability.

Travelling, however, presents more than problems of accessibility, availability, and cost when working unsociable hours. Schroeder (2019, pers. comm., 13 May) states there is a severe disruption to social lives because of working at night, on a Saturday or Sunday, times when most family, social, and community activities take place, and is compounded by the longer time spent travelling to work at such times and on such days. Thus, workers’ ability to participate in social and cultural life is impinged upon and becomes a source of stress, affecting both younger and older workers in different ways. This applies particularly to women workers, who exclaim that they are expected to continue performing their domestic responsibilities of child care, cleaning, cooking and caring for the aged and infirm, concerns Schroeder (2019, pers. comm., 13 May) says are brought up in general meetings held at the CWAO.

Travelling at unsociable hours, more especially when performing night shifts, which women labour broker workers do routinely, also exposes them to the dangers of physical and sexual violence. Factors of safety and security associated with travel at unsociable hours, such as pick-up and drop-off points, and the location and accessibility to and from these points, places women labour broker workers in precarious situations. The GCRO’s QoL V (2017/2018) survey, including previous iterations of the survey, address questions specifically aimed at the satisfaction of respondents to public transport availability, the proximity to the nearest access point to public transport from the place of residence, and respondents’ perceptions of safety within their neighbourhood.

A further consideration is the mode of transport. South Africa’s transport system comprises various modes, operating within rail and road network systems. In Gauteng, the traditional passenger rail and Gautrain systems, and the Metro and Bus Rapid Transit (BRT) systems, are very prominent (Aropet, 2017). Yet the Minibus taxi system accounts for the bulk mode of commuting, particularly for lower-income earning individuals (Jennings, 2015; Aropet, 2017). Schroeder (2019, pers. comm., 13 May) highlighted that given unreliable or difficult to access transport increases the prospect of dismissal for casual workers who already enjoy far less job security than permanent workers. Further, frequent late coming or absence from work because of transport difficulties can lead to workers losing their employment. He says it is a common practice for workers in ‘labour pools’ to be summoned to work at short notice, either the evening before or the same day the worker is expected to render service, and the worker’s ability to meet this expectation is central to retaining employment. Unreliable or difficult to access transport thus constitutes a serious impediment.

If these concerns weren’t inhibiting enough, the COVID-19 outbreak has complicated things even more. Being a respiratory virus, person-to-person transmission through the form of direct contact or respiratory droplets via coughing and sneezing have been isolated as the most likely forms of transmission (Rothan and Byrareddy, 2020; Guo et al., 2020). However, other forms of transmission such as aerosol and contact transmission have also been probable causes of spreading the infection (van Doremalen et al., 2020). These forms of transmission relate to public transport, with transmission becoming increasingly likely given the close proximity people are placed to one another. Zhen et al. (2020) describe the array of factors that could contribute to the spread of the disease in public modes of transport, of which include overcrowding in enclosed spaces, high occupant density, inadequate ventilation and recirculation of contaminated air, and prolonged and repeated exposure to infected people.

In South African cities, public forms of transport form a basic mode of travel for the vast majority of low-income earning individuals. Aropet (2017) and Jennings (2015) demonstrate that the Minibus taxi accounts for the bulk mode of commuting for lower-income individuals and has the highest occupant density for its dimensions. On the 4th of May 2020 the Department of Transport issued revised public transport regulations under the Disaster Management Act, 2002 (Act No.57 of 2002), after the transition from Stage 5 to Stage 4 Lockdown. Under Section 9(3) regarding the loading capacity of public transport vehicles, it was issued that Mini and Midibus Taxis be permitted to carry up to 70% of their maximum licensed carrying capacity, an increase from a 50% limit during Stage 5. This, after the country had been experiencing a steady yet exponential rise in the number of confirmed COVID-19 cases.

Re-iterating Schroeder's (2019, pers. comm., 13 May) perspective, it is clear as to the significance that transport and the associated transit-oriented factors play regarding workers' conditions, and more generally, their quality of life. A further concern are the limiting factors, such as the availability of transport, its duration and even its cost, that influence the ability of labour broker workers to organize, more especially when working unsociable hours. Workers working two- or three-shift systems have difficulty uniting around common problems and demands because they have insufficient time to meet between changing shifts. Workers' inability to organize renders them more susceptible to employer abuse and to gross exploitation and perpetuates their precarious status. It is estimated that labour broker workers earn between 40 and 50% less than permanent workers doing the same or similar work and constitute a significant proportion of the 6.2 million workers nationally earning less than R20 per hour – before the new national minimum wage became effective from January 2019 (van Wyk, 2019). As Schroeder (2019, pers. comm., 13 May) highlights, longer distances to work and higher transport costs directly affect levels of disposable income and quality of life, with less time and money being afforded for family and social use. This goes back to the nature of Gauteng's unique spatiality and its influence, as described by Maharaj (2020), on important accessibility measures.

Concepts of mobility, let alone accessibility, have been neglected by many fields of research. An influential paper in the academic sphere by Sheller and Urry (2006) highlights this and demonstrates how mobility, in respect specifically to how people move and commute, is influenced by many social, geographic, and political factors, and should be carefully considered. These factors necessitate when people move (e.g., COIVD-19 restrictions), how people move (e.g., mode of transport), and if people move (e.g., virtual work). Gaitens et al., (2021) conducted a narrative review exploring the disproportionate effect of COVID-19 on essential workers, highlighting work-, health- and transport-related concerns. The paper outlines the transitioning into virtual work environments by many sectors, yet, precarious forms of work within sectors providing essential services, such as food and agriculture and manufacturing, have to a large extent retained the necessity for in-person work (Gaitens et al., 2021). This, in the global pandemic, has necessitated the continued movement and interaction within essential work environments posing additional elements of vulnerability.

2.3. **Spatial Data Analyses and Measures**

2.3.1. **Urban spatial data analysis and modelling**

The importance of understanding spatial dynamics has become increasingly recognised through influential authors in GIS-related research (e.g., Goodchild et al., 2000; Anselin & Cho, 2002; Sheller & Urry, 2006) describing the innate relationship between mobility, space and a multitude of social, econometric, and political factors. Anselin, Sridharan, and Gholston (2007) distinguish three features of spatial statistical analysis that can be useful in enhancing the understanding of empirical studies in the social and geographical sciences. The first, ‘data integration’, describes the collection and aggregation of data at varying spatial and temporal scales, and is a fundamental feature of GIS. Second, exploratory spatial data analysis (ESDA), founded on broader exploratory data analytical approaches, accounts for spatial autocorrelation and spatial heterogeneity within datasets. This translates to developing methods and techniques to describe and visualise distributions within spatial data, identify patterns, outliers and spatial relationships that can better define the effects of spatial autocorrelation and heterogeneity inherent in spatial data. Examples of ESDA include outlier analyses, hot spot analyses, global and local indicators of spatial autocorrelation, and exploratory regression. Third, confirmatory spatial data analysis, describes the advanced techniques developed to model mechanisms underlying the distributions and patterns within spatial data. An example of techniques performed in confirmatory spatial data analysis are regression analyses. Regression analyses, specifically spatial regression models, have become an increasingly popularised technique for addressing interactions and relationships between observations. Ward and Gleditsch (2018), in their book “Spatial Regression Models”, demonstrate the significance of different types of regression and spatial regression models in measuring the dependence between observations or variables and the effects of spatial autocorrelation and heterogeneity. Types of regression modelling depend on the variable of interest, termed the response variable, in relation to the predictor variable (univariate regression) or variables (multivariate regression), and are broadly categorised into linear and non-linear regression types. Non-linear forms of regression include categorical regression, where the response variable is categorically defined, and ordinal regression, where the response variable is in an ordered categorical form (Ward and Gleditsh, 2018). Spatial regression models have become an increasingly popularised technique because they account for spatial effects, in spatial dependence and spatial heterogeneity, which traditional multivariate regression techniques do not.

Chi and Zhu (2019) provide a comprehensive breakdown of spatial regression models, and describe the varying complexity and application of different models. Typically, models are categorised into those dealing predominantly with spatial dependence, such as the standard linear model and the spatial lag model, and those dealing predominantly with spatial heterogeneity, such as the spatial regime model and the Geographically Weighted Regression (GWR) model. GWR models have gained prominence in the social sciences given their ability to address spatial heterogeneity of social science phenomena. A characteristic feature of GWR that sets it apart from other types of spatial regression models is its ability to generate individual regression coefficients as a continuous function across space, i.e., regression coefficients that can vary across space, producing continuous (smooth) coefficient surfaces. In addition, only a subset of observations is used to estimate coefficient values thus enabling a more refined measure of spatial heterogeneity and spatial dynamics (Chi & Zhu, 2019).

2.3.1. **Understanding accessibility**

Concepts of mobility further transfer into more detailed considerations when trying to not only understand the importance and influence of mobility networks and structures, but when trying to measure the effects of these. Accessibility analyses have become an increasingly prominent methodology. Measures of accessibility can be broadly categorised into two types: Location (place) based accessibility measures and individual (people) based accessibility measures (Makri & Folkesson, 1999). Place-based measures are more dependent on the spatial attributes of land-use patterns and transport systems, yet vary in complexity based on the emphasis of individuals' socio-spatial attributes. People-based measures focus primarily on the individual and account for person-specific experiences and attributes and are thus generally considered superior to many place-based measures (Makri & Folkesson, 1999; Geurs & van Eck, 2001).

Place-based measures include distance, cumulative opportunity, gravity, and utility-based measures increasing in complexity respectively (Makri & Folkesson, 1999). Cumulative opportunity and gravity-based measures are the most common measures for assessing accessibility, with the gravity-based measure still the most widely used (Geurs & van Eck, 2001; El-Geneidy & Levinson, 2007). However, consideration of the lack of a robust theoretical foundation in these measures, distance-based included but utility-based measures to a lesser extent, as addressed by Miller (2018), is important. This consists of the subjective nature of accessibility measures and the absence of an objective, universal accessibility standard. Conversely, people-based measures, most notably space-time measures, address accessibility at a micro-detailed level and overcome numerous constraints inherent in place-based measures (Makri & Folkesson, 1999).

Accessibility as a measure has been very context-specific, because of the multiple variables and considerations that need to be accounted for, and although imperfect, is still an appropriate measure to understand the relationship between land-use patterns and transportation systems (Golub and Martens, 2014). In saying this, there has been research aimed at creating methodological frameworks that are all-encompassing and can be manipulated. Cheng and Bertolini (2013) address the conceptual framework for job accessibility measurements, which addresses the relationship between jobs, workers, and transport whilst accounting for spatial relationships in spatial autocorrelation. This has been a practical measure, implemented as a case study in Amsterdam, Netherlands. Emphasis on public transport-related accessibility analyses in assessing the disparities between different modes (e.g., Chen et al., 2017, Liu et al., 2018) has also shown practical importance and likewise the assessment of a space-time measure for transport analysis in a GIS environment (Miller & Wu, 2000).

However, given South Africa's unique context, transport-related accessibility analyses, if not infrequent, are often founded on measures that do not account for the intricacies of spatial and social dynamics characteristic of the country (Venter and Cross, 2014). The accessibility measures have thus been very general, indicative of the measures used, and whilst informative on certain spatial scales; there has been little in location and context-specific studies. Venter and Cross (2014) addressed this through the adoption of a GIS-based accessibility measure, called 'access envelopes', which accounts for location-specific affordability of job access with respect to different urban transport modes, and further addresses the limitations raised by Cheng and Bertolini (2013). The GCRO has also produced notable works on accessibility for the Gauteng province, making use of their biennial Quality of Life (QoL) surveys boasting tens of thousands of respondents with data being aggregated to a ward level enabling multiple approaches to analysis.

2.4. **Synthesis of Literature**

South African cities have been shaped by a multitude of historic factors, predominantly through the Apartheid era. Johannesburg and the broader GCR are an example, where the racial segregation policies during Apartheid strongly influenced the spatial heterogeneity of the landscape, in that a large proportion of, specifically, black South Africans did and still often reside far from economic centres (Kerr, 2015; Ngarachu et al., 2015). Transport is an essential feature and is influenced by the dynamic and heterogenous nature of the landscape. Transit-oriented factors, such as transport mode, transport cost, and travel duration are important considerations given Gauteng's unique spatiality and present unequal social and economic consequences across race and class.

Culwick et al. (2015) demonstrate the high variability in travel duration and times of travel for African respondents in relation to white respondents, which they found to mirror transport dynamics from surveys carried out in the 1970s. This, contrasted by the Minibus taxi accounting for the bulk mode of commuting for low-income workers, of which black people comprise the majority, highlights the stark reality of transport and transport conditions that influence the vulnerability of workers and ultimately increases the precarious nature of their work and the precarious state they find themselves.

Chapter 3: Methodology – Materials and Methods

3.1. **Study Area**

Gauteng is the core of the Gauteng City-Region (GCR) and serves as the study area for this research project. The GCR is South Africa’s most spatially populated region and largest economic agglomeration, functionally organized around Johannesburg, Ekurhuleni, and Tshwane – the main metropolitan municipalities (Everatt, 2017). According to Statistics South Africa's July 2021 mid-year population estimate Gauteng has a population of 15,810,388, accounting for over 26% of the country's population (Statistics South Africa, 2021, 27). The predominant economic activities include mining, manufacturing, and business and financial services, working in conjunction to constitute a functionally integrated urban economy and single labour market (GCRO, 2021). The Casual Workers Advice Office (CWAO) is based in Germiston, in the Ekurhuleni metropolitan municipality. It is a registered non-profit organization providing labour rights-related advice and support to precarious workers spread across the province. The office is on the corner of Knox and High street, situated directly across from the Germiston Train Station. Its location and situation make it ideal for attracting workers from, first, the surrounding industrial areas in which many work and the surrounding townships in which many reside, and the broader GCR, from Pretoria in the north, Sebokeng in the south, Kagiso in the west, across to Daveyton in the far East Rand.

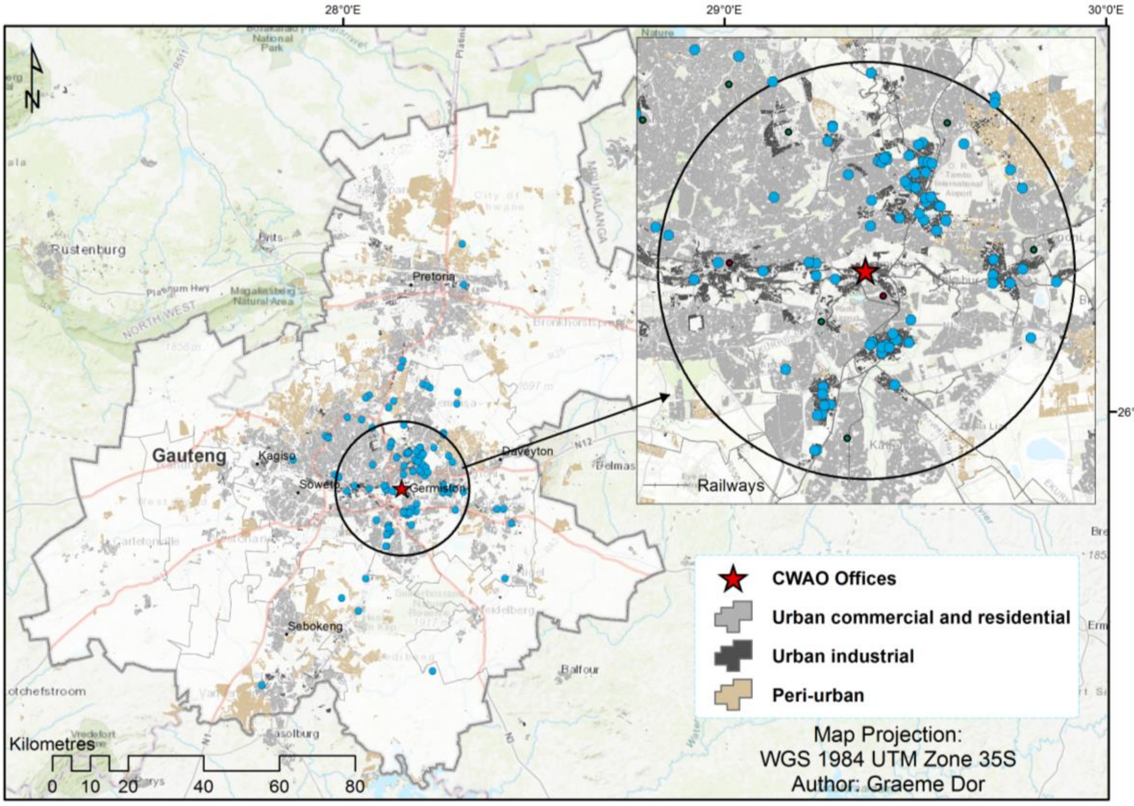


***Figure 3.1**- Locality map of Gauteng province, which serves as the catchment area for the CWAO, centrally in the province. The blue dots represent the distribution of worker-based companies, which are mainly confined to industrial areas as depicted and are relatively central within Gauteng (Data sources: Environmental Systems Research Institute (ESRI), National Geo-spatial Information (NGI), GeoTerraImage (GTI)).*

The CWAO organizes predominantly temporary employments service workers, better known as labour broker workers. The precarious nature of their employment is characterised by low wages, the unsociable hours worked, and difficulty with organizing (I Schroeder 2019, pers. comm., 13 May). However, the precarious and changing nature of work for low-income individuals, particularly workers organized by CWAO, means that the status of workers falls into four categories of increasing precariousness. The unemployed, labour broker workers, casual or contract workers, and permanent workers.

3.2. **Datasets and Analytical Software Used in This Study**

To attempt to assess the intricacies of transit-oriented economic and social impacts of Gauteng's spatiality on precarious workers, analysis will pertain to three primary datasets. The first, membership details recorded by the CWAO, the second, a membership survey conducted by CWAO, and the third, the GCRO Quality of Life (QoL) V (2017/2018) survey data set. The first two datasets comprise workers associated with the CWAO, in which the survey is a subset of the membership population. However, the membership survey is distinct from the membership details, in addressing a different purpose for analysis. An important consideration during analysis, specifically regarding the survey analysis, will be that of the classification and comparison of workers across employment type. The datasets are outlined in greater detail in the proceeding sections discussing data acquisition (section 3.3), pre-processing (section 3.4), and processing (section 3.5) methods.

To perform advanced spatial analyses, both open-source and proprietary software were considered. QuantumGIS and ESRI's ArcGIS are the most popular platforms for these options respectively, each with advantages and limitations (Khan & Mohiuddin, 2018). After comparing the advanced mapping functionalities of ArcGIS and QGIS (Benduch, 2017), ArcGIS Pro was selected as the most appropriate option. An important consideration was ESRI's recently incorporated 'Generalized Linear Regression' (GLR) tool into ArcGIS Pro, which succeeds the 'Ordinary Least Squares' tool. Despite the name, the GLR tool provides options for logistic (binary) and Poisson (count) modelling types (Law & Collins, 2019). In addition, ArcGIS Pro offers a host of advanced techniques in transport-related accessibility analysis with a wide range of literature covering case studies and advice on visualisation, analysis and interpretation of results (Higgins et al., 2020).

3.3. **Data Acquisition**

The first dataset, described as the CWAO membership details, defines all workers who have 'signed' up for a membership with the CWAO, by providing basic identifying information to be used to communicate the likes of newsletters, worker meetings and event dates. The CWAO membership count, as of 13 May 2019, consisted of 2,285 entries, with the number increasing daily in relation to membership. As highlighted, the workers that CWAO advises and offers support to come from across the GCR and work in predominantly industrial settings. One hundred and twenty-one companies, distributed more centrally within the GCR, account for all CWAO associated workers (Figure 3.1). The data to conduct this research project thus comprised secondary locational and attribute data which has, in completing this study, been compiled into a comprehensive database.

At the time of acquisition, the membership database consisted of hard copy membership forms containing information pertaining to workers' details and included identifying information in names, contact information, place of residence, and workplace. In addition, a Microsoft Excel spreadsheet highlighting the number of workers represented across each of the 121 workplaces. The digitisation of membership details, entailing the digital capturing of information from hard copy membership forms, was initiated in June 2020. The result, given multiple capturers of the membership details, was a set of excel workbooks, each consisting of the respective membership information pertaining to each individual member. The CWAO agreed to use of this data for this research, which is attached as part of the ethics application form, in a permission letter. To ensure the anonymity of workers' details, no identifying information, in names of workers or relation to their workplaces, was included in the outputs and results. This follows under GCRO's data collection methodology for QoL surveys (GCRO, 2019).

Second, data was obtained from a membership survey (see Appendix A), jointly developed with the CWAO for this project, to assess transit and socio-economic factors of workers associated with the CWAO, i.e., members. The membership survey was sent out to CWAO members on the 16th of June 2020 through their 'SMS Portal', a contact database platform CWAO uses to communicate with workers regarding a range of issues. The questionnaire was also sent out across workplace organized WhatsApp groups to workplaces that consist of multiple members, to ensure that it reached many workers while accounting for any outdated details in the SMS Portal database.

The questionnaire was developed using the Microsoft Forms platform, for which the CWAO has a subscription, deemed adequate for the questionnaire, having compared it to open-source (Google Forms) and other proprietary (Survey Monkey) platforms. The CWAO conducted all iterations of the survey, and took the necessary measures to ensure that the respondents remained anonymous throughout the process, thus the analysis of the results for the purpose of this research form secondary data analysis.

The questionnaire, developed in English, was translated into isiZulu to accommodate for workers more comfortable responding in Zulu, and comprised 31 questions. However, the skip logic employed in the survey translated to a maximum of 24 questions directed at any one individual. Survey questions ranged several themes, but were primarily structured to elicit defined responses to promote simplicity for response and analytical purposes. Survey questions included dichotomous, Likert-scale, demographic, and multiple-choice-based questions, while limiting the number of open-ended questions in the form of comment and text box. Quantitative and qualitative questions were asked, in which responses could be categorised into two broader themes: spatial and non-spatial. The survey included work/residence-related questions, socio-economic-related questions, and COVID-related questions, most of which elicited responses on workers' spatial distribution and movement in relation to transport and work dynamics. COVID-related questions pertained to health and safety measures implemented during the national lockdown, a result of COVID-19 and the influence of the national lockdown on transit and socio-economic factors.

The raw survey responses were shared for the purpose of this research, and permission was granted by the CWAO to analyse the survey responses, with ethical clearance obtained through the University of the Witwatersrand before conducting any analysis. The survey results will enable a more comprehensive understanding of worker-related transport and work dynamics.

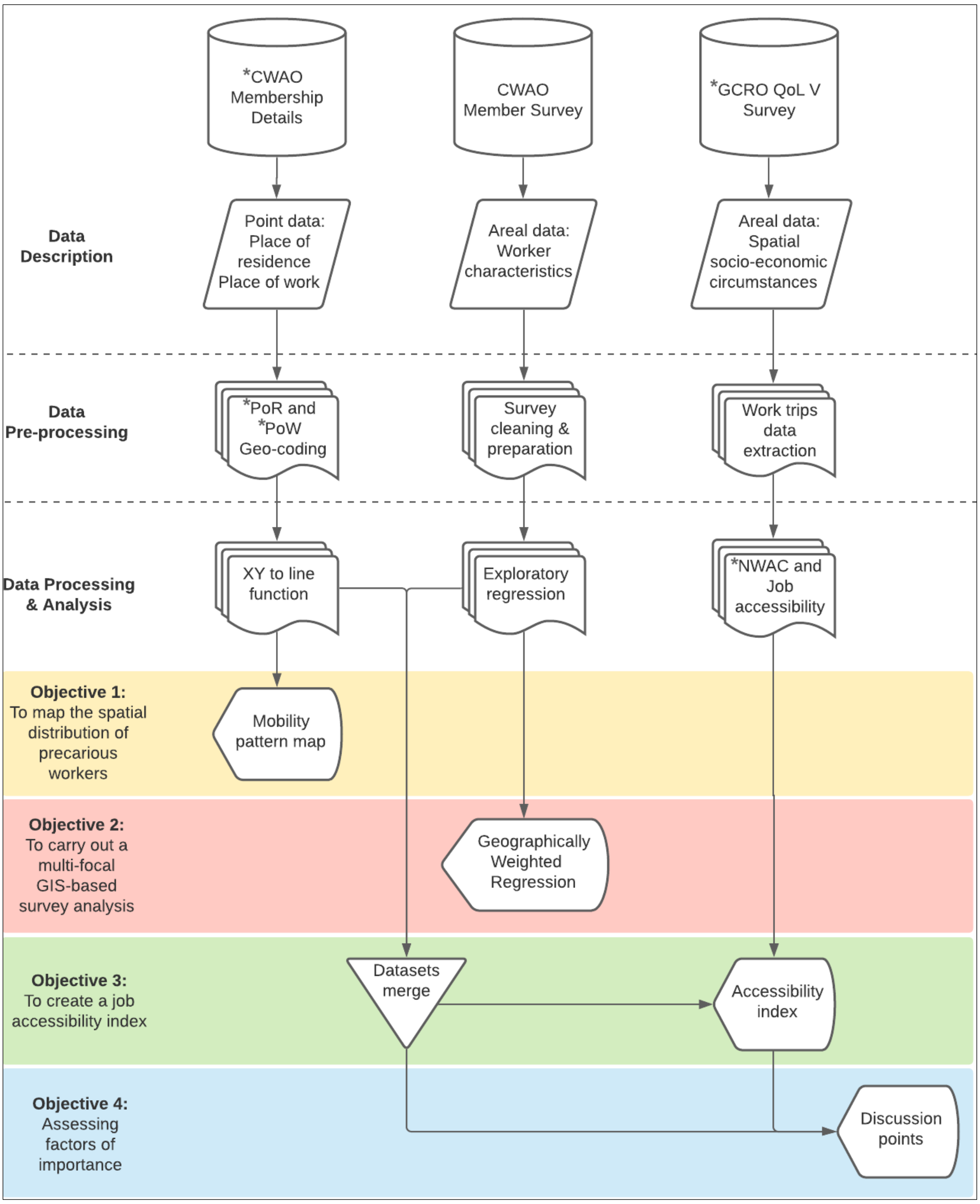
Besides case-specific data in membership details and membership survey responses pertaining to members of the CWAO, GCRO's QoL V survey data conducted in 2017/2018 was obtained from the GCRO to enable a comparative study between general respondents and more context-specific CWAO data. GCRO's QoL V questionnaire included 248 questions across 14 categories, covering questions most pertinent to this research in the category of transport and mobility. The final dataset includes 24,889 respondents from all 529 wards in Gauteng. Table 3.1 outlines the summary information of the three datasets that were used to conduct this research project.

Table 3.1 *- Summary table outlining the data used to conduct this research project*

Dataset *(Data format)*	**Description**	**Spatial resolution**	**Temporal resolution**	**Data source**
Membership Details *(Point)*	Place of residence / Place of work	Subplace / Main-Place	2018 - 2020	CWAO
CWAO Membership Survey *(Areal)*	Work / Transport / COVID-related characteristics	Subplace / Main-Place	2020	CWAO
Quality of Life (QoL) V Survey *(Areal)*	Spatial socio-economic circumstances	Ward level / Subplace / Main-Place	2017/2018	GCRO
Subplace and Main-Place *(Areal)*	Gauteng subplace and Main-Place areal delineation shapefiles	Subplace / Main-Place	2016	StatsSA

3.4. Data Pre-processing

Following the acquisition of the respective datasets, significant pre-processing of the associated data was necessary to prepare the data for spatial and statistical analysis. A summary of the research workflow, clearly outlining the datasets and methodological processes for addressing each objective, is provided in Figure 3.2 to orientate the reader, followed by a detailed explanation of the pre-processing and processing methods.



*CWAO – Casual Workers Advice Office
*GCRO QoL – Gauteng City-Region Observatory: Quality of Life
*PoR – Place of Residence
*PoW – Place of Work
*NWAC – Net Wage After Commute

***Figure 3.2** – Research workflow outlining the datasets and methodological processes for addressing the objectives of the study.*

For completing the first objective (to map the spatial distribution, i.e., place of work in relation to place of residence, of precarious workers associated with the CWAO) place of residence and place of work were essential. Access to the list of companies was granted before completing the digitisation and compilation of the membership forms. This list, including only the names of the respective companies, necessitated the acquisition of coordinates for each of the 121 companies. These were manually generated in a process that involved google searches by company name and extraction of coordinates from google maps, after which validation was performed using company websites and then further cross verified by the CWAO, familiar with most company locations. The second pre-processing step entailed the concatenation of the multiple digitized membership excel workbooks into a single excel spreadsheet, thus enabling easy manipulation of the data. The data was then cleaned to ensure consistency across the database, specifically regarding company names and places of residence. For places of residence, an additional field was created by filtering out all identifying residential information in street names and house numbers, thus creating spatially uniform information at a subplace and main-place scale. De-identification was then performed by removing all categories bar de-identified place of residence and company. Place of residence was then manually geocoded, converting a text-based description of a location, i.e., an address, to location information in geographic coordinates (Zandbergen, 2009). This process entailed creating centroids, using the Centroid Builder in ArcGIS Pro, to generate a point feature class containing the central coordinates of every subplace and main-place, using the respective shapefiles sourced from StatsSA. Lastly, a lookup table was performed using the 'vlookup' function in excel to pull in the coordinates for the place of work from the company list, and repeated for the place of residence using the subplace and main-place extracted coordinates. The final result, a concatenated spreadsheet of all de-identified places of residence and respective PoW, along with the coordinates for each.

Completing objective 2 (to carry out a multi-focal GIS-based survey analysis of the factors, work- transport- and COVID-19-related, influencing vulnerability of precarious workers) again necessitated extensive pre-processing. This entailed data extraction from the Microsoft Forms platform, on which the survey was performed, by exporting the survey results as an excel document. Once exported, the spreadsheet was then assessed for quality and completion of responses. Duplicate and incomplete responses were removed, of which accounted for a small percentage of responses (n=5). Further to this, survey responses were completed in English and isiZulu, necessitating the need to translate all Zulu responses to English, and to align all translated responses to the respective English-phrased survey questions, to simplify analysis. All survey questions were then transformed into unique meaningful abbreviated forms of the question, for ease of use in Stata, the chosen statistical package for analysis, and for descriptive reporting of response outcomes. Responses to all open-ended questions, in text and comment responses, required minimal data cleaning, including capitalisation and spelling checks, to ensure response consistency. This was pertinent to questions eliciting spatial responses in place of residence and place of work. The same methodology as that described earlier was performed to generate the coordinates for these responses. Last, all dichotomous, nominaland ordinal responses in dichotomous, demographic, multiple-choice, and Likert-scale style questions, were encoded in Stata to prepare the data for statistical and spatial analysis (Table 3.2). This entailed creating and coding additional variables, using Stata's 'generate', 'replace' and 'define' commands. Table 3.2 outlines the encoded variables generated for each question, where "Variable Name" describes the variable label, an abbreviated form of the question, and "Category" describes the question, categorised into demographic, transit-oriented, or COVID-specific. "Data type" and "Encoded" describe the underlying data structure before and after encoding. For a complete list of survey questions and response options, including open-ended questions, refer to the survey questionnaire in Appendix A.

Table 3.2 - Summary table outlining all encoded variables for statistical and spatial analysis

Survey Question	Variable Name	Category	Data Type	Encoded
Would you prefer to answer in English or Zulu?	Lang_English	Demographic	Dicothomous	Binary
Are you employed?	Employed	Demographic	Dicothomous	Binary
Are you a:	EmployType_c	Demographic	Nominal	Nominal
- Permanent	Permanent	Demographic	Nominal	Dummy (Binary)
- Labour broker worker	LabourBrokerer			
- Contract worker	Contract			
**Place of Work land cover - Extracted from SANLC dataset*	Comp_SANLC_Industria	Spatial	Nominal	Binary
**Place of Residence land cover - Extracted from SANLC dataset*	Res_SANLC_Formal	Spatial	Nominal	Binary
Do you use: - Public transport - Private transport - Company provided transport	Trans_Public	Transit-Oriented	Nominal	Dummy (Binary)
	Trans_Private			
	Trans_Company			
	Trans_NonMotor			
What type of transport are you using to get to work? (Whether company provided or public transport)	Mode_Walk	Transit-Oriented	Nominal	Dummy (Binary)
	Mode _Taxi			
	Mode_Car			
	Mode_Train			
	Mode_Bus			
	Mode_Taxi2			
Is this the same as before the lockdown?	Mode_Diff_LD	COVID-specific	Dicothomous	Binary
What type of transport were you using before the lockdown?	ModePreLD_Taxi	COVID-specific	Nominal	Dummy (Binary)
	ModePreLD_Car			
	ModePreLD_Train			
	ModePreLD_Bus			
Why have you had to change the transport used?	ModeChange_Safety	COVID-specific	Nominal	Dummy (Binary)
	ModeChange_Time			
	ModeChange_Unavail			
	ModeChange_Cost			
	ModeChange_Company			
How much do you spend on work transport per day?	TransCost_c	Transit-Oriented	Nominal (Ordinal)	Ordinal
Is this more, less, or the same as before the lockdown?	TransCost_Same	COVID-specific	Nominal (Ordinal)	Ordinal
	TransCost_More			
	TransCost_Less			
What time do you leave home to go to work?	DepartTime_pre6	Transit-Oriented	Nominal (Ordinal)	Dummy (Binary)
	DepartTime_6to9			
	DepartTime_9to12			
	DepartTime_12to15			
	DepartTime_15to18			
	DepartTime_post18			
How long does it take you to get to work, from the time you leave home?	TransDuration_c	Transit-Oriented	Nominal (Ordinal)	Ordinal
Is there social distancing: - In the workplace?	Workplace_SocDist_c	COVID-specific	Nominal (Ordinal)	Ordinal
- In transport?	Transport_SocDist_c	COVID-specific	Nominal (Ordinal)	Ordinal
*Is there *PPE: - In the workplace?*	Workplace_PPE_c	COVID-specific	Nominal (Ordinal)	Ordinal
- In transport?	Transport_PPE_c	COVID-specific	Nominal (Ordinal)	Ordinal
On average, how many hours do you work per day?	WorkHours_pd_c	Demographic	Ordinal	Ordinal
On average, how many days do you work per week?	WorkDays_pw_c	Demographic	Ordinal	Ordinal
How much do you earn per hour?	Income_ph_c	Demographic	Nominal (Ordinal)	Ordinal
Is this more, less, or the same as before the lockdown?	IncomeChange_c	COVID-specific	Nominal (Ordinal)	Ordinal
Are you a: Man; Woman?	Gender_Female	Demographic	Dicothomous	Binary
As a woman, is your transport safer under lockdown, compared to before?	TransSafety_c	COVID-specific	Nominal (Ordinal)	Ordinal
As a woman, is your family responsibility under lockdown affecting: Travelling time; Travelling cost; type of transport used?	FamResp_TransDur	COVID-specific	Dicothomous	Binary
	FamResp_TransCost	COVID-specific	Dicothomous	Binary
	FamResp_TransMode	COVID-specific	Dicothomous	Binary

**Non-questionnaire variables
*PPE – Personal Protective Equipment

Questions that elicited unordered nominal responses were converted into dummy (binary) variables, to enable advanced statistical and spatial analysis. For example, type of transport, such as public, private, or company provided, cannot be naturally ordered, and thus the creation of dummy variables enables analysis of the effect that one response produces, if true (equals 1), with all other responses set to zero.

Completing objective three (to create a job accessibility index using membership and survey details of precarious workers associated with the CWAO) required pre-processed data addressed in objectives one and two, combined with data from the GCRO QoL V (2017/2018) survey. Pre-processing of the GCRO QoL V survey data entailed extraction of respondents that responded to the question “Think about the trip that you make most often… What is the purpose of this trip that you make most often?" with "To go to work". This limited the number of responses to 8,089 from a total survey response count of 24,889. Further to this, a second filter was applied to include only respondents who provided locational information down to a subplace, to increase the accuracy of the spatial statistical outputs, which refined the survey to 7,618 respondents to be used for spatial analysis.

3.5. **Data Processing and Analysis**

To accomplish the first objective (to map the spatial distribution, i.e., place of work in relation to place of residence, of precarious workers associated with the CWAO), basic GIS and summary statistics analyses were performed using spatial statistics tools. This necessitated the input of all coordinates into ArcGIS Pro, and then using the *XY to line* function, the spatial relationship between places of residence and PoW were defined, after which summary statistics were produced to assess spatial distribution across the dataset. This is a simple and common technique used to produce both visually appealing and informative maps (see Wray et al., 2014; Culwick et al., 2015). Categorisation of distance intervals by colour graduation was calculated using a geometric distribution, which most closely represents the data spread and then adjusted to create easily interpretable category labels.

The second objective (to carry out a multi-focal GIS-based survey analysis of the factors, work-transport- and COVID-19-related, influencing vulnerability of precarious workers) necessitated the application of spatial regression analysis on the results of the membership survey, to determine the effect and relationship of predictor variables on the chosen response variable. However, to first develop an overview of the relationships between all variables, a pairwise correlation was performed. Pairwise correlation uses a pairwise deletion methodology advantageous because it generates a correlation output if both values are present, whether or not there are missing variables outside of that pair. Next, the employment, a reflection of precariousness, was selected as the response variable to determine the effect elicited by chosen variables. Multinomial logistic regression was selected for this purpose based on the categorisation of employment type (labour broker worker; contract worker; permanent worker). Assumptions of independence among the response variable categories were met, and adherence to sample size guidelines, indicating at least 10 cases per predictor variable (Schwab, 2002; Starkweather & Moske, 2011). As highlighted, Stata (Version 14), the statistical package to perform analysis. Specifically, the 'mlogit' function was used to run multiple iterations of univariate multinomial regression analysis, where mlogit evaluates the categorical dependent variable using maximum likelihood estimation, by producing coefficient values for the associated predictor variables. Relative risk ratios (RRR) were then performed to produce a more interpretable outcome with RRR values indicative of the likelihood of an outcome falling in the comparison group as opposed to the referent group.

After the creation of a correlation matrix (Figure 4.2) and exploring univariate regression coefficients on the survey results in Stata, ArcGIS Pro was used to generate global and local (spatial) regression models (Figure 3.3). Employment type was transformed into a binary variable labelled "Permanent", where '1' stipulated permanent workers and '0' (zero) stipulated non-permanent workers, i.e., labour broker workers or contract workers. A binary variable was created due to the limitation of spatial regression tools in dealing with multinomial variables, but supported on the outputs of the univariate multinomial logistic regression analysis. The analysis necessitated an iterative process, using the exploratory regression tool in the modelling spatial relationships toolbox, for determining a combination of variables that accounted for most of the variation seen in the response variable, i.e., permanent. Careful consideration and selection of candidate predictor variables proved essential to ensure that suggested combinations did not exhibit multicollinearity nor display redundancy. Due to the range and data type of the encoded predictor variables, exploratory regression was repeated multiple times using different combinations of candidate predictor variables.

The next step in the process entailed generating a global regression model. This was achieved in ArcGIS Pro using the newly incorporated Generalized Linear Regression (GLR) tool, which, despite the name, allows for the creation of continuous, binary, and Poisson global regression models. A set of predictor variables was selected based on the multiple outputs of the exploratory regression. Again, an iterative process was performed to determine a set of significant predictor variables accounting for the most variation in employment type, the response variable, whilst ensuring no visual clustering of the standardized residuals. Visually analysing the standardized residuals was necessary to confirm no significant spatial effects went unaccounted. With no visual clustering of the standardized residuals evident, the model with the highest adjusted R-square value and lowest Akaike's Information Criterion (AIC) score was selected, which indicated the most robust model with the smallest prediction error (Ward & Gleditsch, 2018). Following the generation of a global model, accounting for the global effect of variables on workers across the study area, a local regression model was performed. This necessitated statistically assessing the standardized residuals to determine the spatial autocorrelation present, i.e., dispersed, random, clustered. For this, a Global Moran's I test was performed, which provided a measure of spatial autocorrelation on a scale of -1 to 1, where 0 indicates a random distribution, -1 a dispersed distribution, and 1 a clustered distribution. The Moran's I value combined with the z-score and p-value were used to determine the statistical significance of the spatial autocorrelation present in the model. Once satisfied, a Geographically Weighted Regression (GWR) was performed to determine spatially varying relationships by creating a local regression model depictive of coefficients at the local level, essentially creating regression models for each individual feature depictive of an individual worker. Calibration was performed using neighbouring features, with a distance band selected for as the neighbourhood type using ArcGIS Pro's golden search criterion, which implements an AIC methodology to identify the ideal distance for the neighbourhood size. Outlined in Figure 3.3 is the model builder used to generate the GLR and GWR models. The importance of generating a GLR and a GWR model was first to gauge a better understanding of general trends, by assessing the effect of explanatory variables across the entire dataset, and then to determine whether spatial interactions affect the explanatory variables that explain employment type, by identifying the influence of spatial heterogeneity on the overall model performance.

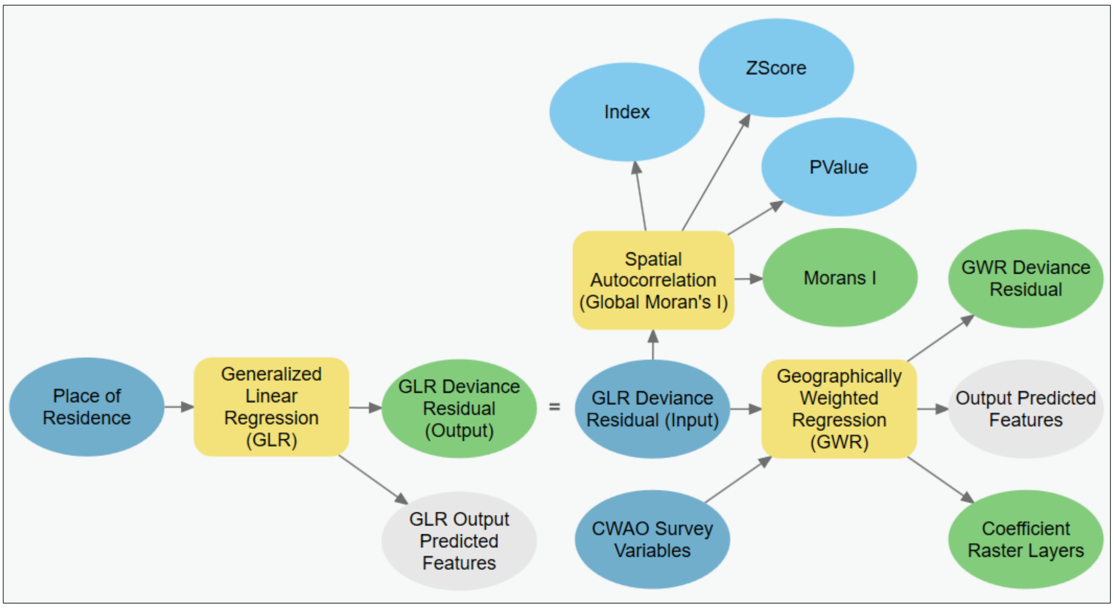


Figure 3.3 – Model builder used to generate the Generalized Linear Regression (GLR) and Geographically Weighted Regression (GWR) models.

The third objective (to create a job accessibility index using membership and survey details of precarious workers associated with the CWAO) entailed the creation of a job accessibility index, using place of work (PoW) and place of residence (PoR) data outlined in the first and second objectives and the GCRO QoL V (2017/2018) survey. The GCRO QoL survey dataset was used to extract underlying demographic information for the study area, due to the limited number of sampling points from the CWAO survey analysis. The analysis required the creation of two spatial layers. First, a Net Wage After Commute (NWAC) layer was developed, using the GCRO QoL survey, followed by the creation of a job accessibility to potential jobs spatial layer, using PoW and PoR data outlined in the first and second objectives.

Venter and Cross' (2014) methodology supported deriving the NWAC spatial layer. Venter and Cross (2014) addressed accessibility through the adoption of a GIS-based accessibility measure, called 'access envelopes', which accounts for location-specific affordability of job access whilst controlling for the number of jobs in an area.

By utilizing existing data on income and cost of transport from the GCRO QoL survey, and generating a distinct layer for job accessibility using the PoW and PoR data from the case-specific CWAO membership and survey details, this study circumnavigated the need to incorporate routed road networks in the analysis - an initial limitation.

To calculate the NWAC, the extracted dataset of respondents from the GCRO QoL survey indicating a confirmed trip to work, having provided locational information down to a subplace, was imported into ArcGIS Pro and matched to the subplace shapefile of Gauteng using the join tool by stipulating a match based on subplace codes. Next, a continuous function for wages was calculated from the categorical responses for the variable coded for income, based on the question "Can you tell me what is the total amount of money brought into the household per month by all household members?", and controlled for by the number of adults listed per household. A continuous function was then calculated for the variable coded for transport expenditure, based on the question "Approximately how much do you personally spend in total every month on transport?", which was then subtracted from the continuous function for wage to generate a NWAC value for each individual. The calculated NWAC value was then aggregated using the stipulated subplace of origin for respective respondents, and plotted at a subplace level. Using the concept of tessellation, outlined in Venter and Cross' (2014) paper, a standardized 5km (diameter) hexagonal tessellation layer was developed to cover the study area, translating into individual hexagonal areas approximately 20km^2. This ensured a standard unit of analysis, in contrast to subplace and main-place spatial boundaries that differ in size and shape, for ease of representation and interpretation. The areal dimensions of the hexagonal tessellation were based on considerations outlined in Venter and Cross' (2014) methodology and the City of Johannesburg's (2020) Nodal Review paper. This enabled the linkage of NWAC attribute data to the tessellated surface, using a spatial join, yielding an output on a uniform and comparable scale.

To determine the job accessibility to potential places of work, the mean distance from each PoR to all potential PoW was calculated using the CWAO membership and survey details, employing a mean distance methodological approach, adapted from Boussauw, Neutens & Witlox (2012) and Cheng and Bertollini (2013). To achieve this, PoW and PoR point shapefiles from the CWAO membership details and the CWAO survey were combined using the merge tool in ArcGIS Pro, after which all duplicates were removed. This produced an extensive point shapefile for all PoR and for all PoW respectively. To calculate the mean distance to potential PoW, a 'generate near table' analysis was performed, by specifying the merged PoR shapefile as the input feature class and the merged PoW shapefile as the 'near' feature class. An output table was generated classifying the distance for each PoR to every potential PoW. Given the extensive number of PoW, equating to 145, and even greater number of PoR a distance value was generated from every single PoR to each of the 145 potential PoW. The dataset was then exported into Stata, and the mean distance to potential PoW for each PoR calculated, which was then imported back into ArcGIS Pro and merged to the PoR shapefile. With the accessibility score calculated for each PoR, an inverse distance weighted (IDW) interpolation was performed to generate a surface layer depicting accessibility scores for each unmeasured location. IDW, a deterministic interpolation method, derives predicted values by weighting only surrounding measured values, thus employing a more traditional neighbourhood relationship based on spatial autocorrelation (Guzman, et al., 2018). The IDW surface satisfied assumptions of spatial autocorrelation representative of job accessibility, and enabled the linkage of accessibility scores to the tessellated areal surface. For this, a spatial join was performed, allowing for the visualisation of spatial dynamics of job accessibility across the GCR.

The two spatial layers, the NWAC and the job accessibility to potential jobs, together form the accessibility index. Adopting this methodology entailed finding a balance between the accuracy of measurement, the complexity of representation, and the ease of interpretation, an essential consideration, as Cheng and Bertolini (2013, 102) note. The accessibility index was therefore formulated:

$$A = \sum_{i=1}^{n} \frac{W - C}{n} . \sum_{i=1}^{n} \frac{d^i}{n}$$

where A is the accessibility score, W is wage, C is cost of commute, n is the number of observations. The first part of the equation thus summarises the NWAC score. This is followed by the calculation of a job accessibility score where d^i is the distance to each potential job from PoR, and n the number of potential jobs. The importance of generating an accessibility index was in determining the spatial heterogeneity of accessibility measures for precarious workers linked to the CWAO more broadly and how this differed across categories of employment type.

Objective four of this study (to assess the relationship of spatial and non-spatial factors to better understand what constitutes vulnerability of precarious workers) aimed at bringing all objectives together to identify the different spatial and non-spatial factors that potentially contribute to the vulnerability of precarious workers. This enabled the presentation of additional exploratory analytical results, performed throughout the study not included in the main analyses, which may serve as reference in future research. The spatial relationship outlining the distribution of the distance that workers reside from PoW across employment types was further explored. This entailed analysis of the distributional properties of workers in different employment types, with focus on the median and Interquartile Range (IQR) measures of central tendency due to non-normality in distributing predictor variables across respective employment types. To assess the influence of additional factors, a comprehensive breakdown of chi-squared tests and multinomial logistic regression results were reported based on the significance of respective variables, allowing for a broader analysis addressing components not covered in objectives 2 and 3. This was covered in greater detail in Appendix D.

Chapter 4: Results

4.1. **Mobility Patterns of Workers Associated With the CWAO**

Addressing the first objective of this study, to map the spatial distribution, i.e., place of work in relation to place of residence, of precarious workers associated with the CWAO, Figure 4.1, presents a flow map depicting the straight-line distances from places of residence (PoR) to places of work (PoW) of workers associated with the CWAO, using the CWAO membership details. PoW indicate the exact location of companies, whereas PoR were determined using the centroid for subplace, where possible, and main-place. Frequently, multiple workers were found to travel to and from the same place. A line technique employing firefly symbology, an ArcGIS Pro style plug-in, was used to indicate density of flow to display this phenomenon. Thus, brighter lines correlate to increased flow density (i.e., higher counts of individuals performing the same trip), and more luminous areas to an increased network of movement across space. The same style was applied to locations of companies, indicated by white markers, where more brightly marked areas correlate to increased densities of companies.

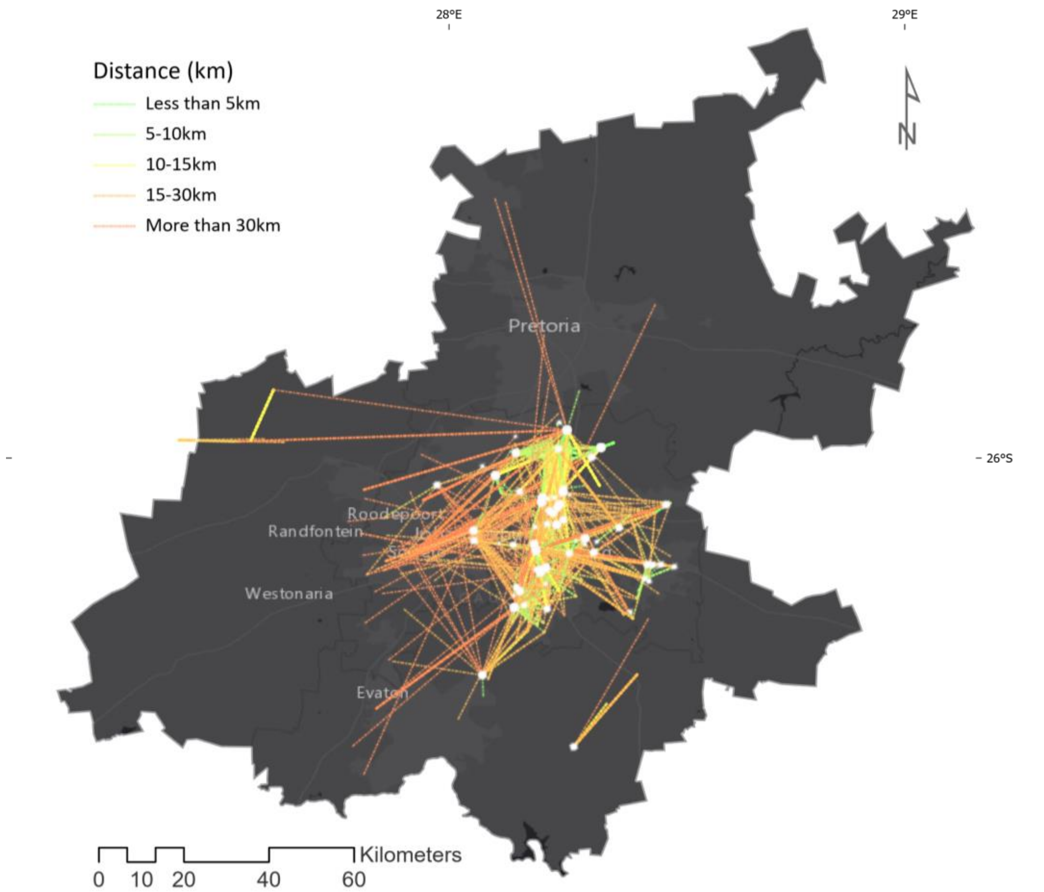


__Figure 4.1__ – Mobility pattern of workers associated with the CWAO, using membership details, within the GCR. Colour graduation defines distance between place of residence and place of work (white markers). Line luminosity and intensity correlates to density of flow.

The intensification of light yellow-green colours, corresponding to distances <10km, culminates more centrally within the geographic bounds of the GCR. Through visual inspection, this strongly correlates to the location of company workplaces, represented by white markers, and highlights the economic hub region of Gauteng (Rogerson, 2018). Contrastingly, there is less intensified density and greater spread of orange and red colours corresponding to distances of >15km. This more closely correlates to the wider spread of workers' PoR.

Spatial summary statistics of the membership details indicated workers reside a mean distance of 14.95 kilometers from work, with a standard deviation of 11.75. The maximum straight-line distance recorded was 69 km, which is markedly longer than the straight-line measure between Johannesburg and Pretoria, approximately 50 km – an important reference in Gauteng's spatiality (Del Mistro and Roodt, 2001). To understand the significance of the measures of central tendency and variability in the data, a comparison was performed against a generalized population of the mean distances that people reside from their place of work, using the GCRO QoL V survey (see Appendix C). The comparison indicated there was no significant difference in the mean distance that individuals reside from their place of work for precarious workers in relation to the generalized population.

4.2. CWAO Member Survey Analysis

Analysis performed on the CWAO member survey addressed the second objective (to carry out a multi-focal GIS-based survey analysis of the factors, work- transport- and COVID-19-related, influencing vulnerability of precarious workers). The CWAO member survey was sent out across all platforms on the 16th of May 2020. The last of the responses were received on the 11th of June 2020, however, 90% of responses were received within the first four days of initiating the survey. 160 survey responses were recorded, with 152 comprehensively completed. The following table outlines the summary statistics of the survey.

Table 4.1 - Summary statistics outlining the survey responses of the CWAO member survey

	Frequency	*% of Sample*
Preferred Language		
English	137	90.26
Zulu	15	9.74
Employment Status		
Employed	125	82.35
Unemployed	27	17.65
Employment Type (Employed)		
Labour broker worker	33	26.83
Contract worker	15	12.20
Permanent worker	75	60.98
Sex		
Male	71	41.32
Female	50	58.68
Transportation Type		
Public	71	57.72
Private	5	4.07
Company provided	27	21.95
Company provided & public	15	12.20
Non-motorised	5	4.07
Transportation Mode		
Taxi	70	57.38
More than 1 taxi	30	24.59
Bus (e.g. Metrobus)	6	4.92
Walking	5	4.10
Car	11	9.02
Transportation Duration		
Less than 15 minutes	8	6.72
Between 16 and 30 minutes	36	30.25
Between 31 and 45 minutes	44	36.97
Between 46 and 60 minutes (1 hour)	18	15.13
Between 61 minutes and 90 minutes	3	2.52
More than 90 minutes	10	8.40
Transport Cost (per day)		
R0–R10	16	14.04
R11–R20	9	7.89
R21-R30	20	17.54
R31-R40	23	20.18
R41-R50	12	10.53
R51-R60	10	8.77
More than R60	12	10.53
Do not know	12	10.53
Income (per hour)		
R21–R25	19	16.24
R26–R30	8	6.84
R31-R35	24	20.51
R36-R40	22	18.80
R41-R45	8	6.84
R46-R50	5	4.27
R51-R80	28	23.93
R80+	3	2.56

The above summary statistics specifically outline demographic factors associated with the survey responses. The summary statistics for ‘type of employment’ highlights the distribution of workers across employment types, which was selected as a measure of precariousness. To determine the measure of association between variables, a correlation matrix was generated (Figure 4.2). In providing a visual overview of the correlation coefficients between variables, the correlation matrix enables swift visual inspection of variable interactions and the significance of these interactions. Although not robust for the purpose of definitive conclusions, it serves as a diagnostic tool and reference for more advanced analyses.

Highlighted in blue are correlation coefficients for variables that exhibit direct relationships, and in red, those that exhibit inverse relationships. Stated in bold are correlation coefficients with significant correlation values. For example, it was easily discernible from the matrix that transport cost and transport duration exhibit a fairly strong direct relationship, indicating that an increase in transport duration correlates to an increase in transport cost across the study group. However, the correlation matrix is not a robust measure given the survey responses and data types associated with each variable, and thus additional, and more advanced analyses were used to address the respective objectives of the study.

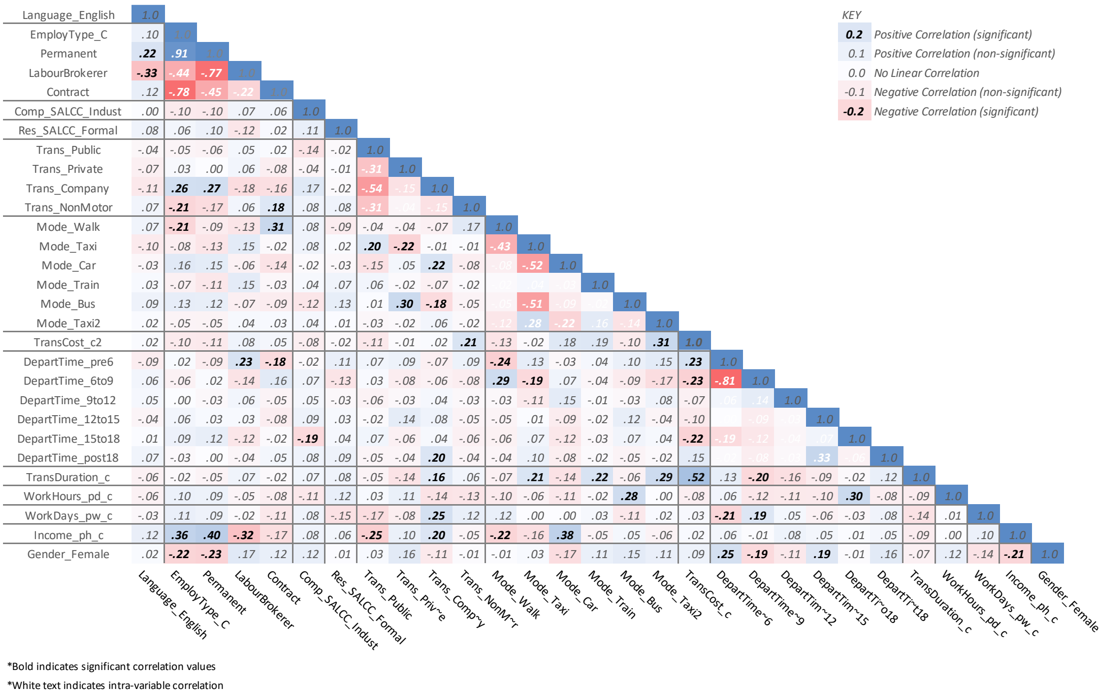


***Figure 4.2** – Correlation matrix of demographic- and transit- related variables, to visualise the relationship of survey responses.*

Specifically focusing on employment type as a response variable, a sequence of chi-square cross-tabulations followed by univariate logistic regression was performed in Stata to identify relationships between employment type and respective independent variables. Similar to the correlation matrix, chi-square tables provide a measure of association between the stipulated variables, but produce more robust outputs for analysis of categorical and binary variables. The generation of χ^2 (chi-square) tables, summarized in Table 4.2, highlighted a few variables of interest that displayed probability values of p<0.05, which are addressed in this section, and several that displayed probability values of p<0.2, which are addressed later in this chapter. A summary of the χ^2 results is outlined in Table 4.2.

Table 4.2 *– Summary table of χ^2 (chi-square) results outlining relationships between independent variables and employment type (dependent variable)*

Survey Question	Category	Encoded	Dependent Variable			
Are you a:	Demographic	Nominal	EmployType_c			
- Permanent	Demographic	Binary	Permanent			
- Labour broker worker			LabourBrokerer			
- Contract worker			Contract			
Survey Question	**Category**	**Encoded**	**Independent Variable**	**$*\chi^2$**	***df**	***Pr**
Would you prefer to answer in English or Zulu?	*Demographic*	*Binary*	*Lang_English*	13.93	2	0.003
***Place of Work land cover - Extracted from SANLC*	Spatial	Binary	Comp_SANLC_Industria	1.28	3	0.734
***Place of Residence land cover - Extracted from SANLC*	Spatial	Binary	Res_SANLC_Formal	5.30	3	0.151
Do you use: - Public transport - Private transport - Company provided transport	Transit-Oriented	Nominal	TransType_c	29.05	8	0.001
		Binary	Trans_Public	0.36	2	0.833
			Trans_Private	0.88	2	0.643
			Trans_Company	8.93	2	0.012
			Trans_NonMotor	5.07	2	0.079
What type of transport are you using to get to work? (Whether company provided or public transport)	Transit-Oriented	Nominal	TransMode_c	21.11	18	0.055
		Binary	Mode_Walk	12.13	2	0.002
			Mode _Taxi	3.10	2	0.212
			Mode_Car	3.47	2	0.177
			Mode_Train	2.63	2	0.269
			Mode_Bus	2.14	2	0.343
			Mode_Taxi2	0.47	2	0.792
Is this the same as before the lockdown?	COVID-specific	Binary	Mode_Diff_LD	0.72	2	0.698
What type of transport were you using before the lockdown?	COVID-specific	Binary	ModePreLD_Taxi	1.95	2	0.378
			ModePreLD_Car	1.82	2	0.403
			ModePreLD_Train	1.82	2	0.403
			ModePreLD_Bus	0.81	2	0.667
Why have you had to change the transport used?	COVID-specific	Binary	ModeChange_Safety	0.46	2	0.795
			ModeChange_Time	1.90	2	0.387
			ModeChange_Unavail	0.14	2	0.931
			ModeChange_Cost	0.37	2	0.832
			ModeChange_Company	1.85	2	0.396
How much do you spend on work transport per day?	Transit-Oriented	Ordinal	TransCost_c	18.44	12	0.103
Is this more, less, or the same as before the lockdown?	COVID-specific	Binary	TransCost_Same	2.71	2	0.258
			TransCost_More	6.49	2	0.039
			TransCost_Less	0.71	2	0.702
What time do you leave home to go to work?	Transit-Oriented	Binary	DepartTime_pre6	8.43	2	0.015
			DepartTime_6to9	4.25	2	0.120
			DepartTime_9to12	0.60	2	0.741
			DepartTime_12to15	0.98	2	0.644
			DepartTime_15to18	1.64	2	0.441
			DepartTime_post18	0.40	2	0.818
How long does it take you to get to work?	Transit-Oriented	Ordinal	TransDuration_c	10.74	10	0.333
Is there social distancing: In the workplace?; In transport?	COVID-specific	Ordinal	Workplace_SocDist_c	13.33	8	0.101
	COVID-specific	Ordinal	Transport_SocDist_c	4.08	8	0.850
*Is there *PPE: In the workplace?; In transport?*	COVID-specific	Ordinal	Workplace_PPE_c	9.86	8	0.275
	COVID-specific	Ordinal	Transport_PPE_c	13.25	8	0.104
On average, how many hours do you work per day?	Demographic	Ordinal	WorkHours_pd_c	11.97	10	0.287
On average, how many days do you work per week?	Demographic	Ordinal	WorkDays_pw_c	17.60	10	0.128
How much do you earn per hour?	Demographic	Ordinal	Income_ph_c	33.17	16	0.007
Is this more, less, or the same as before the lockdown?	COVID-specific	Ordinal	IncomeChange_c	4.13	4	0.389
		Binary	IncomeChange_Same	1.32	2	0.516
			IncomeChange_More	0.43	2	0.807
			IncomeChange_Less	3.79	2	0.151
Are you a: Man; Woman?	Demographic	Binary	Gender_Female	6.36	2	0.042
As a woman, is your transport safer under lockdown, compared to before?	COVID-specific	Ordinal	TransSafety_c	9.43	4	0.051
		Binary	TransSafety_Same	2.25	2	0.325
			TransSafety_More	1.82	2	0.402
			TransSafety_Less	9.29	2	0.010
As a woman, is your family responsibility under lockdown affecting: Travelling time; Travelling cost; type of transport used?	COVID-specific	Binary	FamResp_TransDur	4.12	2	0.128
	COVID-specific	Binary	FamResp_TransCost	3.14	2	0.208
	COVID-specific	Binary	FamResp_TransMode	8.81	2	0.012
***Distance from PoR to PoW*	Spatial	*Cont.	ResComp_Distance	5.30	3	0.151
***Accessibility Index*	Spatial	*Cont.	AccessibilityIndex	7.76	3	0.050

**Non-questionnaire variables
*PPE – Personal Protective Equipment
*χ^2 – Chi-square statistic
*df – degrees of freedom
*Cont. - Continuous
*Pr – Probability

The probability value associated with the χ^2 statistic was used to test the null hypothesis that respective variables, generated from survey questions, are independent from employment type, the dependent variable. Probability values were assigned graduated shades of blue contingent on the strength of effect when compared across employment type categories, with darker shades of blue highlighting more prominent relationships.

Four variables displayed statistical significance of a relationship with employment type at a 1% level of significance, six variables at a 5% level of significance, and four at a 10% level of significance.

The variables encoded for income and gender were the most notable variables based on the body of research on key factors influencing precarious forms of employment (Cassim & Casale, 2018; Francis & Webster, 2019), with the variable encoded for income producing a significant p-value at a 1% level of significance, and the variable encoded for gender producing a significant p-value at a 5% level of significance.

To explore these relationships further, univariate multinomial logistic regression was performed, firstly run on 'Income_ph_c' denoting the ordinal variable for the question "How much do you earn per hour". The outcome of the regression indicated that both labour broker workers and contract workers display inverse (negative) relationships when compared to the base outcome group (permanent workers). The coefficient values for labour broker workers and contract workers were -0.41 and -0.32, respectively. Next, the relative risk ratio (RRR) of the regression was performed to identify the weighting of the relationships. The RRR for labour broker workers and contract workers were 0.66 and 0.73, respectively, suggesting an increase in income by one unit will cause the relative risk of being in the group of labour broker workers or contract workers to be influenced by a factor of 0.66 (95%CI: 0.52, 0.83) and 0.73 (95%CI: 0.54, 0.97) respectively in relation to the referent group. In context, there were one of eight optional income categories a respondent could have chosen. Therefore, an alternative explanation asserts a one unit increase, i.e., category increase, in income per hour is associated with a 34% decreased likelihood of falling in the category of a labour broker worker compared to falling in the category of a permanent worker. Likewise, a one unit increase in income will cause a 27% decreased likelihood for falling in the category of a contract worker as opposed to the likelihood of falling in the category of a permanent worker. The p-values for each scenario were <0.0001 and 0.030, respectively, indicating a significant parameter estimate at a 5% level of significance respectively.

The regression was then repeated to determine the relationship between labour broker workers and contract workers. This was achieved by changing the base outcome (referent) group to labour broker workers. The coefficient value for contract workers of .094 indicates a direct relationship between income and the likelihood of falling within a contract worker group. Again, RRR was performed to determine the weighting of the relationship, with the output indicating an RRR score of 1.10, suggesting the relative risk of falling into a contract worker group (as opposed to a labour broker worker group) would increase by a factor of 1.10 or 10% for every unit increase in income. This is a small factorial change comparatively and the p-value (0.56) indicates that the parameter estimate is not significant at a 5% level of significance.

Univariate multinomial logistic regression was then performed on the dichotomous variable coded for gender, 'Gender_Female', where 1 indicates female. The results indicated that both labour broker workers and contract workers display direct relationships when comparing the outcome to the referent group (permanent workers). The RRR comparing females to males for falling in the category of labour broker workers or contract workers increased by a factor of 2.67 and 3.34 respectively when compared to the referent group, suggesting a higher likelihood of females finding themselves in either group. Both of these outputs were statistically significant, with p-values of 0.02 and 0.04, respectively, compared to the referent group. When rerun, to perform a comparison between the labour broker worker group and the contract worker group, the RRR showed a 1.25 factor increase of the likelihood of females compared to males falling in the casual worker group compared to the labour broker group. However, this output was not statistically significant at a 5% level of significance.

Univariate multinomial logistic regression analysis was performed on all the remaining variables and is outlined in the proceeding sections of this chapter, and the appendices.

Having gained useful insight into the distinctive influence of each variable on the response variable - employment type, the prepared coded dataset was imported into ArcGIS Pro to perform advanced spatial statistical analysis. Here, exploratory regression was performed using several combinations of variables tried and tested in extracting possible regression models based on the response variable encoded "Permanent".

After processing multiple iterations of possible predictor variables and the creation of multiple models, three predictor variables were selected for; income (per day), female (gender), and company provided transport. These variables were then used to run a GLR, to determine a global model for the study area, with the results outlined in Figure 4.3. The GLR model, using income, gender, and company provided transport as predictor variables, accounted for 21.21% of the deviance explained, indicative of the model performance. The coefficients of the respective variables show that income and company provided transport exhibit direct relationships against the response variable, where the odds ratio implies the odds for being a permanent worker are 3.15 times greater for respondents making use of company provided transport. Likewise, the odds of being a permanent worker increase by 1.48 times for every 1 unit or R5 increase in income. Conversely, gender (female) exhibits an inverse relationship against the response variable, where the odds of being a permanent worker for females is 0.38 that of males. Each of the predictor variables were significant at a 5% level of significance, and using the Wald's Low and High values, which indicate the robustness of the odds ratio interpretation, income was found to be the most robust measure. The Variance Inflation Factor (VIF) values, which are indicators of multicollinearity, each approached a value of one, implying that none of the predictor variables were highly correlated with one another. The output also produced a confusion matrix representative of the model's predictive power using the input features as a test dataset, and indicated that the model predicted approximately 73% of the observed outcomes. Finally, a Joint Wald Statistics of 32.09 and respective p-value <0.0001 indicated a statistically significant model.

```
----------------------------------- Summary of GLR Results [Model Type: Binary (Logistic)] -----------------------------------
-------------------------------------------------------------------------------------------------------------------------------
       Variable Coefficient [a] StdError z-Statistic Probability [b] Odds Ratio [c] Wald's Low (95%) [d] Wald's High (95%) [d]  VIF [e]
      Intercept       -1,185798 0,537613   -2,205671       0,027407*       0,305502             0,106510              0,876274 --------
  TRANS_COMPANY        1,147086 0,510248    2,248096       0,024570*       3,149004             1,158354              8,560614 1,047884
    INCOME_PH_C        0,389619 0,108761    3,582346       0,000341*       1,476419             1,192972              1,827211 1,077681
GENDER_FEMALE_C       -0,966458 0,445936   -2,167255       0,030215*       0,380428             0,158739              0,911720 1,056041
-------------------------------------------------------------------------------------------------------------------------------

---------------------------------------- GLR Diagnostics -----------------------------------------
--------------------------------------------------------------------------------------------------
Input Features:                CWAO_Survey_PoR   Dependent Variable:                         PERMANENT
Number of Observations:                    111   Akaike's Information Criterion (AICc) [f]:  127,552959
# of observations equal to 1:               64   Deviance Explained [g]:                      0,212116
Joint Wald Statistic [h]:            32,085668   Prob(>chi-squared), (3) degrees of freedom:  0,000001*
--------------------------------------------------------------------------------------------------

Confusion Matrix
-----------------
        Predicted
            0     1
Actual 0   35    12
       1   18    46
-----------------
```

Figure 4.3 – Generalized Linear Regression (GLR) results output after exploratory analysis was performed to determine candidate variables for inclusion.

Additionally, the GLR tool generated a standardized residuals spatial layer representing the variation, by standard deviation, of predicted versus observed values, which was then used to detect spatial autocorrelation in the dataset. Table 4.3 summarises the test for spatial autocorrelation, providing the Moran's I statistic (-0.02), the z-score (-0.19), and the p-value (0.85), and is visually illustrated in the spatial autocorrelation report produced in ArcGIS Pro, included in Appendix B. Based on the spatial autocorrelation report, and concluding on the z-score, the null hypothesis was not rejected at a 5% level of significance signifying that the pattern of the residuals did not appear to differ significantly from random.

Table 4.3 – Summary statistics of the spatial autocorrelation measures performed on the standardized residuals of the Generalized Linear Regression model.

Spatial Autocorrelation Measure	***Output***
Moran's I	-0.024
z-score	-0.188
p-value	0.851

Satisfied with the absence of spatial autoregression in the GLR model output, a GWR was then performed to generate a local model, using the standardized residuals output layer from the GLR model as the input. The same set of predictor variables were used as input variables for the model, with the results of the model outlined in Figure 4.4. The significance of generating a GWR (local) model was shown by the increase in model fit and performance, signified by the deviance explained by the model, and highlighted the effect of spatial dynamics across the study area. The local GWR model was shown to account for 25.54% of the deviance explained, a 5.38 positive difference when compared to the global GLR. Selection of the best performing global and local models respectively highlights the importance of assessing relationships individually at a local scale, as it provides more predictive capability.

```
------------- Analysis Details ------------
Number of Features:                       111
Dependent Variable:                 PERMANENT
Explanatory Variables:          TRANS_COMPANY
                                  INCOME_PH_C
                                GENDER_FEMALE_C
Distance Band (Kilometers):           49,3592
-------------------------------------------

---------------------- Model Diagnostics ---------------------
Deviance explained by the global model (non-spatial):     0,2121
Deviance explained by the local model:                    0,2545
Deviance explained by the local model vs global model:    0,0538
AICc:                                                   132,6039
Sigma-Squared:                                            1,8181
Sigma-Squared MLE:                                        1,6558
Effective Degrees of Freedom:                           101,0907
--------------------------------------------------------------
```

***Figure 4.4** – Geographically Weighted Regression (GWR) results breakdown summarising the local GWR model performance, compared to the global Generalized Linear Regression model.*

4.3. Job Accessibility Index

In addressing objective 3, to create a job accessibility index using membership and survey details of precarious workers associated with the CWAO, an accessibility index was generated, using the GCRO QoL V survey combined with the CWAO membership and survey data, to better understand the dynamics of Gauteng's spatiality. Using the GCRO QoL V survey data, this objective aimed to address the limitations of inferring spatial dynamics from the relatively small sample size of the CWAO survey, and provided the basis for assessing whether underlying spatial dynamics from a global population had any influence on the spatial distribution of precarious workers across employment type. Using the concept of tessellation, a surface layer depicted the Net Wage After Commute (NWAC), Figure 4.5, generated using the GCRO QoL V dataset based on Venter and Cross' (2017) "accessibility envelopes" methodology and a respective job opportunity accessibility (Figure 4.6) surface, generated from the merged CWAO membership and survey data, to develop a global accessibility score for each areal unit.

The NWAC surface (Figure 4.5) demonstrates the complexity of spatial relationships and patterns within the GCR. Blue parcels highlight areas with a net wage after a commute of less than R3,000 per month, whilst a graduated yellow-red colour scheme was used to display NWAC surface values greater than R3,000. Low NWAC areas are most prominent towards the extremities of the province, however there are noticeable zones with low NWAC surface values concentrated more centrally within the province too. The majority of CWAO survey respondents, represented by the light-blue markers, reside within these zones. As described, there are two prominent clusters of workers' PoR, Tembisa and Katlehong, which consist predominantly of low NWAC scores. Three additional areas, labelled C, D, and E, were highlighted for comparative purposes based on prior knowledge of their demographics from the Gauteng Multi-dimensional Poverty Index (GMPI) developed by Mushongera, Zikhali, and Ngwenya (2017). Alexandra township, labelled C, is also characterised by low NWAC scores, with indication of a small group of workers residing in the township depicted by the brightness of the light-blue marker symbology.

The areas are characterised by comparatively high poverty index scores, with Alexandra representative of an impoverished township (GMPI >40%) and Tembisa and Katlehong representative of highly impoverished townships (GMPI 15-40%) (Mushongera, Zikhali & Ngwenya, 2017). Conversely, Sandton and Midrand, labelled D and E respectively, are characterised by a mix of high NWAC scores, and both represent areas of low poverty indices (GMPI <5%), with no workers residing in either area. The NWAC surface visualises the complexity of Gauteng's spatiality, whilst highlighting the correlation of workers' PoR to low NWAC scores for the majority of survey respondents.

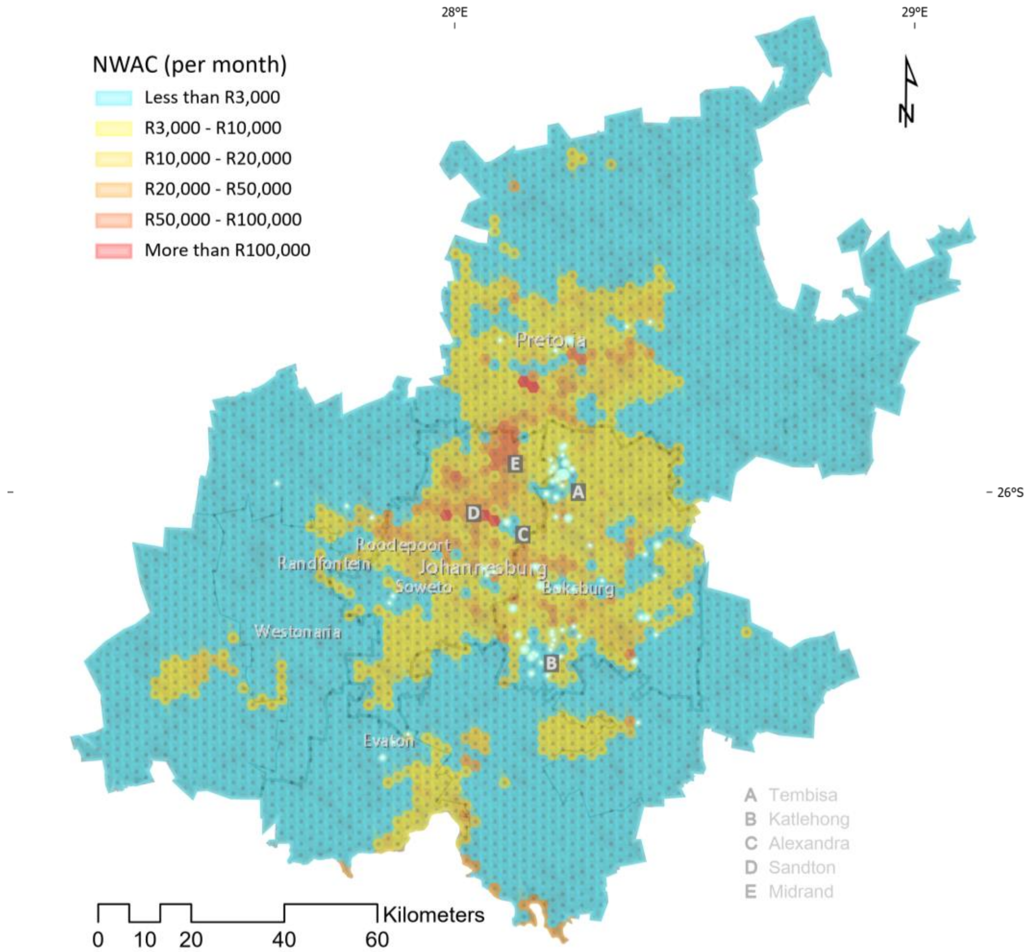


Figure 4.5 – Net Wage After Commute (NWAC) surface of respondents from the GCRO QoL 2017/2018 survey, with light-blue markers representing workers' place of residence.

The job opportunity accessibility surface (Figure 4.6) highlights the nature of the spatial make-up of job locations associated with precarious forms of employment across Gauteng. Job locations, determined from the combined CWAO membership and survey respondents, highlighted in white, are predominantly centrally aggregated within the province. A graduated green-red colour scheme was used to display the change in job opportunity accessibility, with colours on the green end of the scale indicative of higher accessibility, being advantageous, and colours tending toward the red end of the scale indicative of lower accessibility, being disadvantageous. Job opportunity accessibility is shown to wane the further one is from the job location epicenter, in a relatively concentric pattern. In contrast to the NWAC surface, the job opportunity accessibility surface is more uniform and displays a more predictive pattern. However, only distance-based measures have been incorporated into the analysis, which should be considered, yet, it provides a good visual comparison of areas of importance. Tembisa and Katlehong, accounting for the two predominant clusters of workers PoR, are in two distinct job opportunity accessibility categories, 20-25km, and 25-30km, respectively. Alexandra, which accounted for a smaller proportion of workers' PoR, is in the highest job opportunity accessibility category (<20km).

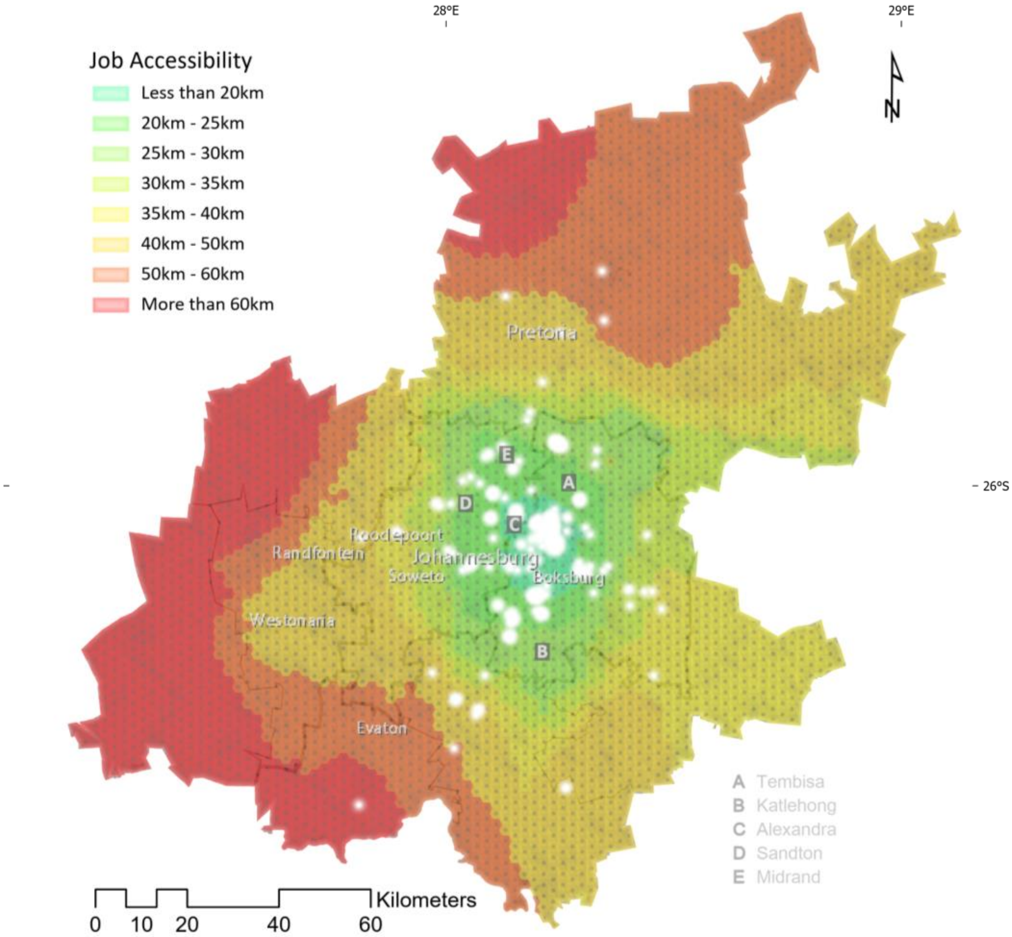
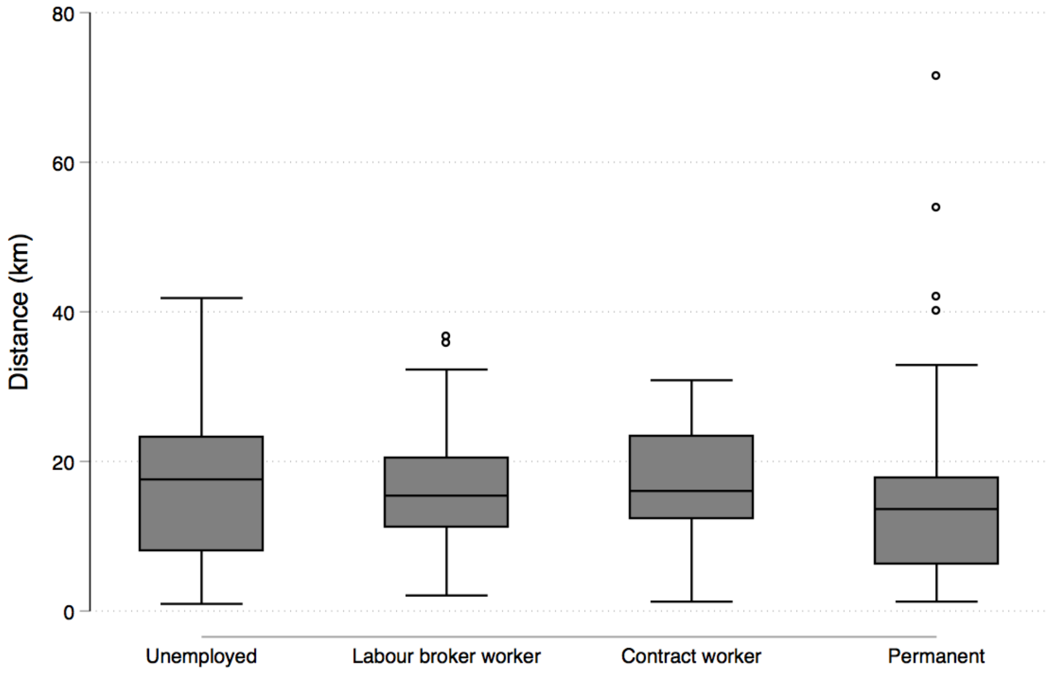


Figure 4.6 *– Job opportunity accessibility surface for workers associated with the CWAO, where white markers represent potential job locations.*

4.4. **Predictive Factors to Assess the Vulnerability of Precarious Workers**

Interestingly, key transport-related variables, namely the duration of transport, the cost of transport, and departure time, were not significant predictive factors in assessing the vulnerability of precarious workers by employment type. Hence, additional spatial variables were generated to further explore the effect of Gauteng's spatiality, most of which again did not show statistical significance as predictive factors. However, physically assessing the distribution of each variable across different employment types highlighted noteworthy differences.

For example, the generated continuous spatial measure depictive of the distance between PoR and PoW, calculated using Euclidean straight-line distance, displayed no significant effect as a predictor of employment type. However, on closer visual inspection of the distribution across employment types, minor trends emerged. Figure 4.7 below displays the box plots and the summary statistical tabulation for straight-line distances (coded 'ResComp_Distance') by Employment Type:




```
Summary for variables: ResComp_Distance
     by categories of: EmployType_c2 (Employment Type)
```

EmployType_c2	N	min	max	mean	p50	iqr
Unemployed	21	.9570987	41.8437	17.84195	17.59961	15.25231
Labour broker wo	32	2.083254	36.66368	16.64086	15.42848	9.182998
Contract worker	14	1.258084	30.85429	16.67267	16.05676	11.07138
Permanent	71	1.263797	71.47337	14.89493	13.63538	11.42895
Total	138	.9570987	71.47337	15.9286	14.61726	10.07753

Figure 4.7 *– Box plot and summary statistics tabulation for straight-line distances (km) between the place of residence and place of work, using CWAO survey results, by employment type.*

Given the non-normal distribution of the distances that workers reside from their PoW, the median and the interquartile range (IQR) were selected as representative measures of central tendency and variability, respectively. Interestingly the median distance for the unemployed group was 17.59km to their previous PoW, whereas the labour broker worker group and contract worker group had a more closely related median of 15.43km and 16.06km, respectively. Conversely, the permanent group had a median of 13.64km. The permanent group, representing the lowest median, however, had the highest maximum distance of 71.47km, along with additional outliers. Among the employed categories, the permanent group had the highest IQR (11.43), followed by the contract workers group (11.07) and then the labour broker workers group (9.18).

Assessing the land-use for workers' PoR using the SANLC dataset showed notable variability across employment type groups, even though the chi-square value (0.15), as reported in Table 4.2, indicated no significant distributional differences at a 10% significance level. The unemployed group had the highest proportion overall (81.82%) of respondents residing in formal settings as opposed to informal. Of the employed categories, the permanent group had the highest proportion (64.79%) of respondents residing in formal settings, followed by the contract worker group (64.29%) and labour broker worker group (51.52%).

The accessibility index, calculated from the interaction between the NWAC (Figure 4.5) surface and job opportunity accessibility (Figure 4.6) surface, was used to determine whether a measure that incorporates aspects of underlying demographic information, transport, and an individual's job accessibility can better inform vulnerability based on employment type. Interestingly, the accessibility index, calculated using the interaction terms from the generated variables for NWAC and job accessibility, scored a notably lower chi-square (0.05) statistic than the NWAC surface alone (0.02). The job opportunity accessibility surface scored a relatively high chi-square of (0.47), which was not surprising given evidence of spatial clustering of workers' PoR, with consideration of the employed distance-based measure.

Additional non-spatial variables were individually assessed for distributional differences across employment types, with noteworthy variables investigated further using univariate multinomial logistic regression to identify the interaction across different employment types (see Appendix D). These results were limited to the appendix due to consistent interpretations of the outcomes, which became apparent across multiple comparisons.

Overall, the results of the chi-square and univariate multinomial logistic regression indicated that only a select few variables showed significant distributional differences across employment categories, at a 5% level of significance. Specifically, the hypotheses for income, gender, company provided transport, and PPE use in transport, when comparing labour broker workers and contract workers to permanent workers, can be rejected based on significant p-values. However, this does not imply there is no relationship across non-significant variables, but merely there is no significant evidence to conclude that the relationship is significant.

Chapter 5: Discussion

The exploratory nature of this research entailed the adoption of an exploratory spatial data analysis (ESDA) approach, to build on the limited spatial research regarding the vulnerability of precarious workers in Gauteng's unique spatiality, considering the limited correlation of studies conducted beyond South Africa. This entailed the intersection of three critical components associated with the broader approach of exploratory data analysis, specifically data integration, ESDA, and confirmatory spatial data analysis (Anselin, Sridharan & Gholston, 2017), with the aim to highlight potential features of interest in the data and to facilitate the discovery process and progression of research in the field.

First, mapping the spatial distribution of precarious workers associated with the CWAO provided a useful graphic of the spatial distribution of workers in relation to place of residence (PoR), across Gauteng. Through visual inspection of the spatial distribution in Figure 4.1, clustering of PoW centrally within the bounds of the GCR was evident, whereas PoR were more widely dispersed. This translated into a pattern suggestive of shorter distances travelled for workers situated more centrally and predominantly longer distances for workers situated further from the centrally clustered PoW. A network of movement for workers travelling longer distances was identifiable to the west of the central PoW cluster, specifically Soweto and Roodepoort. The job opportunity accessibility model in Figure 4.6 highlighted these areas with comparatively lower-scoring accessibility to potential jobs, which could account because workers from these areas perform substantially longer trips to work.

Summary statistics of the straight-line distance between workers' PoR and PoW provided additional insights. The mean straight-line distance between workers' PoR and PoW calculated from the CWAO membership details (15.64 km) was not dissimilar when compared to the mean straight-line distance calculated from the broader GCRO QoL V survey (16.11 km). Culwick et al., (2015) utilized GCRO QoL III (2013) survey data and analyzed the trips to work by race and demonstrated the negligible difference of straight-line distances travelled for work by African and white respondents, approximately 14km. The slight increase in mean distance for the generalized population in the Culwick et al., (2015) study compared to the findings in this research report can most likely be attributed to increased urban sprawl between the GCRO study sampling periods. These findings imply there are neither significant racial nor class differences in the distances that workers reside in relation to PoW across the GCR. This challenges the notion of the inseparability between Apartheid spatial planning and the concept of spatial mismatch, where it is commonly assumed that the distance that workers reside in relation to PoW is highly stratified by race and class (Zenou, 2009; Jennings, 2015). However, it is important to note that neither analyses accounted for spatial impedance in transport networks, or associated travel impedance resulting from different transport modes. The Culwick et al., (2015) study briefly mentioned that there were still differences in reported travel times, where African respondents reported on average longer travel times than white respondents.

The negligible difference in results when comparing precarious workers to the broader GCRO QoL V survey was investigated further, where a comparative analysis was performed on workers occupying different forms of employment (Figure 4.7). As highlighted, the median and IQR were used as measures of central tendency and variability, respectively, given the small sample size of the CWAO survey and due to the non-normal distributions across groups. The most surprising finding was the high median (17.6) found in the unemployed group. One reason that could account for this is a possible change of residence after the onset of unemployment. Alternatively, it could signify a possible cause and effect, in line with concerns brought up by Schroeder (2019, pers. comm., 13 May) on the influence that travel duration relating to late coming has on the potential cause for being dismissed or retrenched. Other notable findings included the comparatively low median score and high IQR for permanent workers, with multiple outliers, suggestive of the potential financial means to reside closer to work or, conversely, to reside far from work (an important consideration of the NWAC calculation).

The next step in the process entailed analysing additional variables from the CWAO survey data to gain a better understanding of the factors, work transit and COVID-related, that influence the vulnerability of precarious workers. In developing an understanding of regression modelling, the outcome of the regression results section emphasizes the importance of defining ‘influence’ as a relationship exhibited between variables, rather than ‘influence’ implying causation. To stress this point, the example of income and gender being significant predictor variables of employment type does not imply that having a specific income will determine what employment type one has, nor gender as a determinant of the employment one holds. Rather, it emphasizes the concept of relationships that exist, and that can be expressed in odds and likelihoods. For example, a worker with a higher income increases their likelihood of falling within a permanent employment type, given the relationship between income and employment type, as depicted by the coefficient term.

Prominence was placed on the variables coded for income and gender due to the collection of literature covering these factors in relation to precarious work, at both local and global levels across comparable dynamic socio-economic settings (Albertyn, 2011; Johansson, 2018; Francis & Webster, 2019; Andrés-Rosales et al., 2019; Bhattacharya & Ray, 2021). The results of the chi-squared tests for independence highlighted that the distributions of both of these variables, income, and gender, were different across employment type categories at a 5% level of significance. This signified the existence of a relationship between employment type and income, and employment type and gender, respectively. Additional exploratory univariate regression highlighted a distinct relationship between permanent workers and labour broker workers, and between permanent workers and contract workers, in both scenarios. However, no significant distinction was evident when comparing labour broker workers to contract workers across income or gender.

The findings of this research depicting an inverse relationship between income and increasingly precarious forms of employment types has been well documented in research (Cassim & Casale, 2018; Francis & Webster, 2019; Andrés-Rosales et al., 2019; Choi et al., 2020). Unsurprisingly, this relationship was pronounced when comparing permanent employment to non-permanent forms of employment (labour broking and casual employment). On closer examination however, this finding raised an important consideration. Often not evident in literature is the actualisation of what different forms of employment entail within the broader categorisation of precarious work. Theron (2005) distinguishes how "casualisation" in casual employment and "externalisation" in labour broking are methods utilised by companies to exploit and gain control over workers, and do not entail significant differences in the work performed by workers across these groups and in relation to permanent workers working for the same company. Schroeder (2020, pers. comm., 20 May) confirms that workers often fall into different forms of employment, working the same job and expected to perform the same work, often not dependent on levels of expertise. This also applies to the variability across employment regarding the period of employment, where labour broker workers and contract workers are often longer-term workers under the pretense of the short-term nature of labour broker or contract work as a means of exploitation.

Conversely, research about the relationship of precarious work and gender is more contextual (Jacquemond & Breau, 2015; Cassim & Casale, 2018). Cassim & Casale (2018) demonstrated an increased proportion of male workers working in the labour broking sector when compared to females, adjusting for population dynamics, identified at a national scale using South African administrative data. Jacquemond & Breau (2015) conducted a regional study in France and demonstrated an increased likelihood of female workers being categorised in precarious forms of employment more broadly. The findings in this research depicted an increased likelihood of females being categorised in more precarious employment types, which was notably congruent with experiences highlighted by Schroeder (2020, pers. comm., 20 May). The findings in this research and the two examples emphasize the contextual nature of the relationship of precarious work and gender, yet the subtle differences in categorisation and analysis of different forms of employment makes comparison across these studies impractical.

Multinomial univariate regression analysis performed across additional variables of significance highlighted the trend in distinct differences between labour broker and permanent workers, and similarly between contract and permanent workers, but not so when comparing labour broker and contract workers. This was an important distinction when transforming the variable for employment type from categorical to binary to enable additional spatial analysis using a local GWR model.

Before addressing relationships at a local level, global trends were first identified through the creation of a global regression model. As highlighted, this necessitated additional exploratory regression analysis to determine a combination of variables accounting for the variations in employment type. Outlined in the output of the GLR, the variables coded for income, gender, and company provided transport were identified as the combination of variables that accounted for the most variation in employment type. Other notable combinations included the combination of income and gender with variables coded for social distancing in the workplace and PPE in transport, respectively.

Notable exclusion of variables displaying strong p-value significance in the chi-square test results include the variable coded for language, and the variables accounting for temporal changes. The variable coded for language (p=0.003) was not an intended question for analysis and therefore excluded from any potential regression models and interpretation. However, it provides a potential element for further analysis and supplementary research. Variables accounting for changes over time, such as the change in the cost of transport or the change in income pre- and post-lockdown, were likely not included in the regression model because of a low response rate, limiting the potential significance in relation to other variables.

A GWR model was then performed to identify the deviance explained by the independent variables, with the influence of spatial heterogeneity. 25.45% deviance was explained by the GWR model, and highlighted a substantial difference when compared to the deviance explained by the global (non-spatial) regression model (21.21%). The increased deviance explained by the GWR model highlights the importance of accounting for spatial heterogeneity, as emphasized by Chi and Zhu (2019). Additional outputs of the GWR model included residuals and raster layers as coefficients, however, these did not show visually discernible spatial relationships given the limitations of the dataset.

Following this, an NWAC and job accessibility index were developed to determine additional avenues for analysis in addressing the spatial landscape dynamics and their effect on employment groups within the CWAO. The creation of an NWAC surface highlighted interesting spatial patterns across the GCR, where unsurprisingly, the extremities of the province experienced predominantly low NWAC values, yet more centrally, a considerably more complex dynamic emerged. What became evident were areas of low NWAC values interspersed within areas of increasing NWAC scores, highlighting the spatial heterogeneity of the central GCR regarding NWAC. Overlaying the PoR shapefile generated from the survey respondents associated with the CWAO highlighted that the majority of workers reside within these low NWAC areas. Further, two clusters were visually apparent, revealing that the majority of the respondents reside in either Tembisa or Katlehong. The location of these settlements, when highlighted on the job accessibility surface, were in medium scoring areas of accessibility to potential workplaces. It highlights that the majority of workers in the study do not reside in areas highly accessible to potential PoW, but neither in areas with low accessibility.

The tentative outcomes of the accessibility index suggest there is no evident spatial relationship to conclude that distance-based accessibility informs on the categorisation of employment types. Given the clustering of job opportunities more centrally within the province, there is no suggestion that workers across employment types experience different (distance-based) accessibility scores. This was congruent with the NWAC surface, which emphasizes the complexity of the spatial distribution of workers across the GCR, with clusters emanating from two distinct townships, Tembisa and Katlehong. The associated chi-square statistic for the NWAC statistic shows significant yet variable distribution across employment types.

Addressing the spatial analyses performed, it is evident that Gauteng's spatiality is complex and requires more research to conclude on the intricacies and influence of spatial factors on precarious workers. However, clearer patterns emerged in the analysis of different forms of employment using non-spatial variables, where there was a trend of significant differences between labour broker workers and permanent workers and between contract workers and permanent workers, and no significant differences between labour broker workers and contract workers. This highlights a well-defined divide between non-permanent forms of employment and permanent employment, which was the basis for the binary categorisation for spatial analysis. However, minor but notable differences were still evident between labour broker workers and contract workers in agreement with the description of the vulnerability of these respective groups, which requires further investigation.

Chapter 6: Conclusion

The purpose of the analyses performed has been to address the broader aim of this research project, to better understand the transit-oriented economic and social impact of Gauteng's post-Apartheid spatiality on precarious workers, using statistical and GIS-based techniques. To accomplish this, exploratory spatial data analysis (ESDA) was performed to quantitatively examine the integrated forms of data using a systematic approach characteristic of ESDA. The intention of employing an ESDA approach was multi-faceted. First, the literature about precarious work and the vulnerability associated with different forms of employment is very limited in a South African context. Second, the post-Apartheid spatiality of Gauteng lends itself to spatial relationships that are unique and unexplored. In attempting to better understand the influence of Gauteng's complex and unique spatiality on precarious workers, this paper provides the groundworks for facilitating the discovery process and progression of research in the field. In developing this research further, it offers the potential to inform on important factors that may influence the associated vulnerability of precarious workers across different forms of employment. Defining the conditions that influence workers' level of precariousness provides the opportunity to implement practical solutions in advice, advocacy work, and organizing strategies, such as collective bargaining, to ensure workers' needs are addressed.

Addressing broader trends in performing ESDA, distinctions emerged when comparing variables across employment types. Most notably, significant differences were a recurring theme between permanent workers and labour broker workers, and between permanent workers and contract workers, when comparing the distribution of variables across these employment types. However, very few significant differences were evident when comparing the distribution of variables between labour broker workers and contract workers.

In concordance with ESDA reporting standards, the spatial distribution of workers associated with the CWAO across the GCR was analysed and shown to portray clustering of workers' places of residence (PoR) and workers' places of work (PoW), respectively. It was immediately evident that workers' PoR were more widely dispersed compared to PoW, which were more central within the GCR, and in closer proximity. Additional analysis performed on spatial distributions of survey respondents associated with the CWAO, showed notable patterns when analysing the NWAC surface, where workers were found to reside predominantly in two townships, Tembisa and Katlehong. The NWAC surface further highlighted the complexity of Gauteng's spatiality, where clusters of low NWAC values were evident more centrally within the bounds of medium and high NWAC areas, and visible correlation between respondents PoR and low NWAC areas. The creation of the accessibility index was however not found to show significant differences in the distribution across employment status. Yet, the individual outputs of the NWAC surface and job opportunity accessibility surface provided important visual identification of broader themes inherent in the spatial distribution of CWAO survey respondents.

The outcome of the global regression analysis, in a GLR, revealed that income, gender, and company provided transport could predict the status of employment. However, these variables, identified as the combination explaining the most variation, explained only 21% of the variation across the CWAO survey dataset, indicating relatively poor predictive capabilities of the model. A local (spatial) regression analysis, in a GWR, was then performed. The outcome of this analysis, using the same combination of variables, revealed the importance of accounting for spatial dynamics across the dataset, and revealed the spatial heterogeneity inherent in the data. A percentage change increase in model performance of 20% produced by the spatial model in contrast to the non-spatial model highlighted the importance of adopting spatially weighted variables in predicting employment status. Still, the predictive capability of the spatial model was relatively weak, indicating a large proportion of unexplained variability. Multiple potential predictor variables were introduced into the model, however, no combination of variables better predicted employment status. Four potential causes were identified as possible reasons for poor model predictive capability; the non-linear nature of the response and predictor variables, failing to identify key variables that would explain a sizeable proportion of the unexplained variability, the limited sample size, or the chance that the distributions of factors across employment status are not substantially discernable and exercise significant collinearity where multiple variables are selected.

The findings in this research project were founded on methods and techniques that can be further developed, by including additional factors for analysis, data sources, and more refined processes, to advance the understanding and interpretation of the outputs. As highlighted, this research nevertheless provides the groundworks for facilitating the discovery process and progression of research in the field. Besides providing the groundwork for future research in the field, this study has assisted the CWAO in centralising their membership data, to enable easy accessibility and usability of the data, which will aid in performing essential work functions and future analyses.

Chapter 7: Limitations and Recommendations

7.1. **Limitations of the Study**

Limitations of this study mainly concerned the accuracy of the measures generated through the creation of models and indices, and the limited research and data available on the subject, which limited the potential interpretation of the results. However, the ESDA approach taken in this paper provides a good basis for future research and potential avenues for comparative research about aspects of importance when addressing the transport-oriented influence of Gauteng's spatiality on precarious workers.

Four spatial variables of interest were generated using GIS techniques to aid the regression analysis and to better understand the spatial dynamics of workers in relation to places of work (PoW) across the GCR. This included the straight-line distance calculation that workers reside from their respective PoW, the extraction of land-use classification for survey respondents, and the creation of an accessibility index which constituted an NWAC surface and a job opportunity accessibility surface. The methods used for each have known limitations that ought to be acknowledged, as these limited the interpretability of results.

The straight-line distance calculation that workers reside from their respective PoW was generated to aid the analysis of the survey question about the transport duration of trips made to work, given the categorical nature of the responses. First, the measure between workers' PoR and PoW was defined using Euclidean straight-line distances, which research has shown differs from road network distances which tend to be substantially longer and are influenced by travel impedance factors (Phibbs & Luft, 1995; Culwick et al., 2015; Yang & Ye, 2018). However, it provided an important exploratory step in determining whether the distance workers reside from PoW correlates to the categorisation of workers' employment type.

The extraction of land-use classes to identify the residential areas that survey respondents reside raised two concerns. First, the locational accuracy of workers' PoR was limited to subplace and main-place in certain instances. Given the resolution, 20 meters, of the land-use dataset (SANLC) used in this study minor changes in location may have influenced the categorisation of land-use type. Second, the nature of the study meant that many workers reside in settlements, of which the spatial classification is highly contentious. In certain circumstances, these settlements can be inherently precarious and spatially fluid (Dovey & Kamalipour, 2017), making them difficult to define (Kamalipour, 2016). This combined with the limited accuracy of workers' PoR likely influenced the accuracy of the classification, and would require a more refined methodology to ensure increased classification precision.

For the creation of the NWAC and accessibility indices, numerous efforts were made to acquire routed networks, recently developed for the informally-run public transport networks of the GCR, developed by WhereIsMyTransport. However, given the perceived "value" of the dataset, the application request for use of the data was declined. Both indices were thus generated without incorporating a routable road network. Specifically, the accessibility scores extracted for each worker were generated from a measure that only incorporated distance-based calculations, thus resulting in relatively reduced accuracy. Again however, this still provided an important exploratory step towards gauging the transit-oriented impact of Gauteng's spatiality on precarious workers.

Regarding the regression outputs, the GLR and GWR models reported low explained deviation. This could have resulted from a range of different factors, as highlighted in the previous chapter. In addition, the outputs of the GWR model included residuals and coefficient raster layers, which did not show visually discernible spatial relationships given the limitations of the dataset, specifically the insufficient sample size compared to the study area.

Last, a critical aspect overlooked when developing the questionnaire was determining the time that an individual had been employed in their respective type of employment. By failing to incorporate this question, it limited the analysis to comparisons across a categorical scale (i.e., labour broker workers, contract workers, and permanents), in which the intra-category differences were potentially variable. To demonstrate this, the survey respondents specifying permanency could have recently acquired permanent status, through victories to gain permanency since joining the CWAO, thus the change to permanent status may have been very recent. The CWAO at the outset could have attracted already permanent workers dissatisfied with other union options, thus their permanent status could be an extensive period. Perhaps a combination of the two scenarios accounts for the proportion of permanent workers in the study. Likewise, the period of employment for labour broker workers and casual workers raises an important consideration. As discussed, labour broker workers and contract workers are often longer-term workers under the pretense of the short-term nature of labour broker or contract work as a means of exploitation. Without knowledge of the period of employment it becomes difficult to quantify the level of precariousness, and thus limits the possible interpretation of outputs.

7.2. **Recommendations for Further Research**

The scope of this project and exploratory nature of analysis raised numerous limitations, and considerations when interpreting the results. Thus, recommendations for future research predominantly concern the analytical methods employed, but also include data collection considerations.

As highlighted, overlooking the temporal aspect of employment limited analyses to comparisons across a categorical scale. Identifying the period of employment could offer additional insight into workers' employment and associated precariousness. Classification of precariousness on a continuous scale as a function of employment type could then be generated, which will offer additional avenues for analysis, with more predictable outcomes regarding regression analyses, given increased robustness when assessing continuous response variables (Ward & Gleditsch, 2018).

Analytically, an important distinction is the varying effect that individual variables reveal versus a combination of variables, which can be pronounced when performing spatial analyses. For example, the individual effect that transport cost, distance, and wages had on employment was different to the effect that a combination of these variables portrayed. Developing spatial regression models and indices, using NWAC and job accessibility, aimed to address this and revealed interesting spatial dynamics. Developing and enhancing methodologies and techniques used to calculate these indices by incorporating additional variables and data sources provides an opportunity to reveal important relationships within the data. One such enhancement would be to incorporate road networks into the NWAC and job accessibility models, which will improve the results and interpretation of the accessibility index.

Furthermore, identifying additional variables to incorporate into models will provide more robust outputs. For example, research has indicated that precarious work differs across age and level of education (Coupaud, 2017; Mai, 2017; Johannson, 2018) besides gender. Although not identified for analysis in this paper, incorporating additional variables such as age and level of education can be important factors to include in addressing Gauteng's unique spatiality and can assist in explaining spatial dynamics that influence precarious workers.

Addressing the limitations of this study by incorporating recommendations for future research will ensure the continued development of research in this field, in trying to dissect the intricate and complex relationships between Gauteng's unique spatiality and the influence on precarious workers.

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Appendix A

Casual Worker's Advice Office (CWAO) questionnaire (and translation)

"This survey will be used to understand work and transport conditions during lockdown. The results of the survey will be analysed and used to strengthen workers transport struggles, and will be shared with you (the workers). The responses you provide are confidential and will remain anonymous throughout the process of the survey. This survey is performed in partnership with a Master's student from the University of the Witwatersrand, who has the responsibility of performing analyses on the results for the purpose of research alone, and which will be made available for use by the CWAO."

Key:
E = English
Z = Zulu

E: Worker transport and work conditions during COVID-19 lockdown!
Z: Ezokuthutha zabasebenzi kanye nezimo zasemisebenzini ngesikhathi se-lockdown ye COVID-19

E: Comrades, please give us a few minutes to complete this survey
Z: Maqabane, ngicela niziphe imizuzwana yokuthi niphendule lemibuzo yalolu cwaningo.

E: This survey will be used to understand work and transport conditions during lockdown, and to see how this relates to conditions before lockdown. The responses you provide are confidential / the information we collect is confidential.
Z: Lolucwaningo luzosetshenziswa ukuthola ulwazi mayelana nezokuthutha zokuza emsebenzini (i-transport yokuza emsebenzini) kanye nezimo enisebenza ngaphansi kwazo emsebenzini njengoba kune-lockdown, nokuthi lezimo zinjani uma uzifanisa nezimo enanisebenza kuzo ngaphambi kokuba kubekhona i-lockdown. Izimpendulo zakho ziyimfihlo yakho okusho ukuthi angeke kwazeke ukuthi uwena onike lezimpendulo ozosinika zona. Ulwazi esizoluthola kulolucwaningo. Imiphumelo yalolucwaningo izokwabelwa abasebenzi ukuze bakwazi ukuthola amandla okulwisana nezinkinga ababhekene nazo emsebenzini.

Questionnaire:
E: Would you prefer to answer in English or Zulu?
Z: Ungathanda ukuphendula nge-English noma ngesiZulu

E: Are you currently employed?
- Yes
- No

Z: Kukhona lapho osebenza khona njengamanje?
- Yebo
- Cha

If answered no
E: When did you last work?

- 3 months ago
- 6 months ago
- 1 year ago
- 2 years ago
- 3 or more years ago

Z: Ugcine nini ukusebenza?

- Ezinyangeni ezintathu ezidlule
- Ezinyangeni eziyisithupha ezidlule
- Onyakeni owodwa odlule
- Eminyakeni emibili edlule
- Eminyakeni emithathu noma ngaphezulu edlule

E: Were you a:

- Permanent
- Labour broker worker
- Contract worker

Z: Ngesikhathi usebenza:

- Ubuqashwe ngokuphelele lapho obusebenza khona
- Ubuwumsebenzi we-labour broker
- Ubuwumsebenzi wenkontileka

E: In your last job, what company did you work for?

Z: Emsebenzini wakho odlule, ubusebenzela yiphi inkampani?

E: Where was your company located? (e.g. Germiston, Isando)

Z: Inkampani yakho beyikuphi nendawo kuqula

E: Why did you stop working?

- Dismissed
- Retrenched

Z: Wayekelani ukusebenza khona?

- Waxoshwa
- Wadilizwa

E: Do you have any form of income, currently?

You can select more than one

- UIF benefit
- SASA grant
- Casual work
- Recycling
- Selling
- Other

Z: Ikhona imali engenayo kuwe njengamanje?

Ungakhetha okungaphezulu kokukodwa

- Okuzuza kwi-UIF

Igranti yakwa-SASA

Imisebenzi eyamatoho

Ukucosha izinto ezisebenziseka kabusha (i-recycling)

Ukudayisa

Okunye okungekho kulokhu okubaliwe

E: Lastly, where do you live? (e.g. Township and section/extension)

Z: Okokugcina, uhlala kuphi? (Ilokishi kanye nesigodi/i-extension)

If answered yes

E: Where do you live? (e.g. Township and section/extension)

Z: Uhlala kuphi? (Ilokishi kanye nesigodi/i-extension)

E: What company do you work for?

Z: Usebenzela yiphi inkampani?

E: Where is your company located?

Z: Inkampani yakho ikuphi nendawo?

E: What type of transport are you using to get to work? (Whether company transport or public transport)

You can select more than one

Taxi

More than 1 taxi

Bus (e.g. Metrobus)

More than 1 bus

ReaVaya

Walking

Car

Lift Club

Train

Z: Usebenzisa hlobo luni lwe-transport ukuya emsebenzini

Ungakhetha okudlulile kokukodwa

Itekisi eyodwa

Amatekisi (Amatekisi axhumanisa uhambo lwami)

Ibhasi (isibonelo. I-Metrobus)

Amabhasi (uthatha ibhasi edlulile kweyondwa)

Usebenzisa i-Rea Vaya

Uhamba ngezinyawo

Uza ngemoto yakho

Unabantu abakugibelisa emotweni yabo

Uza ngesitimela

E: Is this the same as before the lockdown?

Yes

No

Z: Njengoba kuyi-lockdown usasebenzisa lokhu owawukusebenzisa ngaphambi kwe-lockdown ukuya emsebenzini?

Yebo

Cha

E: How much do you spend on work transport per day?

R0 - R10

R11 - R20

R21 - R30

R31 - R40

R41 - R50

R51 - R60

More than R60

Do not know

Z:Usebenzisa malini yokugibela uma uza emsebenzini ngosuku

Kusuka ku-R0 kuya ku-R10

Kusuka ku-R11 kuya ku-R20

Kusuka ku-R21 kuya ku-R30

Kusuka ku-R31 kuya ku-R40

Kusuka ku-R41 kuya ku-R50

Kusuka ku-R51 kuya Ku-60

Ngaphezulu kwa-R60

Angazi

E: Is this more, less, or the same as before the lockdown?

More

Less

The same

Z: Lemali oyisebenzisayo ingaphezulu, ingaphansi noma iyafana nemali owawuyisebenzisa ngaphambili kwe-lockdown?

Ingaphezilu

Ingaphansi

iyafana

E: What time do you leave home to go to work?

You can select more than one if you work different shifts

Before 6:00 (am)

Between 6:00 - 9:00 (am)

Between 9:00 - 12:00 (noon)

Between 12:00 - 15:00 (pm)

Between 15:00 - 18:00 (pm)

After 18:00 (pm)

Z: Usuka ngasiphi isikhathi ekhaya uma uya emsebenzini?

Ungakhetha okudlulile kokukodwa uma usebenza ama-shift ahlukile

Ngaphambili kwa-6:00 ekuseni

Phakathi kwa-6:00 no-9:00 ekuseni

Phakathi kwa-9:00 no-12:00 emini

Phakathi kwa-12:00 no-15:00 ntambama

Phakathi kwa-15:00 no-18:00 ntambama

Ngale kwa-18:00 ntambama

E: How long does it take you to get to work, from the time you leave home?

Less than 15 minutes

Between 16 and 30 minutes

Between 31 and 45 minutes

Between 46 and 60 minutes (1 hour)

Between 61 and 90 minutes

More than 90 minutes

Z: Kuthatha isikhathi esingakanani ukuthi ufike emsebenzini, kusuka esikhathini osuka ngaso ekhaya

Ngaphansi kwemizuzu eyi-15

Phakathi kwemizuzu eyi-16 nemizuzu eyi-30

Phakathi kwemizuzu eyi-31 nemizuzu eyi-45

Phakathi kwemizuzu eyi-46 nemizuzu eyi-60

Phakathi kwemizuzu eyi-61 nemizuzu eyi-90

Ngaphezulu kwemizuzu eyi-90

E: Is there social distancing:

In the workplace

In transport

Always

Often

Sometimes

Rarely

Never

Z: Kukhona ukuqhelelana nabanye abantu:

Ensebenzini

Kwezokuthutha (kwi-transport)

Ngaso sonke isikhathi

Isikhathi esiningi

Ngezinye izikhathi

Isikhathi esincane

Akwenzeki nhlobo

E: Are people using PPE (e.g. Sanitiser, face masks, gloves)

Z: Abantu bayazisebenzisa izinto zokuzivikela (Isibonelo. Ama-sanitiser, izimfonyo (ama-mask) kanye nama-gloves)

E: On average, how many hours do you work per day?

Z: isikhathi esiningi, usebenza amahora amangaki ngosuku?

E: On average, how many days do you work per week?

Z: Isikhathi esiningi, usebenza izinsuku ezingaki ngesonto?

E: How much do you earn per hour?

Z: Uhola malini ngehora?

E: Is this more, less, or the same as before the lockdown?

More

Less

The same

Z: Lokhu kungaphezulu, kungaphansi noma kuyafana nowawukuhola ngaphambi kwi-lockdown?

Kungaphezulu

Kungaphansi

Kuyafana

E: Are you a?

Woman

Man

Z: Ubulili bakho?

Isifazane

Isilisa

E: As a woman, is your transport safer under lockdown, compared to before lockdown?

Z: Njengoba ungmuntu wesifazane, ezokuthutha uzibona ziphephile ngaphansi kwe-lockdown, uma uqhathanisa nesikhathi sangaphambili kwe-lockdown?

E: As a woman, is your family responsibility under lockdown affecting:

Travelling time

Travelling cost

Type of transport used

Z: Njengoba ungumuntu wesifazane, izibopho zakho zasemndenini ngaphansi kwe-lockdown zinamuphi umthelelo:

Esikhathini osisebenzisayo ukuya emsebenzini

Emalilini oyikhokhayo uma uya emsebenzini

Kuhlobo lwe-transport oyisebenzisayo uma uya emsebenzini

Appendix B

Spatial autocorrelation report produced in ArcGIS Pro, Figure A.1, summarizing the spatial autocorrelation outputs based on the standardized residuals produced by the GLR model. The z-score (-0.19) signified that the spatial pattern of the standardized residuals was not significantly different than random, consistent with the Moran's I (-0.02) value tending towards zero signifying random spatial pattern.

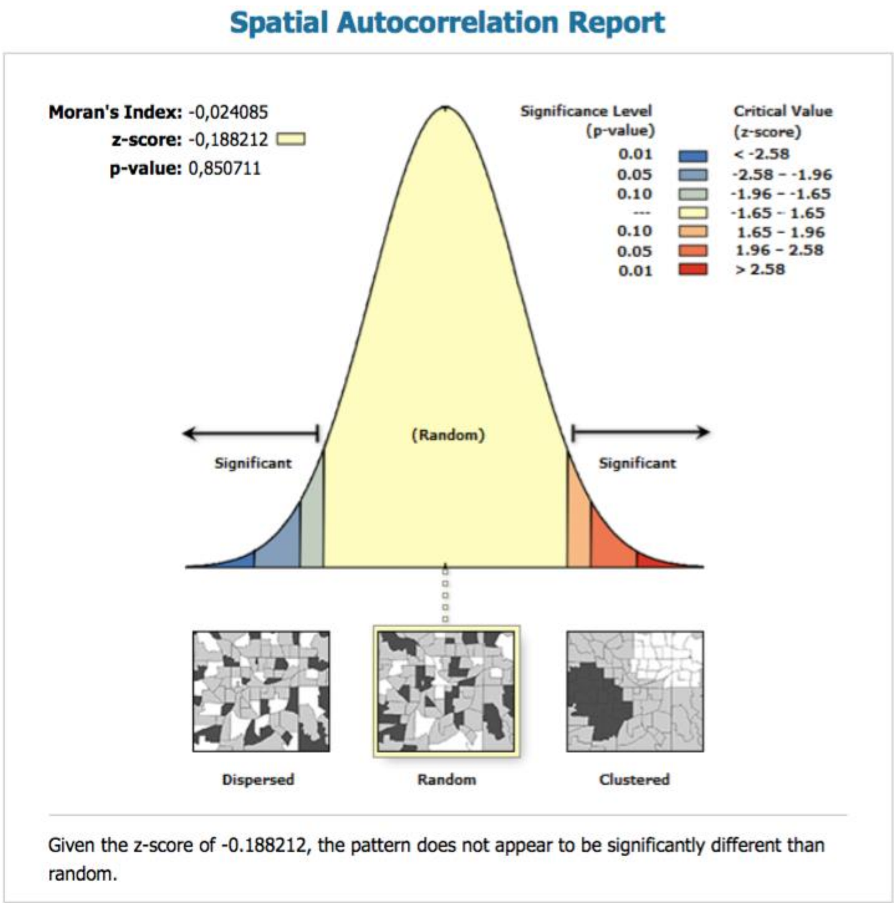

Figure A.1 *– Spatial autocorrelation report providing a measure of spatial autocorrelation present in the standardized residuals output from the Generalized Linear Regression model.*

Appendix C

A comparison between the CWAO membership data and the GCRO QoL V survey data was performed using an independent t-test. For this, an f-test which demonstrates whether the variance of two populations from which the samples have been drawn is equal or not (Rayat, 2018) was first performed to satisfy the assumptions of an independent t-test. The independent t-test was then used to compare the means of the same variable across two groups, assuming equal variances.

Figure A.2 provides a breakdown of the f- and t-tests respectively, in which the f-test fails to reject the null hypothesis that the variance is the same given P(f) = 0.17, thus concluding in favour of the alternative hypotheses stating there is insufficient evidence to show that the variance is different, at a 5% significance level. The independent group t-test again failed to reject the null hypothesis given P(t) = 0.30, thus concluding in favour of the alternative hypothesis stating there is insufficient evidence to show that the two groups differ from 0, at a 5% significance level.

```
Variance ratio test
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	1,700	15.63563	.3464987	14.28651	14.95602	16.31524
1	1,972	16.11268	.3114965	13.83269	15.50179	16.72358
combined	3,672	15.89183	.2317722	14.04471	15.43741	16.34624

```
    ratio = sd(0) / sd(1)                                 f =   1.0667
Ho: ratio = 1                          degrees of freedom = 1699, 1971

    Ha: ratio < 1             Ha: ratio != 1             Ha: ratio > 1
  Pr(F < f) = 0.9164      2*Pr(F > f) = 0.1673        Pr(F > f) = 0.0836
```

```
Two-sample t test with equal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	1,700	15.63563	.3464987	14.28651	14.95602	16.31524
1	1,972	16.11268	.3114965	13.83269	15.50179	16.72358
combined	3,672	15.89183	.2317722	14.04471	15.43741	16.34624
diff		-.4770542	.464818		-1.388381	.4342728

```
    diff = mean(0) - mean(1)                                t =  -1.0263
Ho: diff = 0                                degrees of freedom =     3670

    Ha: diff < 0               Ha: diff != 0               Ha: diff > 0
 Pr(T < t) = 0.1524      Pr(|T| > |t|) = 0.3048         Pr(T > t) = 0.8476
```

Figure A.2 *- Variance ratio test and independent group t-test to assess the comparison of means.*

Appendix D

Additional variables of interest, outlined in the chi-square table (Table 4.2), which form important consideration for future research were also assessed. The process for evaluating the null hypothesis followed a stepped procedure, by determining the level of dependency at decreasing levels of significance. In addition, the RRR were produced to provide a measure of association, to better understand the relationship between type of employment and the respective variables of interest, despite the level of significance. The outputs of a selection of variables of importance, based on prior assumptions, are briefly summarized for reference.

Importantly, all probability values across transport duration and transport cost were not significant at a 5% significance level, as highlighted in the chi-square table (Table 4.2). Nonetheless, the RRR for a unit increase in transport duration was 1.16 and 0.91 for labour broker workers and contract workers, respectively, compared to the referent group. The RRR for a unit increase in transport duration was 0.78 when the labour broker worker group was set as the referent group.

Similarly, this outcome when repeated for reporting the RRR for a unit increase in transport cost showed a factor increase of 1.01 and 0.96 for labour broker workers and contract workers, respectively, compared to the referent group. The RRR for a unit increase in transport cost was 0.95 when the labour broker worker group was set to the referent group.

Likewise, all probability values across transport departure time were not significant at a 5% significance level. Nonetheless, the RRR for a unit increase in transport departure time was 0.89 and 1.08 for labour broker workers and contract workers, respectively, compared to the referent group. The RRR for a unit increase in transport departure time was 1.22 when the labour broker worker group was set to the referent group.

In addition, the outcome of the regression for the ordinal variable of working hours per day indicates that both labour broker workers and contract workers display inverse (negative) relationships when compared to the base outcome group (permanent workers). A one unit increase in working hours per day is associated with a decreased likelihood of workers falling in labour broker and contract worker categories compared to the likelihood of falling in a permanent category. However, this finding is not significant given p-values of 0.55 and 0.61 respectively (group 1 and 2). This is the case as well when comparing labour broker workers to contract workers, with a negative relationship when labour broker workers are set as the referent group. This correlates to a decreased likelihood of workers falling in contract categories with a unit increase in working hours per day. Interestingly, all coefficients and RRR are centred close to 1. This combined with non-significant p-values suggest an equal distribution across the employment type groups respectively. This is shown in the proportion breakdown of the cross tabulation between working hours per day and employment type.

Likewise, working days per week indicates that both labour broker workers and contract workers display inverse (negative) relationships compared to the base outcome group (permanent workers). A one unit increase in working hours per day is associated with a decreased likelihood of workers falling in labour broker and contract worker categories compared to the likelihood of falling in a permanent category.