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Shadows of Extraction: Heat-Related Risk for Marginalised Populations

Name: Jonathan Melamdowitz

Supervisor: Jaap Rozema

Specialisation: Urban Environments, Sustainability, and Climate Change

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Summary

The Earth's climate is changing, and its ecological life-support systems are being compromised. Climate change now represents the single largest threat to population health, both as a direct cause of health conditions, and through secondary effects of climate change exacerbating population health concerns and diseases. Increasing temperatures represent one of the most pressing climate-related health *Risks*, particularly within Global South cities.

Through the case study of Johannesburg, this thesis investigates relationships between the distribution of urban vegetation, and heat-related health risks for marginalised sociodemographic populations. The study uses a combination of spatial and statistical modelling and to analyse heat-related *risk*, conceptualised by the Intergovernmental Panel on Climate Change's as the combined impact of *Hazards*, *Exposure*, and *Vulnerability*.

This study focuses on the role of vegetation in determining degrees of *Exposure* to heat experienced by marginalised populations, and thus increasing *Risk*. The study goes on to investigate whether marginalised populations are also more vulnerable to the adverse effects of heat. As *Vulnerability* represents a second component of *risk*, this would further amplify heat-related *Risk* for marginalised populations. The study concludes with a summary map showing the extent of correlation between marginalisation, low vegetation levels, increased heat *Rxposure*, and increased *Vulnerability*, and thus outsized *Risk* when compared to less marginalised populations.

The thesis emphasises the importance of targeted spatial interventions that address the equitable distribution of urban vegetation, nature-based solutions, and green infrastructure to address interconnected and systems social and climate challenges. It also underscores the importance of understanding human and environmental health and wellbeing as fundamentally interconnected, promoting an approach to urban development that targets mutually reinforcing social and environmental justice.

Summary of Findings

1. Vegetation levels are a significant predictor of Heat Exposure, demonstrating the applicability of nature-based solutions in addressing heat-related health risk.
2. Marginalised sociodemographic populations experience increased heat-related risk, due to the increased heat exposure that results from unequal distribution of vegetation.
3. Marginalised sociodemographic populations are also more vulnerable to the adverse effects of heat exposure, further amplifying heat-related risk.
4. While vegetation plays an important role in determining heat exposure, the allocation of park space has little effect in determining heat exposure. These findings provide valuable insights for policymakers and planners, emphasising the importance of maintenance and care for ecosystems rather than merely technocratic planning of park spaces.

Keywords

Planetary Health; Heat; Risk; Exposure; Vulnerability; Social Justice; Environmental Justice; Nature-based Solutions

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Foreword

Climate change represents the single greatest threat to human health and wellbeing. Following the global and multilateral response to the COVID-19 pandemic as a critical health risk – bringing the world’s economy to a standstill – one may ask, what if climate change were to be confronted with equal gravity? This thesis project lays the groundwork for such explorations, investigating the disproportionate climate risks faced by already-marginalised populations who, although bearing little responsibility for the climate crisis, are most affected by its consequences. The project’s emphasis on the role of vegetation distribution in the creation of risk for marginalised populations not only serves to guide policymakers and planners on the importance of targeted, equitable, and just urban interventions and care for ecological assets, but also to demonstrate the immense potential for Nature-based Solutions to address heat-related climate risks, while providing a range of additional benefits for both humans and the biosphere.

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Abbreviations

Abbreviation	Full form
BMJ	British Medical Journal
DV	Dependent Variable
G*	Getis-ord
GCRO	Gauteng City Region Observatory
GDP	Gross Domestic Product
GI	Green Infrastructure
HDI	Human Development Index
HIV	Human Immunodeficiency Virus
IHS	Institute for Housing and Urban Development Studies
IV	Independent Variable
NbS	Nature-based Solution
OLS	Ordinary Least Squares
PHQ2	Patient Health Questionnaire-2
NDVI	Normalised Difference Vegetation Index
IPCC	Intergovernmental Panel on Climate Change
LST	Land Surface Temperature
NDVI	Normalised Difference Vegetation Index
QOLS	Quality of Life Survey
SEM	Spatial Error Model
TB	Tuberculosis
UHI	Urban Heat Island
UHII	Urban Heat Island Intensity

1. Introduction

1.1 Background

Climate Change and Urbanisation

Anthropogenic activity has fundamentally altered the Earth's climate, with significant adverse effects on its life-support systems. In the period 2011-2020, global surface temperature has increased by 1.1°C above pre-industrial levels as a direct consequence of global greenhouse gas emissions – and this figure is expected to continue rising (Lee et al., 2024). Temperature regulation represents a critical component of the planet's life-support systems, affecting interconnected health of both natural and human systems (Kjellén & Virgin, 2009). Human health and wellbeing is fundamentally dependent on the Earth's life-protecting ecological systems, and temperature increases associated with the degradation of these systems disproportionately affects “those already vulnerable, poor, and marginalised” (Rockström et al., 2023, p.105). These effects are both direct – through the physical *Exposure* to high temperatures – and indirect, with global warming's systemic impacts on the biosphere and increased risk associated with long-term shocks and short-term stresses (Steffen et al., 2015).

Additionally, patterns of urbanisation multiply threats to the Earth's life-support systems. Unequal and unjust urban development compound the adverse impacts of urbanisation on ecological systems, while amplifying the consequences of this systemic collapse for marginalised populations (Dodman et al., 2023; Li et al., 2022). Despite the citation of various forecasts and metrics, there is widespread consensus on the phenomenon of exponentially increasing rates of urbanisation globally, and low-income countries having far higher rates than high-income counterparts (UN HABITAT, 2022). There is similar agreement on the concentration of biosphere-affecting anthropogenic activities within urban areas (Steffen et al., 2015; Theodorou, 2022), and the disproportionate experience of adverse effects from climate change, particularly for the most vulnerable residents within urban areas (Dodman et al., 2023).

Heat Exposure and Vegetation in Cities

Increasing temperatures represent a primary example of anthropogenically catalysed climate-related *Hazards* that are concentrated within urban areas, due to the Urban Heat Island (UHI) effect. UHI describes the phenomena of urban areas experiencing increased temperatures at a greater relative intensity, due to the large amount of solar radiation absorbed and re-radiated by materials used to construct traditional urban infrastructure, such as concrete and asphalt (Phelan et al., 2015). Heat exposure is a significant health risk, and is garnering increasing attention within medical research, with the *British Medical Journal* reporting on increasing rates of heat-related morbidity, as well as the exacerbating effects of heat *Exposure* on the severity of pre-existing non-communicable diseases, which represent factors that increased the *Vulnerability* to negative effects of heat exposure (Romanello et al., 2023).

Localised Urban Heat Island Intensity (UHII) – or the localised temperature increase resulting from urban infrastructure – is widely recognised to be inversely related to the presence of healthy vegetation, which provides cooling through transpiration, shading, and displacement of materials that absorb and re-radiate heat (Han et al., 2023; Oke, 1989; Oliveira et al., 2011). The mitigation of heat exposure through such nature-based solutions has important benefits for health outcomes, reducing heat-related morbidities and the cascading impacts of heat exposure for co-morbidities, while also providing additional co-benefits for human and ecological health (Romanello et al., 2023). However, heat-mitigating vegetation is often unequally distributed within urban environments, resulting in uneven spatial distribution of heat exposure for populations that inhabit areas with lower levels of vegetation (Klopfer & Pfeiffer, 2023).

Distribution of Risk

Understanding the systemic and interconnected nature of Risk associated with climate change and the destruction of the Earth’s biosphere is critical to the effective and targeted interventions, across strategic urban planning, policymaking, and financing of urban interventions. Heat-related *Risk* within urban areas is the product of three ‘components’ of *Risk* – *Hazards*, *Exposure*, and *Vulnerability* – which represent the dynamic and interconnected relationships between social and ecological systems (Calvin et al., 2023; Dodman et al., 2023). While the heat *Hazards* are already present within globally (*figure 1*), particularly within urban environments, and are predicted to increase further (Romanello et al., 2023; Souverijns et al., 2022), *Vulnerability* and *Exposure* within urban areas are dynamic and frequently unevenly distributed along sociodemographic lines, with poor and marginalised populations experiencing greater *Exposure* (in part as a result of having reduced access to temperature-regulating vegetation), and increased *Vulnerability* to its effects, due to factors such as age, higher prevalence of co-morbidities and reduced access to health insurance. Impacts of urbanisation and the fabric of urban development on climate-related risks play out across multiple timescales, with *longue durée* and shorter-term social and urban trends interacting to create and perpetuate the production of increased risk for marginalised populations.

1.2 Case Study: Johannesburg

The growth of Johannesburg as the urban economic centre of Southern Africa provides a high-resolution example of the relationships between unequal and segregated urbanisation, access to green spaces and vegetation, heat *Exposure*, and *Risk* that result from dynamic relationships between climate change and sociodemographic status. The city’s origins as a mining town were underpinned by colonial imaginaries of both mineral resources and non-Western human labour as commodified, extractable resources. Lindsay Blaire-Howe describes how black miners and industrial workers were forced to live within “*sacrifice zones*” – peripheral urban spaces situated close to environmentally degraded and polluted sites of extraction – justified as being necessary to fuel processes of urbanisation and representational of “a nexus between the environmental damage, urbanisation processes, and socio-spatial inequality” (Blaire Howe, 2022). Racially segregated urban planning was further formalised during the first half of the Twentieth Century, ironically justified by urban health policies (Smit & Parnell, 2012) and later under the apartheid regime as “an unparalleled example of state-directed socio-spatial structuring” (Maharaj, 2020) which continues to define spatial inequality within the city (Ballard & Hamann, 2021; Totaforti, 2020).

These manifestations of segregated urban development have created and perpetuated conditions of unevenly distributed vegetation across the city, concentrated within wealthier, mostly white neighbourhoods, intensifying the impact of UHIs on already marginalised and vulnerable populations – exacerbating socio-economic, health, and wellbeing inequalities (Götz & Schäffler, 2015). While Johannesburg’s case of formalised spatial segregation is relatively unique, it is nevertheless representational of global trends of unequally distributed urban vegetation, and the consequences of ontological distinctions between human and ecological systems within colonial narratives of development (Chen, 2024; Klopfer & Pfeiffer, 2023; Kureethadam, 2017; Pawlyn & Ichioka, 2022).

1.3 Problem Statement

Ontological distinctions between human and ecological systems represent fundamental tenets that underpin social, economic, and political hegemonies of growth and development on a finite planet – foundational principles that have catalysed the conditions that give rise to already-present climate polycrises (Pawlyn & Ichioka, 2022). However, the inherent interconnectedness of social-ecological systems is increasingly evident within context of anthropogenic climate change, as demonstrated by increasing attention to the concept of *planetary health* – describing the dependence of human health and wellbeing on a well-functioning and flourishing biosphere and the Earth’s life-support systems.

While systemic interdependence and interrelatedness of social and ecological wellbeing and vulnerability is gaining increasing traction in academia and policymaking, critical gaps remain within both the understanding of how these interactions produce increased climate-related risks for socially marginalised urban populations. This is especially the case within urban systems which are already inherently unequal – conditions which, as in the case of Johannesburg, can be traced to the same colonial ontological distinctions which have given rise to the climate polycrisis.

1.4 Research Objectives and Hypothesis

This thesis explores the production of *Risk* as a dynamic interaction within complex and interdependent social-ecological systems. This research study aims to enhance understanding of the dynamics through which socio-spatial inequality and climate change result in disproportionate *Risk* for marginalised populations. The study assesses whether the uneven and unequal spatial distribution of vegetation within Johannesburg results in increased heat *Exposure* for *Marginalised Sociodemographic Populations*, and whether this intersects with increased *Vulnerability*, thereby amplify heat-related *Risk*. In doing so, it highlights the requirement for equitable and integrated social and ecological urban planning and policymaking strategies that address the needs of the most vulnerable populations.

As a result, the following hypothesis is presented:

Marginalised sociodemographic populations in Johannesburg experience increased risk associated with the adverse effects of heat, as the unequal spatial distribution of vegetation results in greater levels of exposure for these groups, while also being more vulnerable to the adverse effects of heat exposure.

Under this hypothesis, no claim is made for a direct causal link between marginalisation and heat-related *Risk*. Rather it claims that marginalised sociodemographic populations tend to experience increased heat-related *Risk* due to their living in areas with reduced vegetation levels, and hence increased temperatures, and increased heat *Exposure*. Similarly, it also claims that marginalised populations tend to experience higher *Risk* due to their having increased levels of *Vulnerability*.

1.5 Research Questions

The study is led by a primary research question pertaining to the production of *Risk* for marginalised populations in Johannesburg, as a result of their experiencing increased *Exposure* to heat due to uneven and unequal distributions of vegetation. In order to identify the relationships between marginalised populations and heat-related *Risk*, the research sub-questions address various causal and correlated relationships that produce disproportionate *Risk*, including the role of vegetation in reducing *Exposure*, and whether more exposed populations are also more vulnerable to the adverse impacts of heat *Exposure*.

Research Question:

To what extent do marginalised sociodemographic populations experience aggravated heat risk as a result of the uneven and unequal spatial distribution of vegetation in Johannesburg?

Sub-Questions:

1. Does the spatial distribution of vegetation affect Land-Surface Temperature (*LST*), as a proxy for local heat exposure?
2. Does the unequal distribution of vegetation increase heat exposure for marginalised sociodemographic populations within Johannesburg?
3. Are marginalised sociodemographic populations, more vulnerable to the adverse effects of heat exposure in Johannesburg?
4. Do increased heat-exposure and vulnerability intersect to produce outsized heat-related risk among socio-spatially marginalised populations within Johannesburg?

1.6 Significance of the Study

This research aims to demonstrate the outsized *Risk* to heat experienced by marginalised populations in Johannesburg, by demonstrating that the uneven distribution of vegetation results in increased *Exposure* for these populations, and that they are also more vulnerable to

the ill-effects of heat. In doing so, the research presents significant implications for policymakers and planners, both within Johannesburg and beyond, identifying the need for targeted interventions that address both the social and environmental determinants of *Risk*, and informing the implementation of climate-resilience strategies that prioritise the needs of vulnerable populations.

At the same time, the findings suggest that strategic investments in nature-based approaches to tackling heat *Exposure* within historically disadvantaged areas can achieve outsized returns for mutual human and ecological wellbeing – reducing heat *Risk* and alleviating the burden of heat-related health conditions on healthcare systems, improving overall quality of life, and economic activity, while promoting flourishing urban ecological systems. While not addressed specifically within this paper, the research lays the foundation for future studies to explore the potential for ‘counterfactual reporting’ on the impact of both mitigation and resilience-building interventions by quantifying the potential benefits and savings associated with reducing climate-related population health risks – reframing the impact accounting and evaluation for social and environmental action.

In addition to the immediate implications for policymakers and planners, this study provides an empirical contribution to a growing body of discourse on the interconnectedness of ecological and human health. It challenges the hegemonic, anthropocentric narratives of growth and development through extraction and destruction of the biosphere that underpin interconnected climate and social polycrises. This highlights the need for eco-centric paradigm shifts in planning and policymaking that recognise human and ecological flourishing as inherently interdependent and inseparable.

1.7 Scope and Limitations

While the scope of the Johannesburg case study is clearly defined, within the context of the city’s unique history of segregated urban development, it is nevertheless reflective of wider trends of uneven and unequal urban development, and distribution of climate risk (Dodman et al., 2023; Satterthwaite et al., 2020; UN Population Division, 2018). Specifically, the study addresses the increased levels of *Risk* experienced by marginalised sociodemographic populations, by assessing the role of vegetation distribution in reducing heat *Exposure* for populations who are also more vulnerable to the negative impacts of heat. The study employs a quantitative and spatial analysis of secondary data, to examine dynamics of heat *Exposure* and *Vulnerability* for marginalised socio-demographic populations.

Limitations

1. Case Study specificity

While the case study of Johannesburg is representative of wider global trends, specifically within the Global South, its unique history of formalised segregated urban development – initially as a mining town and later under the apartheid regime – have fundamentally shaped the specific spatial nature of socio-ecological inequality. These context-specific dynamics should be considered within the generalisation of the study’s findings to other urban contexts.

2. Temporal of Limitations Secondary Data Used

This study makes use of secondary data, collected during three distinct periods. The aggregation of this data may present some inherent accuracy limitations, however within the context of *longue durée* urban trends, these are not foreseen to have significant effects for the findings of the study. South African National Census (2011) is selected as the most up-to-date and comprehensive study at the time of writing, due to substantial issues pertaining to the reliability of the more recent 2022 national census. Where possible, the Gauteng City Region Observatory (GCRO) Quality of Life Survey (2020/21) is used to cross-reference the efficacy of the census data. The Quality of Life Survey (QOLS) is also used as a source for sociodemographic data within Johannesburg, where census data is insufficient. As a result, there is a ten-year difference between the census and QOLS data used. In order to mediate this difference, climate and vegetation data from the midpoint of this period – the summer of 2016/2016 is selected.

The analysis of heat *Exposure* and vegetation from a limited sample period produces an addition potential temporal limitation, as it does not inherently capture longer-term patterns of heat *Exposure* and vegetation cover. However, this period is chosen for its representation of a particularly hot summer, with little precipitation and cloud cover – therefore increasing the accuracy and clarity of satellite imagery. The data has been compared with longer-term retrospective and prediction data for the area of study, and deemed to be sufficiently representative (Souwerijns et al., 2022).

3. Selection of Indicators

NDVI and LST

The use of *NDVI* and *LST* as proxies for vegetation coverage and heat *Exposure* represents a widely accepted research convention. However, the 30x30m resolution of Landsat 8 satellite imagery prevents more fine-grain local analysis of these factors. Further the use of *LST* as a proxy for heat *Exposure* is inherently limited by its measurement of the temperature of the surface, rather than ambient air temperature – therefore disregarding confounding factors such as wind direction and speed. However, such data is currently unavailable at this scale within the study area, requiring expensive and time-consuming data collection processes. As both *NDVI* and *LST* represent commonly accepted measures for vegetation coverage and heat *Exposure*, including by the Lancet medical journal, these limitations are not deemed to have a significant impact on the study within the academic fields in which it is located.

Vulnerability

This study focuses on specific measures for inherent and generalisable vulnerabilities to extreme temperatures derived from medical research. However, *Vulnerability* is often mediated by localised actions, strategies, and behaviours that increase adaptive capacity and resilience. While these factors are beyond the scope of this study, they represent an important line of research and topic of further study.

4. Ward-Level Analysis

The aggregation of this data at ward-level – the scale of analysis used for both the 2011 National Census and QOLS 2020/12 – in order to examine relationships between heat, vegetation, and sociodemographic data. This scale may neglect more nuanced variations within the wards. However, the delineation of wards is nevertheless the result of historic patterns of segregated urbanisation, and does not represent an entirely arbitrary unit of analysis as it is inherently related to *longue durée* urban development patterns.

1.7 Thesis Structure

This study is comprised of five chapters. Chapter 1 – the introduction – provides a background to the thematic and contextual subject matter of the thesis, as well as an outline of the research motivations, objectives, and questions. Chapter 2 presents a literature review that identifies existing theory on climate change and heat in cities, the role of vegetation in mitigating heat *Exposure* and co-benefits of green infrastructure (GI), the relationship between climate change and health, and the production of *Risk* through the determinants of *Hazards*, *Exposure*, and *Vulnerability*, before introducing the hypothesis of the study. Chapter 3 provides an outline of the variables identified for the study, data collection, and overview of the analysis methodologies employed. This informs the analysis and discussion of results contained within Chapter 4. Chapter 5 concludes with a summary of the findings within the context of the research questions, presenting implications for planners and policymakers and opportunities for further research.

2. Literature review and Conceptual Framework

2.1 Literature Review

2.1.1 Climate Change and Urban Heat Islands

Global Warming

It is undisputable that global temperatures are increasing due to anthropogenic effects on the world's climate systems. Atmospheric and ocean temperatures are on the rise and, according to the Intergovernmental Panel on Climate Change, “[i]t is virtually certain that hot extremes (including heatwaves) have become more frequent and intense across most land regions since the 1950s” (Lee et al., 2023; Romanello et al., 2023). Global and regional temperature records are being broken on a consistent basis, with 2023 recorded as the warmest year on record, at approximately 1.45°C above pre-industrial records (Calvin et al., 2023; WMO, 2024).

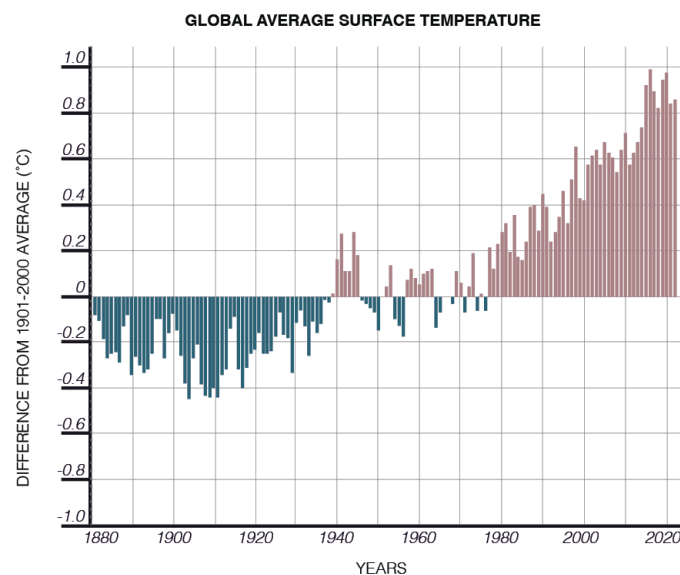


Figure 1: Global Average Surface Temperature (Lindsey & Dahlman, 2024)

Urban Heat Islands

Such increases in temperatures are compounded by unprecedented rates of urbanisation, alongside expanding of grey infrastructure networks – which increase temperatures by absorbing and re-radiating solar radiation – and concentrated heat-generating anthropogenic activities, exacerbating UHI effects, and increasing heat *Exposure* within densely populated areas (Rizwan et al., 2008). As a result, urbanisation not only results in increased temperatures at approximately three times rate of average global temperature increases (Romanello et al., 2023, p.2358), but also greater *Exposure* for larger numbers of people due to increasing densification within these areas.

Through their summary review of the vast literature on factors that increase the generation of UHI effects, Rizwan et al. (2008) demonstrate that the re-radiation of heat from urban structures represents the most significant exacerbating factor of Urban Heat Island Intensity (UHII). However, there are multiple contributing factors to increased UHII, including reduced ventilation due to dense urban built form, and the emission of heat from air conditioners, vehicles, and industrial activity (Kim & Brown, 2021). Increased urban temperatures contribute to multiple adverse conditions, including heat-related disease and mortality, reduced productivity, infrastructural failure, and reduced quality of life (Santamouris, 2014).

2.1.2 Urban Vegetation, Nature-based Solutions, Green Infrastructure and Ecosystem Services

Within the context of urban heat mitigation, the presence and health of vegetation, or its replacement by traditional built grey infrastructure, represent well-acknowledged determinants of UHII (Saaroni et al., 2018; Tiwari et al., 2021; Zölch et al., 2016). While extensive urbanisation and proliferation of grey infrastructure is associated with increasing UHII (re-radiating solar radiation, as described previously), vegetation decreases temperatures through evapotranspiration (the movement of water from soils and plants to the atmosphere, by evaporation and transpiration), and the mitigation of heat re-radiation by displacing traditional infrastructure materials such as concrete and asphalt. Marando et al.'s (2022) study of the role of vegetation in mitigating heat within 601 European cities finds that green areas in cities result in an average of 1.07° C of cooling, and a 16% increase in tree cover delivering an average of 1°C cooling in urban spaces. While increased vegetation coverage does not represent a silver bullet in addressing urban heating, it does provide an important factor in determining the extent. Such approaches to tackling a variety of spatial challenges using natural systems are frequently referred to as 'Nature-based Solutions' (NbSs).

As climate change and global warming become increasingly prominent within urban policy agendas, the capacity for NbSs to promote resilience alongside diverse additional co-benefits is garnering increasing attention – including acknowledgement within mainstream multilateral agreements such as the Paris Agreement of 2015, the United Nations' 2030 Agenda for Sustainable Development, and UN Habitat's 2016 New Urban Agenda – highlighting the important role of healthy ecosystems in maintaining the function of the planet's life-support systems (Culwick et al., 2019).

Similarly, the concept of 'green infrastructure' (GI) refers to these capacities for natural ecosystems and environmental features to provide diverse and multifunctional services that benefit human populations while conserving and preserving the continuation of natural ecosystem functions and wider life-support systems of the biosphere (Nieuwenhuijsen, 2021). It comprises an interconnected set of assets that include both pre-existing and planned green spaces, landscapes, trees, wetlands, and parks, as well as the incorporation of vegetation within buildings such as green roofs, which "form an infrastructure network providing services and strategic functions in the same way as traditional 'hard' infrastructure." (Schäffler et al., 2013). Such functions are often referred to as 'ecosystem services' – a vague and contested term which refers variously to the economic, cultural, material, or health benefits of natural systems and assets (Wallace, 2007).

The diverse health benefits of GI have been widely acknowledged, including improved pregnancy outcomes, positive impacts on mental health, and diseases such as diabetes and cardiovascular disease – in part resulting from the role of natural ecosystems in reducing air and noise pollution, heat *Exposure*, and promotion of social interaction and exercise (Nieuwenhuijsen, 2021; Romanello et al., 2023). At the same time, GI and NbSs provide important resilience-enhancing services conventionally performed by traditional infrastructure, such as stormwater management and flood mitigation, with permeable surfaces enhancing urban drainage, with secondary benefits for population health and wellbeing by reducing the impacts of flooding and associated water-borne diseases such as cholera (Jayasooriya & Ng, 2014).

Despite the significant potential of GI to address urban challenges receiving increasing attention, in a study of 1041 urban centres, Romanello et al. (2023, p.2366) have found vegetation levels within low-HDI cities to be shrinking. Schäffler & Swilling (2013) describe the challenges in conveying the beneficial impacts and trade-offs of GI and NbSs to policymakers, both in the provision of services normally supplied by traditional ‘grey’ infrastructure and in accounting for additional interconnected benefits of green assets across urban systems. Efforts to integrate the impact of GI approaches within urban investment accounting systems seek to address the favouring of grey infrastructure as a politically motivated symbolic investment within under-serviced cities in the Global South.

Such challenges in advocating for mutually-enhancing human and natural systems alludes to the ontological undercurrents that distinguish between (and often contrast) sociotechnical economic development and ecological care – the very same narratives that justify the exploitation of the planet and (often indigenous) marginalised populations in the name of development (Pawlyn & Ichioka, 2022). In order to fuel urban development in accordance with imaginaries of modernisation and growth, Lindsay Blaire-Howe (2022), Vanessa Castán Broto and Martín Sanzana Calvet (2020) and Martín Arboleda (2016) describe the creation of ‘sacrifice zones’ – spaces of landscape-degrading and polluting industry and infrastructure on the spatial or psychological urban periphery – often inhabited by marginalised worker populations and justified in the name of urban development and growth. These *longue durée* processes frequently result in marginalised populations living in polluted, unhealthy environments, where natural ecosystem services as well as traditional infrastructure services are lacking. The causal relationship between unevenly distributed vegetation and marginalised populations’ experiencing disproportionate levels of heat *Exposure* has been explored within both so-called ‘developed’ and ‘developing’ contexts. While patterns of unequal *Exposure* are pervasive, they are particularly pressing within the Global South, with increased inequality, and higher rates of urbanisation (Chen, 2024; Klopfer & Pfeiffer, 2023; Zhou et al., 2023).

Legacy impacts of degraded landscape and ecological assets within these ‘sacrifice zones’ places additional strain on the resilience of urban areas occupied by marginalised populations, which interacts with contemporary social inequality and climate-related hazards to produce increased *Risk* for inhabitants of disadvantaged regions. Investments in green infrastructure often and paradoxically neglect, or even negatively impact “marginalised urban groups” – a phenomenon widely studied and critiqued, and giving rise to concepts of ‘green gentrification’ and entrenched urban inequalities (Anguelovski et al., 2018).

As a final note, within discussion of green infrastructure and ecosystem services, care should be taken to avoid a simple reframing of natural systems and nonhuman entities purely in terms of their utility to human population wellbeing and economic stability – which risks reproducing the slippery slope towards capitalist extractive dualisms, in which nature exists to serve and supply economic growth and thus the very same extractive perspectives from which the climate crisis originates (Sara & Bigger, 2022). While such discussion is beyond the scope of this study, it is a vital consideration in its reading and bears mentioning. Rather, GI and ecosystem services are considered here as the integration of urban resilience within the context of an interconnected web of a well-functioning and life-sustaining biosphere.

2.1.3 Planetary Health

The British Medical Journal's (BMJ's) annual *Lancet Countdown* report presents a medical case for the destruction of the Earth's life-support systems as the most significant risk to human health. Mobilising this argument has given rise to the concept of *planetary health* – “the health of human civilization and the natural systems on which it depends” (Horton et al., 2014, p.847). The 2023 report of the *Lancet Countdown on health and climate change* presents a medical case for the impact of temperature increase on population health *Risk* both directly (through heat-related illness and mortality) and indirectly, as a *Risk*-multiplier in exacerbating the prevalence and severity of other health concerns, including depression, cardiovascular disease, respiratory conditions, and immunodeficiencies, including Tuberculosis (TB) and HIV – diseases that are particularly prevalent in the Global South and South Africa (Cele et al., 2020).

Medical research also highlights the health impacts of increasing temperatures in the undermining of wider “natural and human systems on which people rely for good health” (Romanello et al., 2023). This includes threats to economic productivity, water security, food production, flooding, and air quality (among multiple other factors), all of which represent multiple overlapping feedback loops of environmental determinants of health. Carolin Kruger (2023) demonstrates how socioeconomic inequality and marginalisation acts as a mediator on the impacts of heat-related *Risk* demonstrating compounding nature of heat *Exposure* on social inequalities.

The health impacts of heat *Exposure* on economic activity, both through direct impact of heat on productivity and work-days missed due to heat-related diseases, affects individuals as well as large-scale regional and national economies. The 2023 *Lancet Report* values the global financial cost of heat-related mortality in 2022 at \$164 billion (based on measuring the cost of ‘years of life lost’) – a 146% increase from 2000-2004 averages, and approximately 0.17% of global GDP, while labour losses in 2022 cost approximately \$863 billion, or 0.87% of global GDP – primarily affecting agriculture industries within the Global South (Romanello et al., 2023, p.2375). Increasing temperatures place outsized economic strain on poor and middle-income countries, by reducing labour capacity at a cost of between 3.8% and 6.1% of their gross GDP – further exacerbating pre-existing global inequalities (Romanello et al., 2023). It is predicted that the cost of labour-loss due to heat is anticipated to rise by 50% over the next thirty years, and that this will be concentrated in the most vulnerable global economies – further entrenching inequality and *Vulnerability*, and reducing resilience to subsequent impacts of climate change and heat *Exposure* (De Sario et al., 2023; Romanello et al., 2023).

Not only does this indicate the uneven *Exposure* and costs borne by increasing temperatures, but also demonstrates the reinforcing and cascading downstream effect of climate change impacts on health outcomes, disproportionately affecting socioeconomically disadvantaged and marginalised populations (De Sario et al., 2023; Godde et al., 2021).

2.1.4 Risk: Hazards, Vulnerability, and Exposure

The Intergovernmental Panel on Climate Change (IPCC) describes climate-related *Risk* as the combined product of three factors– (i) *Hazards*; (ii) *Exposure*; and (iii) *Vulnerability* (Oppenheimer et al., 2015), pertaining both to current and potential future prospects of risk (Dodman et al., 2023). Understanding the dynamics of *Risk* associated with extreme heat, and other climate-related events in urban areas, it is therefore vital to understand the nature of *Hazards*, *Exposure*, and *Vulnerability*, represented by the formula:

$$RISK = [HAZARDS] \times [EXPOSURE] \times [VULNERABILITY]$$

HAZARDS

Within this framework, *Hazards* represent physical climate-related events which may have adverse impacts on human and ecological wellbeing in diverse ways, including affecting livelihoods, health, economies and infrastructure (Oppenheimer et al., 2015). Although the relationships between climate change and various *Hazards* associated with its short-term shocks and long-term stresses are often unacknowledged and contested, increasing temperatures represent a well-recognised and primary example of a climate-related *Hazard* (Dodman et al., 2023).

EXPOSURE

Exposure describes the proximity of human and ecological systems that can be affected, whether through spatial proximity, or more systemic relationships such as *Exposure* via the effects on economic, social, political, or economic systems (Oppenheimer et al., 2015). Definitions and evaluations of heat *Exposure* within urban environments commonly follow a logic of spatial correlation of high temperatures and assets or populations, using various spatial measures of temperature. While studies such as that by Scherer et al. (2014) utilise mean daily temperature, and Local Climate Zone classification (Stewart & Oke, 2012) represents a promising methodology for assessing *Exposure*, as used by Gilabert et al. (2021) in their study of *Exposure* to extreme temperatures in Barcelona, *LST* remains the most commonly-used technique for *Exposure* analysis (Marando et al., 2022).

VULNERABILITY

Finally, *Vulnerability*, refers to the likelihood of climate-related events to have an adverse effect on human or ecological systems (Oppenheimer et al., 2015), or the ability “to anticipate, cope with, resist, and recover from the adverse effects of physical events” (Cardona et al., 2012). Within the framework of *Vulnerability* as a component of *risk* the IPCC’s 2023 *Synthesis*

Report acknowledges that “many of those who have least contributed to climate change to date being most vulnerable to its impacts” (Lee et al., 2023). The IPCC recognises that “[v]ulnerability is dynamic and context-specific, determined by human behaviour and societal organisation” – acknowledging ‘marginalisation’ as one potential contextual social factor to increase vulnerability, by reducing local adaptive capacities to climate-related *Hazards* (Oppenheimer et al., 2015). Thus, *Vulnerability* is not simply a factor of climate change, but the result of complex and systemic interactions between its threats, and social, ecological, political, and economic conditions.

Increasing temperatures interact in dynamic ways with societal and ecological systems to distribute varying extents of *Vulnerability* to its effects. Certain populations are more susceptible to the health-affecting consequences of *Exposure* to heat, such as the very young and old, people with underlying health conditions (including HIV, TB, and mental health), and those without access to medical insurance (Cele et al., 2020; Romanello et al., 2023).

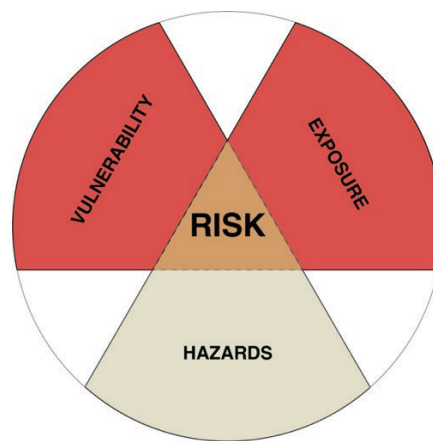


Figure 2: IPCC’s conceptualization of the three components of Risk (adapted from Oppenheimer et al., 2015)

SOCIOSPATIAL INEQUALITY AND RISK

Current rates of urbanisation are concentrated in the Global South, and by 2050, it is expected that almost 60% of Africa’s population will live in cities (Li et al., 2022), while processes associated with urbanisation combine with climate change to increase both *Exposure* and *Vulnerability* to climate-related *Hazards*, shocks, and stresses (Dodman et al., 2023). The rise in urbanisation in Africa and Asia represents 90% of global urbanisation, indicating that the increased vulnerability associated with urbanisation processes will be largely felt in these regions, and particularly within so-called “less-developed regions” (Satterthwaite et al., 2020; UN Population Division, 2018).

Within the determination of climate-related *Risk*, it is important to acknowledge that social factors that affect *Vulnerability* and *Exposure* can dramatically increase *Risk* factors, even in the relative stability of *Hazards* (Dodman et al., 2023; Ziervogel et al., 2017). Existing socio-economic inequalities often result in greater *Exposure* to climate challenges, as well as increased *Vulnerability* to negative effects. Those living within ‘informal settlements’ – with reduced infrastructure, adequate housing, and services to mediate the effects of shocks and

stressors associated with climate change – are disproportionately vulnerable, and face outsized risk (Satterthwaite et al., 2020).

Following current trends, heat-related deaths are predicted to rise by 370% by the middle of the 21st Century, with Africa having experienced the most significant increase in heat-related deaths since 2000-2005 (Romanello et al., 2023). Additionally, climate change and heat have outsized impact on certain demographics, with old, young, and people with co-morbidities being more susceptible to harmful effects of increased temperatures (Romanello et al., 2023), including the exacerbation of cardiovascular and respiratory-related conditions (Ebi et al., 2021). It is therefore important to understand not only sociodemographic vulnerabilities that reduce resilience capacities, but also the often-connected heat-risk multipliers that have greater prevalence within marginalised populations, such as diabetes and cardiovascular disease. To these social and environmental determinants of health, uneven access to medical services act as an additional vector of increasing *Risk* for socio-economically vulnerable demographics.

2.2 Conceptual Framework

The conceptual framework (figure 3) for this study adopts the IPCC’s conceptualization of *Exposure*, *Vulnerability*, and *Hazards* as the three components of *Risk*, in order to understand the heat-*Risk* faced by marginalised demographics. The presence of heat *Hazards* is understood as a ubiquitous *a-priori* phenomenon (figure 4), as elaborated in Section 2.1.1. As a result, the uneven distribution of *Risk* is presented as a result of two factors. Firstly, the study assesses *Risk* for marginalised populations as a result of the uneven *Vegetation Distribution* causing increased *Exposure*. *Exposure* (through the proxy of *LST*) operates as an intervening variable between *Marginalised Sociodemographic Populations* and *Risk*. *Exposure* also acts as a dependent variable to the independent intervening variable of *Vegetation Distribution* – which is assessed for spatial correlation with *Marginalised Sociodemographic Populations* (figure 5). Secondly, the study assesses whether marginalised populations also experience increased *Risk* as a result having increased *Vulnerability* (as an intervening variable) to the adverse effects of heat, also resulting in increased *Risk* (figure 6). Finally, the study will examine whether there is overlap between *Risk* factors of *Exposure* and *Vulnerability* while taking the presence of heat *Hazards* as an *a-priori* phenomenon.

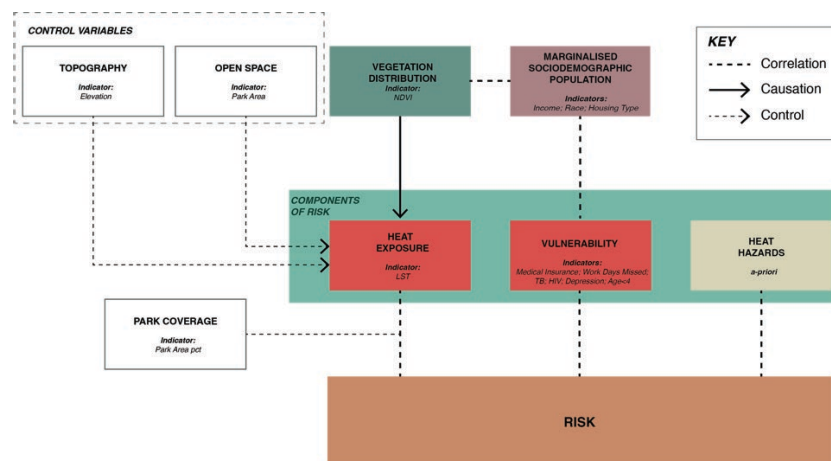


Figure 3: Conceptual Framework (Overall)

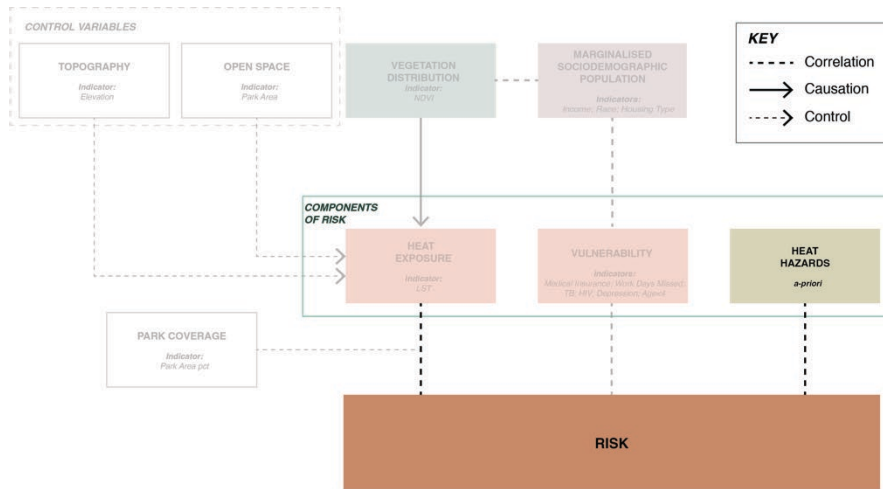


Figure 4: a-priori assumption of heat-related Hazards

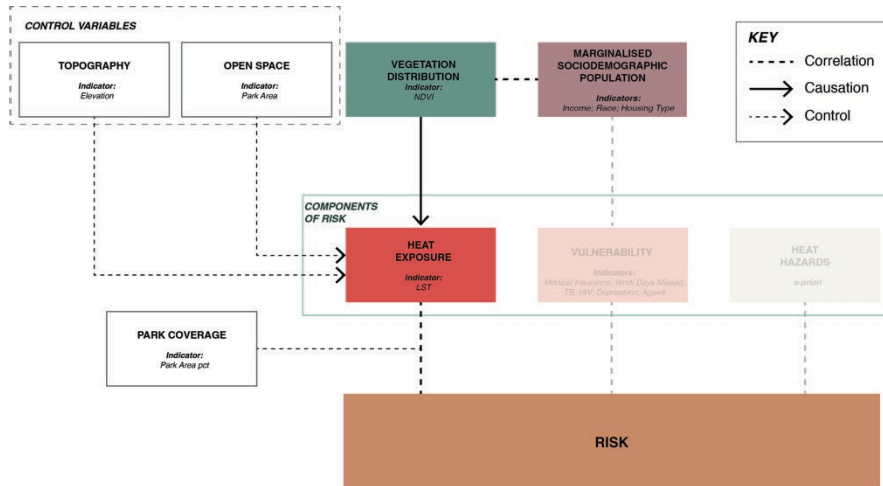


Figure 5: Increased Risk as a result of increased Exposure resulting from lower levels of vegetation

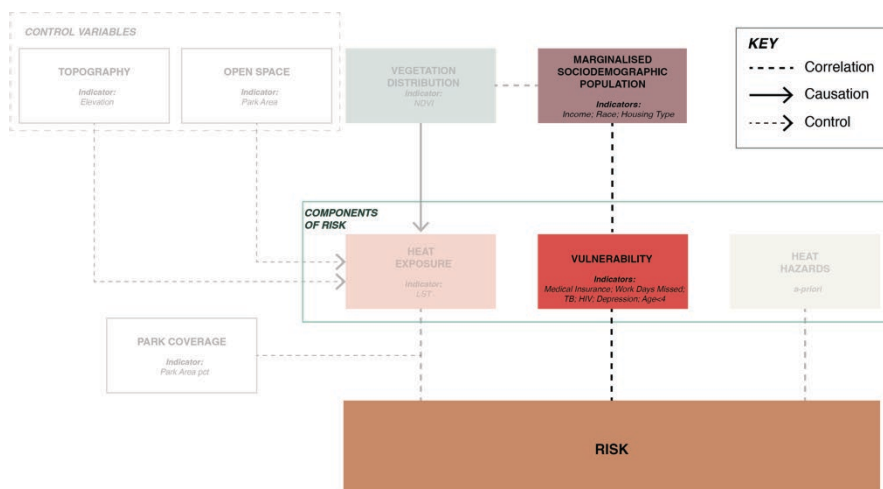


Figure 6: Increased Risk as a result of increased Vulnerability correlated with marginalised populations

3. Research Design and Methodology

3.1 Introduction

In order to study the production of increased heat-related *Risk* for *Marginalised Sociodemographic Populations*, the case study of Johannesburg is selected for its highly segregated spatial context, with historical patterns of urban development, and the allocation of space and resources for vegetation and green infrastructure taking place along sociodemographic lines. While the South African context is somewhat unique in the extent of its formalised racial segregation, spatial separation also follows economic and sociodemographic strata that are comparable to other contexts. Johannesburg's contemporary urban landscape remains highly divided along sociodemographic lines, with the legacies of formalised policies of segregation still visible in the city's social and spatial fabric, with a lack of attention to the spatial location of investments in core services exacerbating social inequalities in line with *longue durée* racial socio-spatial separation (Pieterse & Owens, 2018). These cycles of socio-spatial marginalisation manifest in a myriad of challenges, including separation of income levels and lack of access to adequate housing which, compounded by rates of urbanisation and lack of access to land within historically affluent areas, results in the proliferation of informal settlements and unplanned backyard dwellings (Ballard & Hamann, 2021).

Disparities in vegetation distribution, and relationships between marginalisation and increased *Vulnerability* to the ill-effects of heat *Exposure*, such as correlations with prevalence of comorbidities, vulnerable age profiles, and reduced access to resilience-enhancing services such as medical insurance, have been observed internationally, and particularly within the Global South, as discussed in Chapter 2. Nevertheless, the socio-spatial separation within Johannesburg, and the unequal distribution of vegetation are particularly striking, offering a significant illustration of the production of increased *Risk* to heat *Exposure* for marginalised populations, with the segregated development playing out alongside the formation of unequally distributed green infrastructure (Culwick et al., 2019; Khanyile & Culwick, 2023; Venter et al., 2020). The development of Johannesburg's urban forest is closely interconnected with its extractive mining history, with much of the early planting taking place through schemes that sought to provide materials to support underground tunnels and excavation infrastructure, and prevent the spread of dust pollution from the mines towards the affluent white property owners on the Northern areas of the early settlement (Schäffler et al., 2013; Turton et al., 2006).

Similarly, within contemporary vegetation patterns, Schäffler et al. (2013) describe how the distribution of trees within Johannesburg is highly uneven, with the (historically affluent, white) Northern suburbs having tree coverage of approximately 24% while poorer areas to the South of the mining belt have only 6.7% coverage. The exception indeed proves the rule in this case, with Alexandra – an apartheid-era township adjacent to Sandton, an affluent Northern Johannesburg suburb and business centre – notably having almost no tree coverage at all, in contrast to its wealthy surroundings (Schäffler et al., 2013).

3.2 Research Strategy, Operationalisation, and Design

3.2.1 Research Strategy

This research utilises a case study approach in order to better understand dynamics of heat-related climate *Risk* arising from unequally distributed urban vegetation. It focuses on the City of Johannesburg (CoJ), South Africa – an example of an important urban metropolis in the Global South – and is suited to an exploration of the research questions due to its segregated spatial development and relatively accessible and relative high-quality of sociodemographic data. The research is undertaken through a quantitative approach to the secondary analysis of existing data (van Tiel, 2014, Table 5.2). The use of both spatial analysis and statistical modelling is appropriate to develop an understanding of the relationships contained within the research questions set out in Chapter 1. This combined spatial and static analytical model takes the following format:

1. A spatial analysis of the distribution of vegetation and temperature, using GIS processing and analysis of remote-sensing Landsat 8 satellite data accessed via the United States Geographical Survey (USGS) at ward-level in Johannesburg, followed by a statistical analysis that aims to establish whether there is a causal relationship between the distribution of vegetation and land-surface temperature as a proxy for heat *Exposure*.
2. Spatial analysis of sociodemographic data, accessed from the South African National Census of 2011, and the Gauteng City Region Observatory's Quality of Life Survey 6 (2020/21), to establish the distribution of marginalised populations at ward-level in Johannesburg.
3. Statistical analysis that assesses spatial correlation between decreased vegetation (and resultant increased temperatures) and marginalised populations by ward in Johannesburg, to determine whether marginalised demographics are more exposed to heat.
4. Statistical analysis assessing the correlation between marginalised sociodemographic populations and increased vulnerability to the ill-effects of heat exposure.
5. Cluster analysis, assessing the spatial overlap of *Exposure* and *Vulnerability* as components of *Risk* that contribute towards, and multiply heat-related climate *Risk* – representing how *Vulnerability* and *Exposure* intersect and contribute to the *Risk* experienced by marginalised sociodemographic populations.

3.2.2 Operationalisation

The following indicators are derived from the literature reviewed in Chapter 2, aligning with the research questions, as follows:

Marginalised Sociodemographic Populations

Indicators selected to represent marginalised demographics respond to the context of segregated development in Johannesburg, while remaining applicable across a wide range of international urban environments, particularly in the Global South (Ballard & Hamann, 2021). *Race* is selected as it represents historic and contemporary categories of urban segregation which prioritised the needs of white people, and is this recoded as a binary percentage of white and non-white residents per ward. *Income* is recoded as the average income per ward, introducing a widely applicable measure across contexts. Finally, *Housing Type* is recoded to denote the percentage of housing units constructed from materials associated with ‘informal’ and self-constructed or temporary housing inhabited by residents who lack access to formal housing, such as shacks, tents, or backyard dwellings.

Heat Exposure and Vegetation Distribution

As *Heat Exposure* represents an intervening variable in the relationship between *Marginalised Sociodemographic Populations* and *Risk*, and the degree of *Exposure* is hypothesised to be affected by vegetation levels, the relationship between vegetation and heat must be assessed. In this instance, *Vegetation Distribution* represents an independent intervening variable, and *Heat Exposure* a dependent intervening variable. Intervening variables provide a pathway through which the independent variable (IV) relates to a dependent variable (DV). Within the context of this study, the IV to directly act on the DV, but rather the intervening variables provide a causal pathway for establishment of a relationship between the IV and DV.

Variables for the analysis of heat *Exposure* and vegetation use the widely accepted proxies of *LST* and *NDVI* respectively (Klopfer & Pfeiffer, 2023). In the evaluation of the role of vegetation in determining heat *Exposure* (and thus increased *Risk*), park area and elevation are used as control variables, which represent potential external factors that may influence the results of the study. Changes in topography can affect *LST* in numerous ways, through the creation of microclimatic conditions and variations in wind patterns, impact on solar radiation, and effect on vegetation (Bindajam et al., 2020; Crétat et al., 2024).

Park area per ward represents an important control variable insofar as it focuses the study on the quality and density of vegetation (represented by *NDVI*), rather than simply the presence of open space and absence of built urban fabric, with associated effects on UHII (Yang et al., 2016). Establishing *Park Area* as a control variable lends additional significance to this study for policymakers, in differentiating between the allocation of open park space and the enhancement of urban vegetation in mitigating heat *Exposure*.

Vulnerability

Similarly to *Exposure*, *Vulnerability* is an intervening variable between marginalised populations and *Risk*. Although data on wider health and social adaptation capacity factors would enhance the study's analysis of vulnerability, the use of accessible health-related data from public surveys to describe *Vulnerability* is a product of:

- (i) the intention to develop a widely applicable and transferrable model that highlights the interconnected impacts of climate and health, and desire to provide the groundwork for development of a model through which to quantify the systemic benefits of equitable investments in green space; and
- (ii) constraints in data availability in the quantification of social and communal adaptation capacities – a challenge not only within the time limitations of this study, but also within resource- and data-scarce contexts more generally
- (iii) sufficient attention to ethical considerations for the complex and sensitive nature of primary collection of healthcare data is beyond the timeframe scope of the research period. As a result, metrics identified in medical literature on the relationships between heat-vulnerability and health are used (Cele et al., 2020; Romanello et al., 2023).

Age is considered as a factor affecting *Vulnerability* levels. However, this study's analysis of age-related *vulnerability* is limited to young populations and excludes elderly people due to a correlation between life expectancy and historic privilege and income levels (Cele et al., 2020). *TB* and *HIV* are identified as indicators for comorbidities and health conditions exacerbated by heat *Exposure*. They are selected for their prevalence within a South African context – resulting in widely available and reliable diagnostic data. Further, these diseases are often associated with other health conditions due to their long-term effects on immune systems, and are supplemented by indicators for work missed due to poor health (Cele et al., 2020; Romanello et al., 2023).

The availability of data on *Depression* – another widely accepted disease that is exacerbated by heat *Exposure* – provides important and understudied insights into dynamics between heat and mental health. Data for *Depression* is made available by QOLS data, which uses the PHQ2 standardised survey questions to provide a replicable and medically accepted standard of assessment (Löwe et al., 2005). Adaptive capacity that focuses on health-related *Vulnerability* is addressed through *Medical Insurance* which indicates access to healthcare and is further supported by current public-sector acknowledgement of the insufficiencies in public healthcare, and imperative of national health insurance, evidence by the tabling of a National Health Insurance Bill at the time of writing.

Risk

As *Risk* is assessed as a direct product of *Exposure* and *Vulnerability*, it is evaluated by comparing normalised measures of *Exposure* and *Vulnerability* across various levels of marginalisation. Increased *Exposure* and *Vulnerability* are considered to independently represent increased *Risk* respectively, and findings of overlapping increases in both are considered to have an outsized effect on *Risk*.

The table on the following pages provides an overview of the operationalisation used.

Variable	Sub-Variable	Indicator	Variable Type	Unit	Name	Source
Independent Variable						
Marginalised Sociodemographic Population	Race	Percentage of non-white residents per ward	Continuous	Percent	<i>Race</i>	(Ballard & Hamann, 2021)
	Income	Average household income per ward	Continuous	South African Rands (ZAR) Normalised to 0;1 Min-Max for K-means	<i>Income</i>	(Ballard & Hamann, 2021)
	Housing Material	Percentage dwellings classified as being constructed from of 'informal' materials	Continuous	Percent	<i>Housing Type</i>	(Ballard & Hamann, 2021)
Dependent Variable						
Risk	N/A	Degrees of <i>Exposure</i> and <i>Vulnerability</i>	Categorical Ordinal	Score between 0 and 1	<i>Risk</i>	(Dodman et al., 2023)
Intervening Variables (between <i>Marginalised Sociodemographic Populations</i> and <i>Risk</i>)						
Vegetation Distribution (Independent Intervening Variable)	Normalised Difference Vegetation Index (NDVI)	Average <i>NDVI</i> per ward	Continuous	Score between -1 and 1 Normalised to 0;1 Min-Max for K-means	<i>NDVI</i>	(Klopper & Pfeiffer, 2023)
Heat Exposure (Dependent Intervening Variable)	Land-Surface Temperature (LST)	Average <i>LST</i> per ward	Continuous	Degrees Celsius Normalised to 0;1 Min-Max for K-means	<i>LST</i>	(Klopper & Pfeiffer, 2023)
Vulnerability	Medical Insurance	Number of respondents per ward with medical insurance (QOLS)	Continuous	Percentage Normalised to 0;1 Min-Max for K-means	<i>Medical Insurance</i>	(Romanello et al. 2023)
	Number of work days missed due to illness	Cumulative number of work days missed per ward	Continuous	Average number of work days missed Normalised to 0;1 Min-Max for K-means	<i>Work Days Missed</i>	(Romanello et al. 2023)
	Tuberculosis	Cumulative self-reported TB cases per ward	Continuous	Percentage Normalised to 0;1 Min-Max for K-means	<i>TB</i>	(Cele et al., 2020)
	HIV	Cumulative self-reported HIV cases per ward	Continuous	Percentage Normalised to 0;1 Min-Max for K-means	<i>HIV</i>	(Cele et al., 2020)

	Risk of Depression	Cumulative phq2 score per ward	Continuous	Average PHQ2 score Normalised to 0;1 Min-Max for K-means	<i>Depression</i>	(Romanello et al. 2023)
	Age	Number of children under 4 years of age per ward	Continuous	Percentage Normalised to 0;1 Min-Max for K-means	<i>Age<4</i>	(Cele et al., 2020; Romanello et al. 2023)
Control Variables (Relationship between <i>Vegetation Distribution</i> and <i>Heat Exposure</i>)						
Topography	Elevation	Average elevation per ward	Continuous	Metres above sea-level	<i>Elevation</i>	Bindajam et al., 2020; Crétat et al., 2024
Open Space	Park Area	Total park area per ward	Continuous	Square meters	<i>Park Area</i>	Yang et al., 2016
Instrumental Variable (Relationship between <i>Vegetation Distribution</i> and <i>Heat Exposure</i>)						
Park Coverage	Park Area pct	Percentage of ward covered by parks	Continuous	Percent	<i>Park Area pct</i>	

3.2.3 Research Design

The following table provides an overview of the research design, including the combination of spatial and statistical methodologies used, and is elaborated and explained in Section 3.2.4 below.

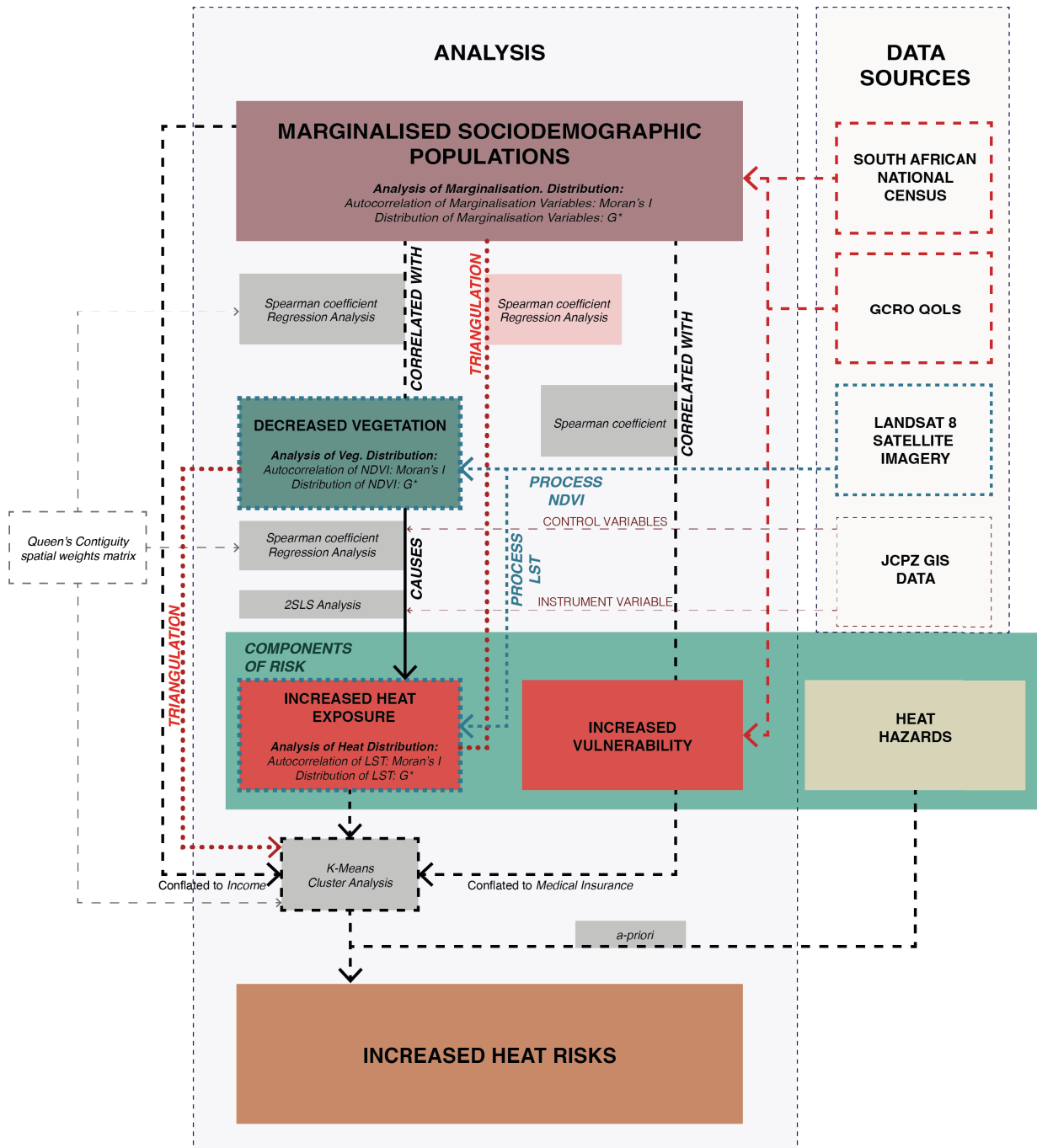


Figure 7: Research Design

3.2.4 Research Methodologies

3.2.4a Distribution of Vegetation and Heat: Data Processing

Spatial Data Processing for Vegetation

The distribution of vegetation and heat *Exposure* will be analysed using Geographic Information System (GIS) software, using data obtained by processing Landsat 8 satellite imagery, accessed via the USGS. *NDVI* information, a metric quantifying the quality and density of vegetation coverage on a scale of -1 to 1 will be used to understand the distribution of vegetation across the city, by combining red and near-infrared bands (Band 4 and Band 5 from Landsat 8) in accordance with widely accepted methodology (U.S. Geological Survey, 2023), according to the formula:

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \quad \text{or,} \quad NDVI = \frac{(Band\ 5 - Band\ 4)}{(Band\ 5 + Band\ 4)}$$

NDVI represents the most commonly used methodology for quantifying vegetation at an urban scale, and is widely acknowledged as an effective way to quantify both the presence and health of vegetation (Gascon et al., 2016; Huang et al., 2021). *NDVI*, derived from satellite imagery, is a commonly chosen method due to its low-cost, accessibility, and relative accuracy. Originally developed by Kriegler (1969), *NDVI* can now be calculated at a resolution of 30x30m for many parts of the globe using satellite data from sources such as Landsat 8. While the use of *NDVI* methods has proliferated with increasing attention to climate and environmental science, it has several limitations, including cloud-cover and atmospheric effect, as Raileigh scattering causes the radiance in the red region to be larger than that of the NIR – though these can be mitigated through careful selection of images and image sources, with Landsat correcting for this effect (Huang et al., 2021). *NDVI* is frequently used in the assessment of UHI effects and mitigation, including use in the Lancet report – an internationally recognised benchmark for research on the effects of climate change on population health (Romanello et al., 2023). *NDVI*'s use in medical research – a field known for thoroughness and double-blind testing – lends particular credence to this methodology.

Spatial Data Processing for Heat

As described above, *LST* is used as a widely accepted proxy for heat *Exposure*. Mean *LST* values are aggregated at ward level, having been derived from the GIS processing of Landsat 8 satellite imagery (Digavinti et al., 2017; Goldblatt et al., 2021). The processing of satellite data involves several steps (elaborated in *Appendix 3*), summarised as follows:

1. *Calculation of Top-of-Atmosphere (or the amount of solar energy absorbed by the earth, and reflected)*
2. *Conversion of Top-of-Atmosphere to Brightness Temperature (BT) as a measure of infrared radiation from the surface, without interference from intervening factors such as vegetation*
3. *Calculation of NDVI as above*
4. *Calculation of Proportion of Vegetation Index (Pv), to estimate the fraction of the Earth's surface covered by vegetation*
5. *Calculation of Emissivity (E), quantifying the variable amount of radiation emitted from the Earth's surface*
6. *Calculation of LST to provide a value in Degrees Celsius*

The results from the *NDVI* and *LST* analysis for all sample days are aggregated by ward, and represented initially as an average value per ward, per study day, and then as a total average value of the study days for each ward.

3.2.2.4b Spatial Autocorrelation and Clustering of Indicators

Moran's I

In order to understand the spatial distribution of vegetation, heat *Exposure*, and marginalised populations, global Moran's I calculations (using GeoDa software, version 1.22.0.4) are utilised, identifying whether respective indicators for each variable are autocorrelated, following the methodology employed by Klopfer and Pfeiffer (2023). Moran's I analysis provides a measure for spatial autocorrelation of values, quantifying the extent to which similar values are located in similar areas (ie clustering), which is indicative of underlying spatially-related factors and suggesting that these variables are relevant to the study. In order to identify spatial proximity between ward values and assess their spatial relatedness, and conduct a pairwise comparison between the wards, neighbouring wards are identified through a spatial weights matrix derived through the queen's contiguity function. Moran's I values are reported on a scale of -1 to 1, with values of 1 representing complete positive autocorrelation. Values of -1 correspond with negative autocorrelation, and zero indicates no autocorrelation.

Getis-Ord (G*) Analysis

Getis-Ord analyses are used to understand the clustering of spatial observations by assessing individual data points within the context of neighbouring data, identifying the presence of statistically significant areas with similarly high and low values (Cigerci et al., 2024; Grigoraş & Urişescu, 2018).

The statistically significant $P < 0.05$) clusters of spatially autocorrelated high and low values are calculated and visualised using GeoDa software, elaborating on the spatial distribution of high and low clusters for an initial visual analysis of spatial patterns and overlaps. Both the Moran's I and G^* confidence intervals are the result of 999 permutations, automated using GeoDa software. Row-standardised weights are used, normalising the weights matrix, allowing for comparable and balanced spatial influence between ward-level observations.

Within this study, overlaps and spatial clustering are an important step in the identification of indicators that have an underlying spatial logic, and assessment of whether this logic aligns with the hypothesis that there is indeed a spatial relationship between marginalisation, vegetation distribution, and heat *Exposure*. Initial visual inspections serve to assess whether the distributions of these variables appear to be correlated, and whether they follow the logic of historic and contemporary patterns of socio-spatial inequality. *Vulnerability* is excluded from this stage, as it is not inherently spatial, but rather socio-economic in nature.

3.2.4c Relationships Between *Vegetation Distribution*, *Heat Exposure*, *Marginalised Sociodemographic Populations*, and *Vulnerability*

This section provides a description of the quantitative methods used to understand the relationships between different variables within the research study.

Spearman Correlation

Spearman's Correlation coefficient is used to quantify the linear relationship between variables which have different units of measurement and dimensions (Ali Abd Al-Hameed, 2022). It is measured on a scale of -1 to 1, with zero indicating no correlative relationship, while values closer to 1 have a stronger positive correlation, and values closer to -1 having a stronger negative correlation. In this study, the Spearman's coefficient is used for two main purposes.

On the one hand, at each stage of analysis between variables, Spearman's Correlation is used to provide an overview of whether there are statistically significant (non-spatial) relationships between indicators, and whether these relationships are in-line with the hypotheses. In the case of understanding whether marginalised populations are correlated with increased *Vulnerability*, the Spearman coefficient is sufficient. However, as the correlative relationship between marginalisation and vegetation distribution are correlative relationships are spatial in nature, this is captured by the use of spatial regression modelling, explained below. Similarly, as the causal relationship between *NDVI* and *LST* are spatial, and additionally causal, Spearman's coefficient serves as an initial indication that this relationship is as expected. Finally, the Spearman coefficient also provides a tool for simplifying variables by conflating the indicators for use in the K-Means Cluster Analysis (described below).

Normalisation of Data

In order to ensure consistency when comparing the predictive value of independent variables, the data used for independent, dependent, and control variables is normalised by rescaling the values to a range of 0 and 1 using Min-Max normalisation. This means that the highest ward-

value is represented by a value of 1, and the lowest value by zero, and allows for comparison across variables of differing scales and units.

Ordinary Least Squares (OLS)

OLS regression are used as a point of departure for assessing the relationships between the independent, dependent, and control variables, using the following formula:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots + \beta_n X_n + \varepsilon$$

Where:

Y = Dependent Variable (*DV*)

β_0 = Intercept

$\beta_{1...n}$ = Slope Coefficient

$X_{1...n}$ = Independent Variable (*IV*)

ε = Error Term

While OLS regressions are limited insofar as it assumes linear relationships between the variables, independence and homoscedasticity (that there is consistent variance of residuals), it is an important starting point that both provides an overview of relationships between variables, providing important information on whether more accurate spatial regression models are required, by facilitating the Moran's I and Lagrange Multiplier tests below.

Moran's I and Lagrange Multiplier tests

In contrast to the Moran's I test used above, which aims to assess spatial patterns through autocorrelation of a single variable, the Moran's I test and Lagrange multiplier test for spatial dependence within the OLS model aims to establish whether there is spatial autocorrelation between the residuals within the regression analysis of spatially-related variables (marginalisation/*NDVI*; *NDVI/LST*; and triangulation of marginalisation/*LST*). The presence of spatial autocorrelation – indicated by a positive and significant value for Moran's I (showing spatial clustering) and for the Lagrange multiplier test (suggesting spatial autocorrelation) – is indicative of the need to use a spatial regression model which accounts for the impact of spatial proximity on the results.

Spatial Regression Modelling

A spatial regression, and more specifically a spatial error model, makes use of a spatial weights matrix (W) – which quantifies the spatial proximity between the locations of data points (in this study municipal wards) – in order to account for the potential for spatial factors that may affect the dependent variable and are not directly captured by the variables used or data available. Queen's contiguity is used in this study to account for spatial weights – identifying neighbouring wards as spatially related.

Analysing the spatial relationship between *Marginalised Sociodemographic Populations* (as the overall independent variable) and *NDVI* (as the independent intervening variable), and the subsequent analysis of the relationship between *NDVI* and *LST* (as the dependent intervening variable), the spatial error model provides greater insight into the nature of the correlation when accounting for spatial components of the relationship. In the case of analysing whether there is a causal relationship between *NDVI* and *LST*, control variables of *Park Area* and *Elevation* are included for greater insight in assessing the predictive role of *NDVI* in determining *LST*. This will be further supplemented by the instrumental variable analysis below, in attempt to isolate whether there is a causal relationship between the *NDVI* as the independent intervening variable, and *LST* as the dependent intervening variable. Within the context of heat *Exposure*, urban, social, and atmospheric factors interact in complex systems, with potential impacts on the dependent variable of *LST* that are beyond the scope of this study.

The formula for the spatial error model replaces the error term in the OLS formula to account for spatial autocorrelation, where one error term (u) represents a weighted average of neighbouring error terms, while the second error term (ε) has no autocorrelation. The impact of unaccounted interactions is captured by the proxy term (λ). The spatial error model is therefore represented by the equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots + \beta_n X_n + (\lambda W u + \varepsilon)$$

Where: $(\lambda W u + \varepsilon)$ = the function of unexplained residuals and neighbouring error terms

Two-Stage Least Squares Regression using Instrumental Variable

This section assesses the nature of the relationship between *vegetation distribution* and heat *Exposure* to determine whether vegetation is a predictor of heat *Exposure*, and the overlaps between all variables to understand how they collectively impact *Risk* associated with heat *Exposure*, using a combination of quantitative statistical analysis methods.

In order to investigate whether there is a potential for causality between the independent and dependent intervening variables, an instrumental variable approach is taken, using a two-stage least squares (2SLS) regression model, carried out in STATA software (version 18.0). This requires the identification of a relevant instrumental variable which serves as a predictor of the independent (intervening) variable, yet has little relationship with the dependent (intervening) variable, thus allowing the isolation of the effect of the independent intervening variable on the dependent intervening variable (bearing contextual limitations in mind). The first part of this two-stage process involves a series of iterative regressions, informed by theory and by the context of the study to identify a relevant instrument through the F-statistic, followed by a second-stage regression model which uses the prediction of the value of *NDVI* from the first regression, to assess the impact on the dependent intervening variable of *LST* while controlling for the Instrumental Variable.

Due to the complex and interconnected nature of multiple spatial and social factors that correlate with both *NDVI* and *LST* in Johannesburg, and limitations in terms of data availability, identifying valid instruments presents a challenge. The limited number of relevant instruments is a significant limitation for this 2SLS regression, inhibiting the capacity to test for correlation

between the instrument and error term in the second-stage regression, the presence of which may cause biased and inconsistent results. In response, the instrumental variable should be checked for multicollinearity by assessing correlation with other variables in the model, and be justified theoretically and conceptually.

K-Means Cluster Analysis

In order to understand whether marginalised sociodemographic populations experience greater heat-related *Risk* due to their (a) being more exposed to heat as a result of having reduced access to vegetation, while simultaneously (b) being more vulnerable to the ill-effects of the heat *Exposure*, a K-Means cluster analysis is used – drawing from the methodology employed by Klopfer and Pfeiffer (2023). A K-Means (Cluster) analysis describes the distribution of wards that share multiple similar characteristics, within a pre-defined number of clusters, using GeoDa software. As previously, queen's contiguity is used to define spatial relationships between wards – identifying neighbouring wards as being spatially dependent. The number of clusters (two) is determined through an iterative process – assessing whether the representation of n number of clusters is meaningful within the research context – as well as a consideration of the context of research itself. As the research is primarily concerned with understanding whether marginalised populations experience increased heat *Risk*, two clusters (indicating high- and low- *Risk* areas) and associated average variables within those areas is deemed sufficient.

In order to determine whether marginalised sociodemographic populations experience increased heat-related *Risk* as a result of the uneven distribution of vegetation, the normalised values for the respective clusters are analysed. The variable of *Vegetation Distribution* is hypothesised to affect heat *Exposure*, and therefore increase heat-related *Risk*, and is maintained for triangulation, ensuring that the pattern of reduced vegetation remains correlated with increased *Exposure* and therefore *Risk*. As *Vulnerability* represents an additional component of *Risk*, the K-means cluster analysis assesses whether clusters in which marginalised populations have increased *Exposure* also experience increased levels of *Vulnerability*. The normalised values are used in order to rescale and compare values with different units. Vegetation levels are also included here for triangulation.

4. Results, analysis and discussion

4.1 The Johannesburg Case Study

Johannesburg's urban vegetation is frequently discussed in terms of the city's substantial tree-coverage. While no official tree surveys exist for Johannesburg, it is estimated that there are up to 10 million trees within the city (Schäffler et al., 2013). While this represents a significant ecological asset, the distribution of the city's trees follows the spatial logic of segregation along racial lines. The development of Johannesburg's urban forest is closely interconnected with its extractive mining history, with much of the early planting taking place through schemes that sought to provide materials to support underground tunnels and excavation infrastructure, and prevent the spread of dust pollution from the mines towards the affluent white property owners on the Northern side of the Westcliffe Ridge (Schäffler et al., 2013; Turton et al., 2006).

Schäffler et al. (2013) describe how the distribution of trees within Johannesburg is highly uneven, with the (historically affluent, white) Northern suburbs having tree coverage of approximately 24% while the areas to the South of the mining belt have only 6.7% coverage. The exception indeed proves the rule in this case, with Alexandra – an apartheid-era township adjacent to Sandton, an affluent Northern Johannesburg suburb and business centre – notably having almost no tree coverage at all, in contrast to its wealthy surroundings (Schäffler et al., 2013). Throughout Johannesburg's expansion, both before and during apartheid, various “mechanisms for control” were mobilised to enforce racial segregation, including town planning schemes and health regulations (Bremner, 2010, p.160). The segregated development of Johannesburg along racial lines has dictated the uneven distribution and access to green infrastructure (Culwick et al., 2019; Khanyile & Culwick, 2023; Venter et al., 2020).

Johannesburg provides both a unique and transferrable case study to understand the interplay between socio-spatial inequality, vegetation coverage, and heat *Risk*. While the specific history of urban segregation is not necessarily ubiquitous, it nevertheless serves to provide a high-resolution example of the impacts of unevenly distributed ecological assets along sociodemographic lines – a phenomenon widely shared across Global South and international contexts (Anguelovski et al., 2018; Dodman et al., 2023). Additionally, the interplay between urban morphology and climate change in producing increased temperatures within Johannesburg follows internationally observed trends, and makes for a transferrable and applicable case study (Phelan et al., 2015; Souverijns et al., 2022).

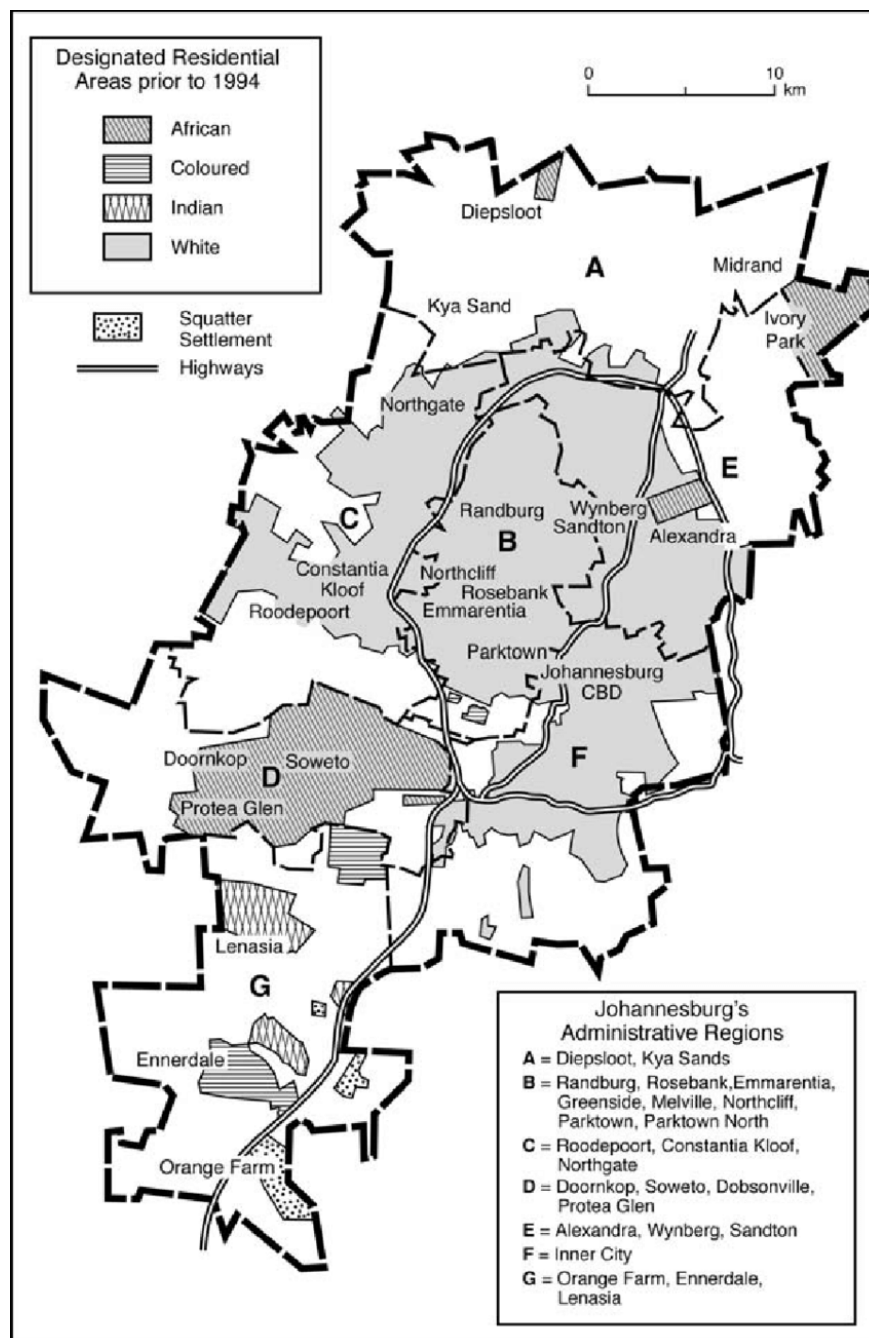


Figure 8: Racial segregation in Johannesburg prior to 1994 (McKay & Bell, 2011)

4.2 Results and Analysis

4.2.1 Distribution of Vegetation and Heat Exposure

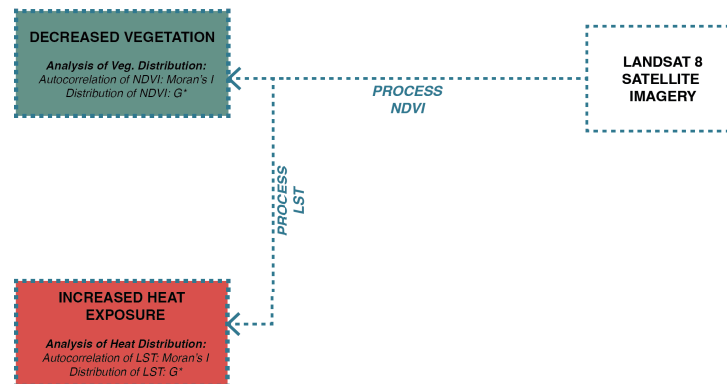


Figure 9: Analysis of Vegetation Distribution

4.2.1.1 Distribution of Vegetation

As described above, the distribution of vegetation in the City of Johannesburg is highly uneven, and unequal, as a result of the city's historic urban development patterns. In order to better understand and quantify the distribution of vegetation, mean *NDVI* (scale of -1 to 1), is calculated at ward-level from Landsat 8 satellite imagery, from three days in the summer of 2015/2016. The mean value of ward average *NDVI* for the 130 CoJ wards used in this study, within the study period, is 0.33, with a standard deviation of 0.09. The minimum average *NDVI* value is 0.13, and the maximum average ward value is 0.49. The distribution of *NDVI* values is indicated in the box plot graph in *figure 10* below.

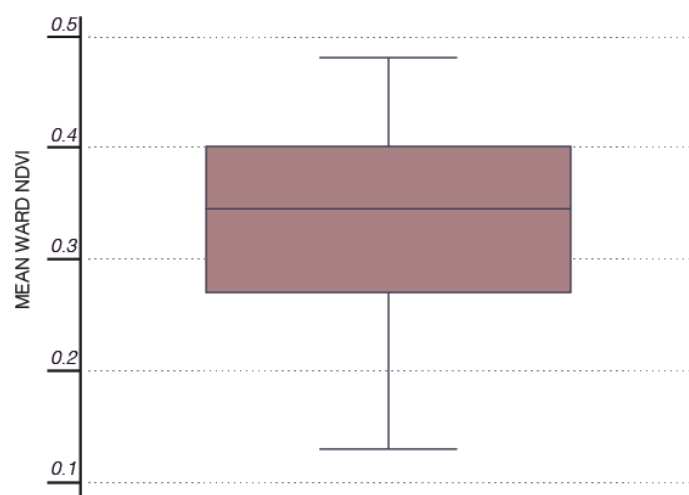


Figure 10: Box Graph showing distribution of mean *NDVI* values at ward-level

Moran's I for *NDVI*

Analysing the spatial distribution of vegetation (*NDVI*) as the independent intervening variable, hypothesised to impact the dependent intervening variable of *LST* (as a proxy for *Exposure*) and thus heat-related *Risk* within Johannesburg, Moran's I for *NDVI* is determined to be 0.585, indicating positive spatial autocorrelation. It demonstrates that wards with similar *NDVI* values are spatially correlated with each other (as shown in the scatter plot *figure 11* below). The upward trajectory of the slope, with a concentration of points in the upper-right and bottom-left quadrants suggests that wards with a high *NDVI* value – indicating strong presence of vegetation – are likely to be close to other wards with high values, and that wards with lower *NDVI* values more likely to be located adjacent to other wards with lower levels of vegetation. Further, the Moran's I value of 0.585 represents a moderately strong positive autocorrelation, suggesting that the similarity of vegetation levels within adjacent wards is likely related to other spatial factors (such as population distribution, urban policy, or climate, among other potential informants). Poor quality or missing satellite data for *NDVI* and *LST* was found for five wards within CoJ, and these have been omitted from the analysis by removing isolates within the weighting of ward neighbours, to avoid returning values that assume wards to have neighbours with values of zero.

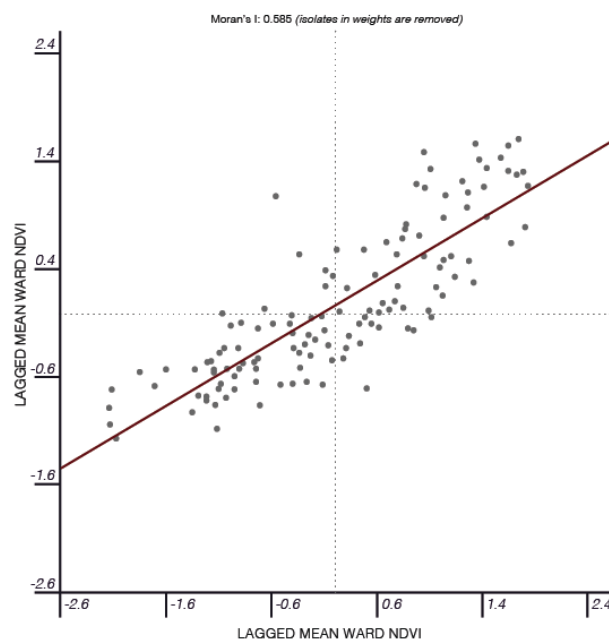


Figure 11: Moran's I Scatterplot for the Distribution of Vegetation

Getis-Ord Analysis of Vegetation

G* clusters are identified for *NDVI* values using row-standardised weights, to identify the spatial locations of high and low vegetation levels. The G* analysis shown in *figure 12-13* indicates that significant ($P < 0.05$) wards with higher levels of vegetation tend to be situated to the North of the mining belt, with clusters of wards with low levels of vegetation in the South-West in the region of Soweto township, around Alexandra township, and Ivory Park township – all historically segregated and underserved areas allocated for black populations, as well as the Johannesburg Central Business District.

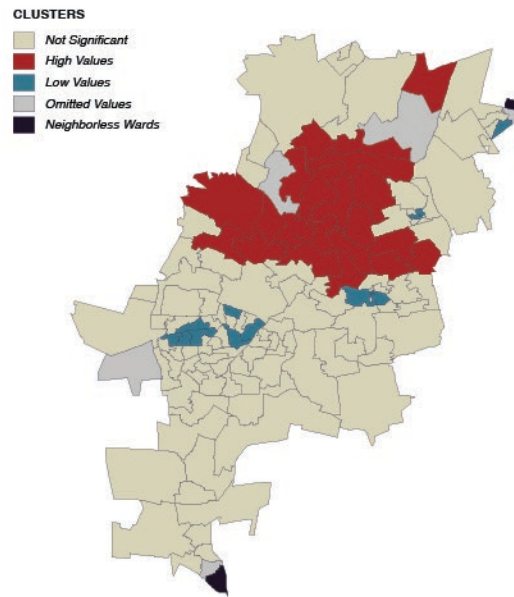


Figure 12: Distribution of Ward average NDVI, indicating the amount and quality of vegetation per ward, on a scale of -1 to 1

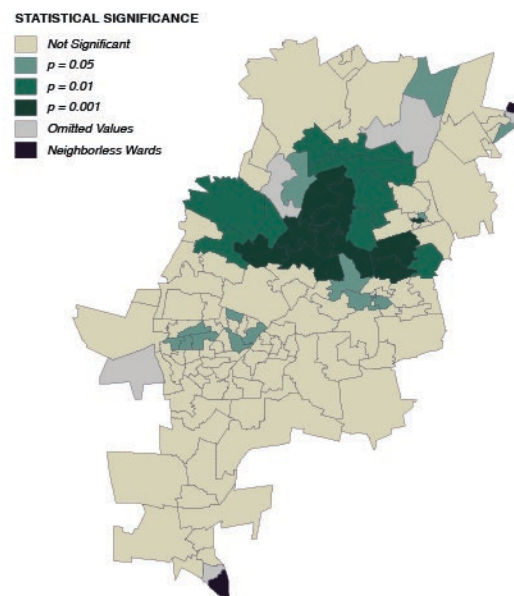


Figure 13: Significance of clusters, suggesting that the results of the Getis-Ord analysis are statistically significant at a minimum confidence interval of 95%

4.2.1.2 Distribution of Heat Exposure

As in the analysis of vegetation distribution, the spatial distribution of heat *Exposure* is analysed by processing Landsat 8 data to determine mean *LST* at ward-level, as an accepted proxy for ambient air temperature and urban heat islands (UHIs) (Goldblatt et al., 2021; Klopfer & Pfeiffer, 2023), used for its convenience, affordability, and capacity to capture and compare data over large areas and time periods.

Three days during the summer of 2015/2016 were selected for the following reasons:

1. Being a particularly hot summer (Africa Data Hub, 2024). Please see *Appendix 2: Historic CoJ Climate Data* for average monthly temperatures in CoJ for 2011-2020.
2. Having relatively low cloud cover, ensuring additional accuracy (Africa Data Hub, 2024). Please see *Appendix 2* for average monthly precipitation in CoJ for 2011-2020.
3. Being temporally equidistant between the 2011 census and 2020/2021 GCRO QOLS.

The average LST during the period for the 135 wards analysed 34.69°C, with a standard deviation of 1.58. The lowest average ward LST is recorded as 30.94°C degrees, while the maximum average ward LST is 39.06°C, as indicated below.

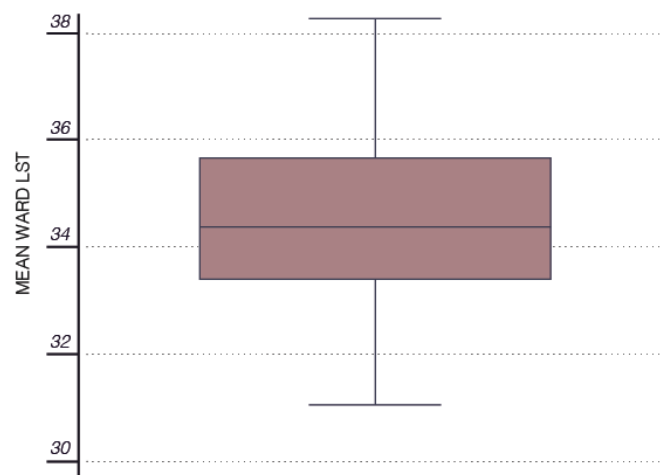


Figure 14: Distribution of Ward mean LST values, as a proxy for heat Exposure per ward, in degrees Celsius.

Moran's I for *LST*

The spatial autocorrelation of *Heat Exposure* (as the dependent intervening variable) is determined through the same process used for *NDVI* (above). The resulting Moran's I value of 0.734 for *LST* again shows positive spatial autocorrelation, and that wards with similar *LST* values are spatially correlated with each other. The upward trajectory of the slope, and distribution of points suggests that wards with a high heat *Exposure* are likely to be located in similar areas, and vice-versa. As in the analysis of *NDVI* above, the positive and relatively high spatial autocorrelation of *LST* at ward-level suggests significant clustering of heat *Exposure*, and may be related to other spatially spatially-related factors, one of which could be the distribution of vegetation.

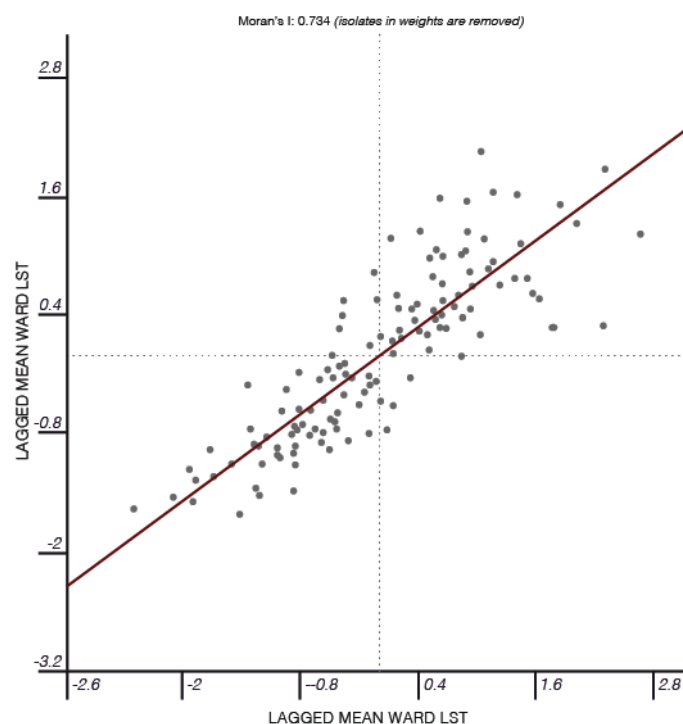


Figure 15: Moran's I Scatterplot for the Distribution of Heat Exposure

Getis-Ord Analysis of Heat Exposure

The locations of spatially clustered high and low temperatures are determined through the same Getis-Ord process used for *NDVI*, revealing autocorrelation of values between neighbouring wards, with a maximum P-value of 0.05, or a 95% confidence interval.

The G* maps shown below indicates a general trend of wards with higher temperatures being located within the Southern parts of CoJ, while the low temperature clusters are situated to the North of the mining belt (significant at a minimum level of $p=0.05$). This is in-line with the hypothesis that not only is temperature exposure spatially clustered, but that it follows a similar pattern to the distribution of vegetation, as well as sociodemographic disparities between North and South.

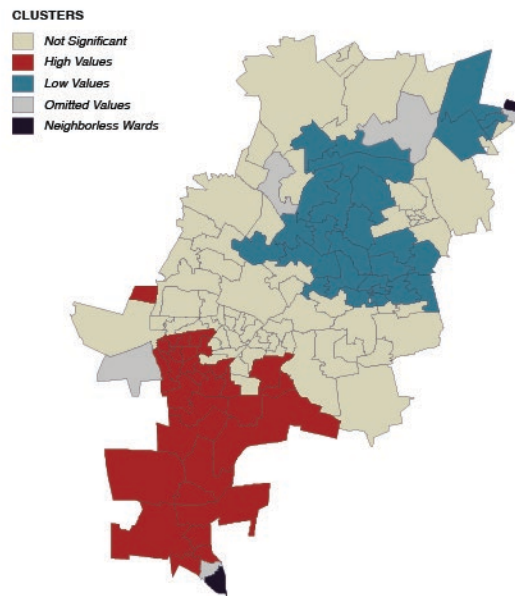


Figure 16: Getis-ord clusters of high and low mean LST values per ward

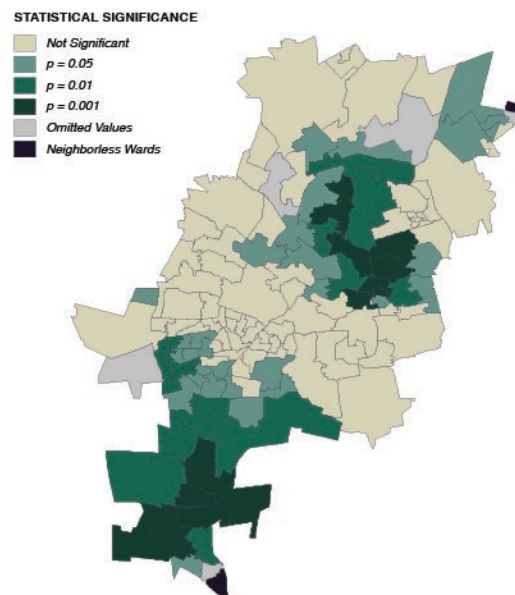


Figure 17: Significance of relationships between ward mean LST values

4.2.3 Relationship Between Distribution of Vegetation and Heat Exposure

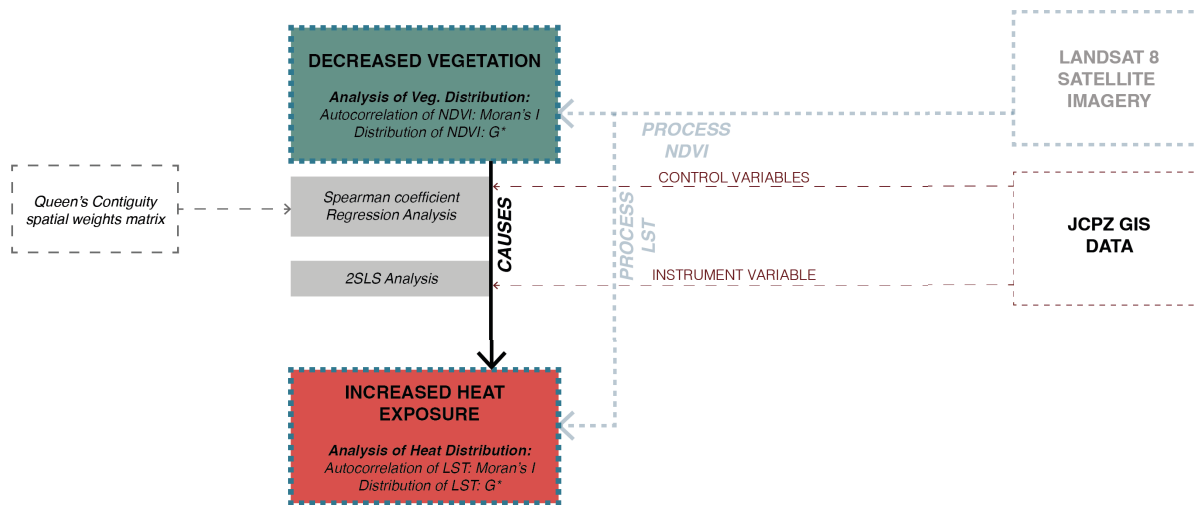


Figure 18: Analysis of the impact of vegetation levels on heat exposure

Effect of Vegetation Distribution on Heat Exposure

This section addresses *RQ1: Does the spatial distribution of vegetation affect Land-Surface Temperature (LST), as a proxy for local heat exposure?*

The maps below (figure 19-20) indicate mean *NDVI* values, and mean *LST* values (as a proxy for *Exposure*) distributions at ward level. Initial visual inspection suggests the expected negative correlation between heat and temperature, as wards with higher vegetation levels appearing to also have lower average temperatures. As established through the *G** analysis of *NDVI* above, the Northern areas of CoJ have noticeably higher average vegetation levels, and lower average temperatures. Alexandra Township, situated in the Northern part of CoJ is a conspicuous exception, with lower measures of vegetation and higher average temperatures. However, this provides further justification for the hypothesis that marginalised populations experience increased heat *Exposure* and have lower levels of vegetation. Alexandra Township is a historically ‘Black’ area, established in 1912 as a ‘native township’ with the further entrenchment of the area as a segregated space for black migrant workers under the apartheid regime’s Group Areas Act in 1950 (Mgquba & Vogel, 2004). Similarly, Soweto – the largest apartheid-era township in South Africa – located in the South-Western areas of the CoJ, is noticeable for its lower levels of vegetation and higher temperatures. In contrast, the anomalous high vegetation levels and slightly reduced temperatures to the East of Soweto and South of the CBD correspond with historically white (working class) neighbourhoods. This further supports the hypothesis of there being a link between vegetation coverage and heat *Exposure*, and that these variables are distributed in-line with historic and contemporary socio-spatial inequalities.

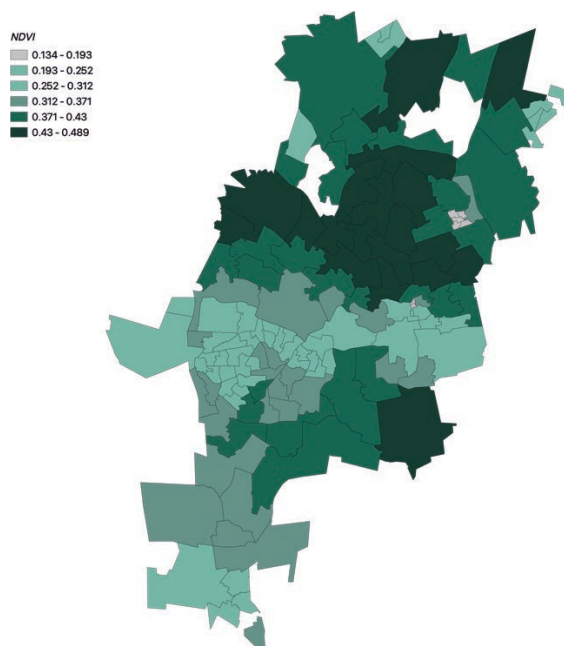


Figure 19: Mean Distribution of Vegetation (NDVI)

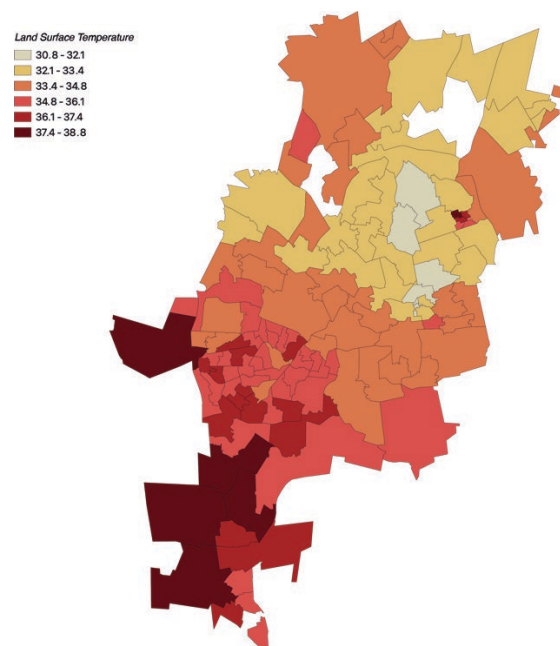


Figure 20: Mean Land Surface Temperature (LST)

Variable	Observation	Mean	Std. dev.	Min.	Max.
<i>LST</i>	130	0.49	0.19	0	1
<i>NDVI</i>	130	0.54	0.25	0	1
<i>Park Area</i>	130	0.09	0.14	0	1
<i>Elevation</i>	130	0.59	0.19	0	1

Table 1: Min-Max Normalised Summary Statistics for *LST*, *NDVI*, *Park Area* and *Elevation*

Spearman Correlation and Regression Modelling

The relationship between vegetation and temperature has been long-established, and represents a physical relationship further demonstrated by a significant ($P=0.000$) Spearman correlation coefficient of -0.4409 (Table 4) between *NDVI* and *LST* – suggesting a moderately strong negative relationship, and that as vegetation levels increases, heat tends to decrease. Table 2 describes an estimation of the relationship between normalised values for vegetation (*NDVI*) and heat *Exposure (LST)*, with the inclusion of *Elevation* and *Park Area* as control variables. The summary statistics of the normalised Independent, Dependent, and Control variables are shown below, and full regression results can be found in Appendix 4: *Regression Output*.

The Ordinary Least Squares regression analysis (1a; 2a; 3a) provides an initial exploration of the interaction between independent, dependent, and control variables, and justifies the use of a spatial regression model. Holding all other variables constant, it suggests that there is a statistically significant inverse relationship between *NDVI* and *LST* as expected. Meanwhile, *Park Area* per ward has a surprising inverse relationship, significant in regression 1c, and is associated with an increase in *LST* – representing an important distinction between the role of

vegetation distribution and allocation of open public space in reducing *Heat Exposure* in cities. *Elevation* is associated with a statistically significant decrease in *LST*, however it is notable that *NDVI* is a far stronger predictor of *LST* than either *Elevation* or *Park Area*.

However, the OLS regressions have low R-squared values, suggesting limited explanatory power in the regressions. Additionally, as explored through the Moran's I tests above, autocorrelation has been detected within both the independent (intervening) variable (*NDVI*) and dependent (intervening) variable (*LST*). This is further supported by a spatial diagnostic test for dependence in the OLS regression output (table 3), with the significant positive Moran's I value indicating spatial clustering, and Lagrange multiplier test (which tests for autocorrelation within the error terms) suggesting spatial dependence in the error terms (or residuals). These factors can affect the validity of the OLS regression, and due to the likelihood of a direct connection between wards based on their proximity to one another. As a result, a spatial regression is required to more accurately assess the relationships between variables. A spatial error model is selected, addressing the spatially-dependent nature of the data, addressing autocorrelation, and represents a good fit to the data (Log-Likelihood = 107.68).

Within the more accurate SEM model, the significant *NDVI* coefficient of -0.28 shows, as expected, that an increase in vegetation within an area is associated with lower temperatures, and therefore lower heat *Exposure* for the occupants of that area. Again, this is contrasted with *Park Area* which, like *NDVI*, would be expected to have an inverse relationship with *LST*. However, this relationship is not statistically significant in the SEM model. Even if the coefficient for *Park Area* were to be meaningful, it has a consistently positive coefficient across all OLS and SEM regressions, supporting its distinction from *NDVI*. Similarly, the coefficient of *Elevation* is not statistically significant. The significant positive Lambda value of 0.82 in 3b suggests that there is indeed positive spatial autocorrelation of the error terms, and that the choice of a spatial regression model is justified, while there is a good balance between complexity and fit when compared to the OLS model ($AIC_{1a} < AIC_{1c}$), and is supported by the Schwarz Criterion (BIC) results.

Regressor	OLS			Spatial Error Model (Robust)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
<i>NDVI</i>	-0.31*** (0.06)	-0.35*** (0.06)	-0.39*** (0.07)	-0.26*** (0.06)	-0.27*** (0.05)	-0.28*** (0.08)
<i>Park Area</i>		0.19 (0.13)	0.21* (0.12)		0.06 (0.07)	0.04 (0.07)
<i>Elevation</i>			-0.24** (0.08)			-0.18 (0.12)
Intercept	0.65*** (0.03)	0.66*** (0.04)	0.82*** (0.07)	0.61*** (0.05)	0.61*** (0.05)	0.71*** (0.08)
Lag Coeff. (Lambda)				0.84***	0.83***	0.82***
R ²	0.16			0.75	0.75	0.76
Adj R ²		0.17	0.21			
Log-Likelihood	40.34	41.98	46.24	106.51	106.90	107.68
AIC	-77.68	-77.95	-84.38	-209.02	-207.80	-208.08
BIC	-71.94	-69.35	-73.01	-203.27	-199.2	-196.61

Table 2: Regression Analyses of normalised *NDVI* and *LST*, with controls

Diagnostics	
Test	Statistic
Moran's I	27.58***
Lagrange Multiplier	9.251**

Table 3: Diagnostics tests

Finally, in support of a claim for the *Vegetation Distribution (NDVI)* having an impact on heat *Exposure (LST)*, an instrumental variable is used that draws on the findings above, which shows the variable *Park Area* to have a positive correlation with *NDVI*, yet very little association with *LST*. Based on these findings, the percentage of park coverage per ward (*Park Area pct*) is used as an instrumental variable in a two-stage regression as described in Chapter 3. While the following stages do not definitively prove causality between the *NDVI* and *LST*, they do demonstrate a strong case for causality – in line with literature reviewed in Chapter 2. The first stage regression identifies percentage of park coverage per ward (*Park Area Pct*) as a relevant instrument and strong predictor of *NDVI*, with a correlation of an F-statistic of 21.01 (greater than the threshold of 10) and statistically significant coefficient ($P < 0.0001$). Further, the second stage regression demonstrates the significant negative impact of *NDVI* on *LST* through the instrumental variable estimation (coeff. = -9.21, $P < 0.05$), and therefore that increased levels of vegetation are associated with decreased local heat *Exposure*. The 2SLS regression results can be found in *Appendix 4: Regression Output*.

As there is only one instrument identified, the theoretical significance of this relationship is understood through historical and contemporary underinvestment in care for ecological and spatial infrastructure within marginalised neighbourhoods in Johannesburg (Blair Howe, 2022; Pieterse & Owens, 2018). This is supported by the negative correlation between *Park Area pct* and *NDVI* (-0.48), and small, yet positive relationship with *LST* – an important finding for policymakers and planners as described above, indicating that it is the distribution and characteristics of vegetation, rather than allocation of public open space, that reduces heat *Exposure*.

4.2.4 Relationship Between Marginalised Sociodemographic Populations Heat Exposure

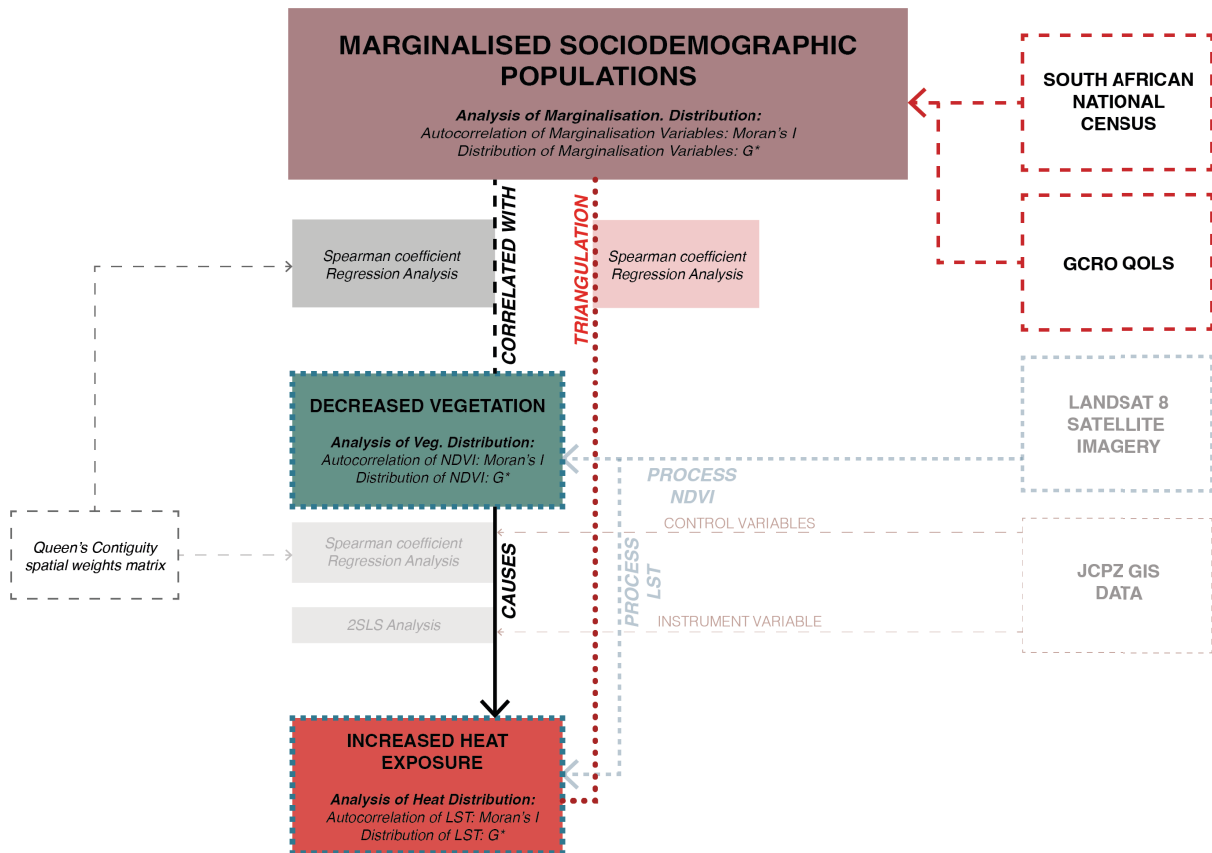


Figure 21: Relationship between Marginalised Populations and Heat Exposure

This section addresses *RQ2: Does the unequal distribution of vegetation increase heat exposure for marginalised sociodemographic populations within Johannesburg?*

Spatial Distribution of Marginalised Populations

South Africa's history of apartheid and colonialism, race represents a historic determinant of social, economic, and cultural marginalisation. In order to assess whether marginalised populations experience increased heat *Exposure*, an understanding of the spatial distribution of sociodemographic population groups is required. This section will analyse the spatial distribution of marginalised demographics, using the sub-variables *Race*, *Income*, and *Housing Type* (Ballard & Hamann, 2021)

With racial segregation and discrimination in South Africa playing a fundamental role in determining both longue-durée and contemporary spatial planning and urban morphology, it is important to understand the CoJ's racial demographic profile. According to the 2011 census, 76.4% of residents in the City of Johannesburg are Black African, and only 12.3% are White. Under the discriminatory apartheid regime, and colonial history, non-white citizens have been historically marginalised. As legacies of apartheid and colonialism are still present, racial demographics will be aggregated as a percentage of non-white residents per ward, in order to develop an understanding of distribution of populations historically marginalised due to racial discrimination.

An initial visual inspection of maps showing ward-level comparisons of mean *Income*, *Housing Type* associated with marginalised demographics, and percentage of residents who identify as a historically disadvantaged *Race* (ie not white) suggests that these indicators are clustered both internally – with similar values similar areas – and similarly correlated between each other. In order to fully understand the nature of these clusters internally, Moran’s I and G* analyses will be conducted for each – following the same process as *NDVI* and *LST* above – followed by Spearman’s correlation and regression analyses to understand the relationships between these sociodemographic indicators.

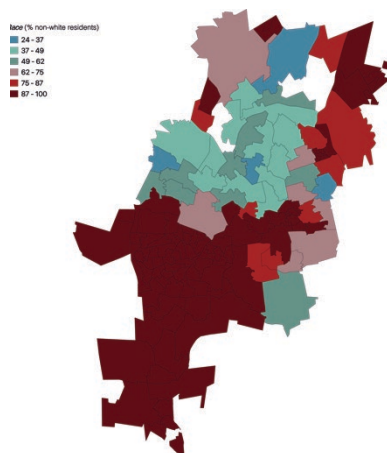


Figure 22: Percentage of non-white residents per ward

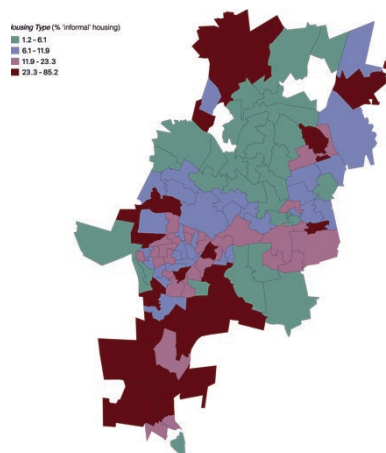


Figure 23: Percentage of Informal Dwellings

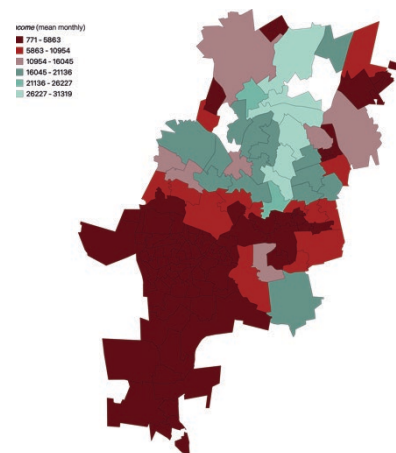


Figure 24: Mean Income

Moran’s I for Sociodemographic Status

Once again using queen’s contiguity to define spatial relationships between wards, Moran’s I for *Race* and *Average Income* shows that similar values for these variables are situated in similar areas. *Race* and *Average Income* have identical values of 0.748, indicating strong positive spatial autocorrelation, while the Moran’s I value for *Housing Type* is 0.383, indicating a slightly weaker, nevertheless present autocorrelation. This demonstrates the continued presence of socio-spatial inequality as the variables are spatially related, and the possibility that similar sociodemographic profiles will have access to similar levels of vegetation and be exposed to similar levels of heat.

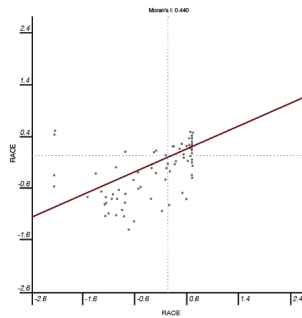


Figure 25: Race

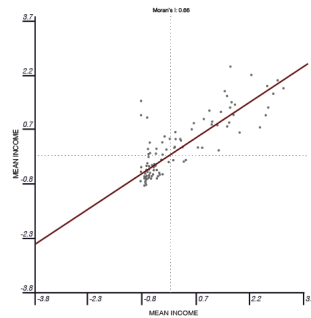


Figure 26: Income

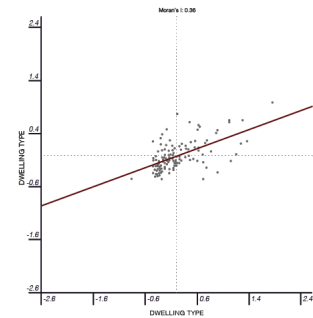


Figure 27: Housing Type

Getis-Ord Analysis of Marginalised Demographic Variables

The locations of spatially clustered sociodemographic variables are indicated by the statistically significant G^* statistics, shown in *figure 28* below. Visual inspection of the maps suggests not only spatial correlation (with wards with similar values being in close proximity to other wards with similar values), but also that these variables follow somewhat similar patterns to each other, as well as the *NDVI* and *LST* clusters, with significant clusters separated by the mining belt, which runs from East to West through the centre of Johannesburg.

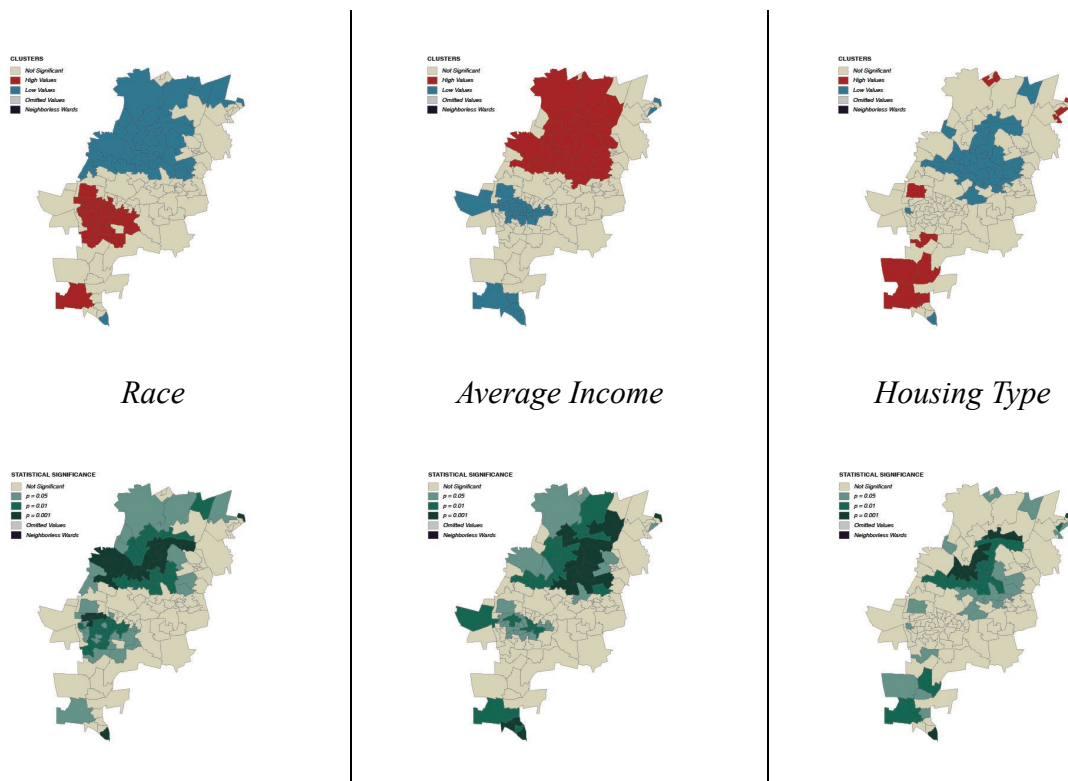


Figure 28: G^* Clusters (top) and Statistical Significance of clusters (bottom)

Combining Sociodemographic Variables

The below Spearman's correlation analysis is used in order to further understand the relationships between racial profiles, average income, and housing type per ward, exploring the potential of combining and conflating indicators in order to simplify the model.

Spearman's Correlation between sociodemographic variables, *** significant at 0.001 level, ** significant at 0.01 level, * significant at 0.05 level.

Variables	Race	Income	Housing Type	NDVI	LST
Race	1	-0.8185***	0.5366***	-0.7014***	0.5876***
Income	-0.8185***	1	-0.6661***	0.7149***	-0.5967***
Housing Material	0.5366***	-0.6661***	1	0.4380***	0.4380***
NDVI	-0.7014***	0.7149***	-0.4416***	1	-0.4409***
LST	0.5876***	-0.5967***	0.4380***	-0.4409***	1

Table 4: Spearman's Correlation of Sociodemographic variables, NDVI, and LST

The above correlation analysis shows that the variable of *Income* has a very strong negative correlation with *Race*, significant at 0.001 level, and a strong negative correlation with the use of *Housing Type*. As a result, *Income* will be used to represent all three sociodemographic variables. This is further supported by visual inspection of the similarities in the Getis-Ord clustering, indicated above. A final consideration in the selection of *Income* as a proxy for sociodemographic status is that income not only encompasses racial and housing considerations, but also allows for wider comparison across international urban contexts, in which race may be as significant in determining sociodemographic status.

Similarly, increased marginalisation across the three indicators is consistently correlated with increased heat *Exposure* (increased *LST*) and decreased vegetation (lower *NDVI*) – providing further justification for conflating the variables when studying these relationships. The resulting relationship between *Income* as a proxy for sociodemographic marginalisation, access to distribution of vegetation, and heat *Exposure* is represented in the graphs below.

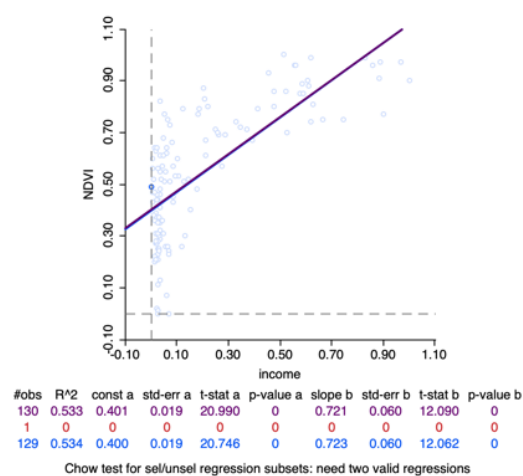


Figure 29: Relationship between Income and vegetation

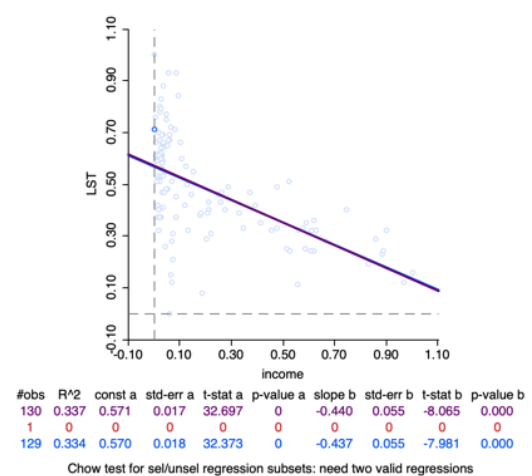


Figure 30: Relationship between Income and heat Exposure

Regression Analysis of Marginalised Demographics, Distribution of Vegetation, and Heat Exposure

While this section does not aim to establish causality in the relationship between sociodemographic status and the distribution of vegetation, it nevertheless employs OLS and spatial regression modelling to develop a more nuanced understanding of these relationships at ward-level. It follows the same procedure as in the OLS and SEM used above, and outlined in Chapter 3, to better understand the visually apparent correlation between sociodemographic clusters and vegetation clusters, and the resulting differential heat *Exposure* (building on the relationship between *NDVI* and *LST* already established). Regression modelling of marginalisation and *LST* is used to triangulate the conclusion that decreased levels of vegetation within areas occupied by marginalised populations does indeed result in increased heat *Exposure*. The results of the below OLS and spatial error models confirm the expected statistically significant positive relationship between *Income* and *NDVI*, and statistically significant negative relationship between *Income* and *LST*. The results also demonstrate that these relationships are spatially dependent – suggesting that not only are marginalised sociodemographic populations correlated with lower levels of vegetation and increased heat *Exposure*, but also that this relationship is indeed spatial. This is determined by comparing the results of the spatial error model, which captures the spatial dependence using queen’s contiguity spatial weighting, with the OLS model. In both the *NDVI* and *LST* regressions, the spatial error model has a better fit (higher R-squared value), and shows spatial autocorrelation within the model ($\text{Lambda} > 0$, $P < 0.0001$).

Regressor	NDVI		LST	
	OLS (3a)	Spatial Error Model (3b)	OLS (4a)	Spatial Error Model (4b)
<i>Income</i>	0.72*** (0.06)	0.64*** (0.09)	-0.44*** (0.05)	-0.27** (0.07)
Intercept	0.4*** (0.02)	0.39*** (0.04)	0.57*** (0.02)	0.53*** (0.04)
Lag Coeff. (Lambda)		0.69*** (0.07)		0.79*** (0.06)
R ²	0.53	0.69	0.33	0.72
Log-Likelihood	44.2	63.95	55.79	102.51
AIC	-84.41	-123.91	-107.59	-201.02
BIC	-78.68	-118.17	-101.85	-195.28

Table 5: Regression Analysis of Marginalised Populations, Distribution of Vegetation, and Heat Exposure

As it has already been established that reduced levels of vegetation result in increased temperatures (and therefore increased *Exposure*), the association between marginalised populations and lower *NDVI* values suggests that marginalised sociodemographic populations will experience greater heat *Exposure* due to the uneven distribution of vegetation – increasing their risk of suffering from the ill-effects of climate change, and global warming. This has been triangulated by showing that there is indeed positive, significant association between marginalisation and increased *LST* values (as a proxy for *Exposure*).

4.2.5 Relationship Between Marginalised Sociodemographic Populations and Vulnerability to the Ill-Effects of Heat Exposure

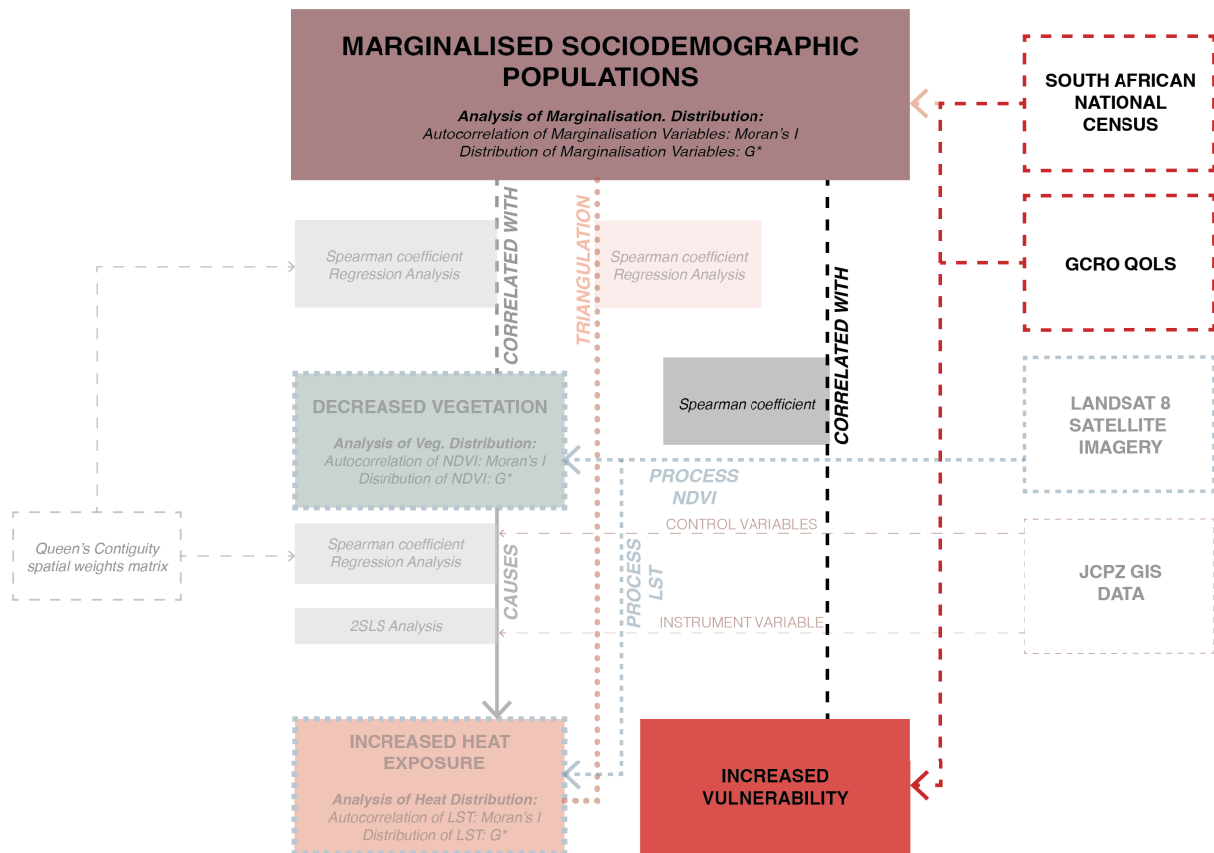


Figure 31: Analysis of relationships between marginalisation and Vulnerability

This section addresses *RQ3: Are marginalised sociodemographic populations more vulnerable to the ill-effects of heat exposure in Johannesburg?* Hazards associated with increasing temperatures are now in little doubt, and the uneven nature of exposure to heat (as a climate-related *Hazards*) within Johannesburg has been demonstrated above. While sociodemographic status is not conflated in this study with *Vulnerability* – as the ability “to anticipate, cope with, resist, and recover from the adverse effects of physical events” (Cardona et al., 2012, p.32) – the two are often correlated. While this study does not directly address ability to anticipate heat events, it remains an important topic for future investigation.

As described in Chapter 2, inequality often results in increased *Vulnerability* to heat for marginalised populations. Following from the above findings that marginalised populations experience increased heat-related *Risk* due to increased *Exposure*, *Vulnerability* is explored as an additional factor that affects *Risk*. *Vulnerability* to heat, as shown in the literature above, is the result of multiple complex and interconnected environmental and social health factors. Heat *Exposure* interacts dynamically with existing health conditions – exacerbating both the direct ill-effects from heat, as well as the severity of co-morbidities. These interactions between heat and pre-existing conditions, as well as the direct effects of heat and heat-related morbidity are amplified for children under 4 years and elderly people, who are therefore more vulnerable. The severity of both heat-related diseases and co-morbidities are further exacerbated by a lack of access to medical care, which is often reliant on access to medical insurance. Thus, this study

focuses on whether marginalised populations experience greater *Vulnerability* as a result of their experiencing increased prevalence of co-morbidities, lower rates of medical insurance, and larger populations under four years of age. Elderly populations are excluded from this analysis, as in the case of Johannesburg – and many global contexts – increased age is correlated with decreased marginalisation due to the increased life-expectancy associated with healthier lifestyles, increased wealth, and better access to medical care.

Spearman's Correlation of Marginalised Demographics and Vulnerability

While the above analyses rely on spatial correlation between marginalised populations and decreased levels of vegetation, which results in increased heat *Exposure*, this section takes a sociodemographic approach – which aims to assess the correlation between marginalisation (conflated to the indicator of *Income*) and indicators of *Vulnerability* described in Chapter 2 and Chapter 3 (*Age<4*, *Medical Insurance*, *Work Days Missed*, *TB*, *HIV*, and *Depression*). As these relationships are not inherently spatial, Spearman's coefficients (table 6) are used to evaluate correlation between marginalisation and *Vulnerability*. It demonstrates that marginalisation (*Income*) is significantly correlated with all six indicators of *Vulnerability*, with increased *Income* associated with decreased *Vulnerability*. As would be expected, the relationship between *Income* and *Medical Insurance* has a very strong positive correlation, at 0.83 – particularly significant as an indicator of the relationship between *Income* (and sociodemographic status) and ability to cope with and respond to heat-related health effects. This clearly demonstrates that, as is expected from reviews of existing literature in Chapter 2, marginalised sociodemographic populations experience increased *Vulnerability* to heat.

Spearman's Correlation between *Vulnerability*, *Marginalisation*, *NDVI*, and *LST* variables, *** significant at 0.001 level, ** significant at 0.01 level, * significant at 0.05 level.

Variables	Average Income (Sociodemographic proxy)	NDVI	LST
<i>Age<4</i>	-0.4004***	-0.2007*	0.2986***
<i>Medical Insurance</i>	0.8292***	0.6560***	-0.4001***
<i>Work Days Missed</i>	-0.3937***	-0.2485**	0.3718***
<i>TB</i>	-0.2883**	-0.2031*	0.1984*
<i>HIV</i>	-0.5520***	-0.3710***	0.4329***
<i>Depression</i>	-0.6240***	-0.5067***	0.4472***

Table 6: Spearman's Correlation of Marginalised Demographics and Vulnerability

These results are triangulated by the Spearman coefficient of *Vulnerability* variables and levels of vegetation (*NDVI*) and *Exposure* (*LST*), which produce the expected results of increased *Vulnerability* (associated with increased sociodemographic marginalisation) also being significantly correlated with lower levels of vegetation and increased *Exposure*. While the coefficients of these relationships are relatively lower than the correlation between *Vulnerability* and *Income*, this is likely the result of the spatial component of these relationships not being captured by the Spearman coefficient.

4.2.6 Relationship Increased Heat-Related Risk for Marginalised Sociodemographic Populations

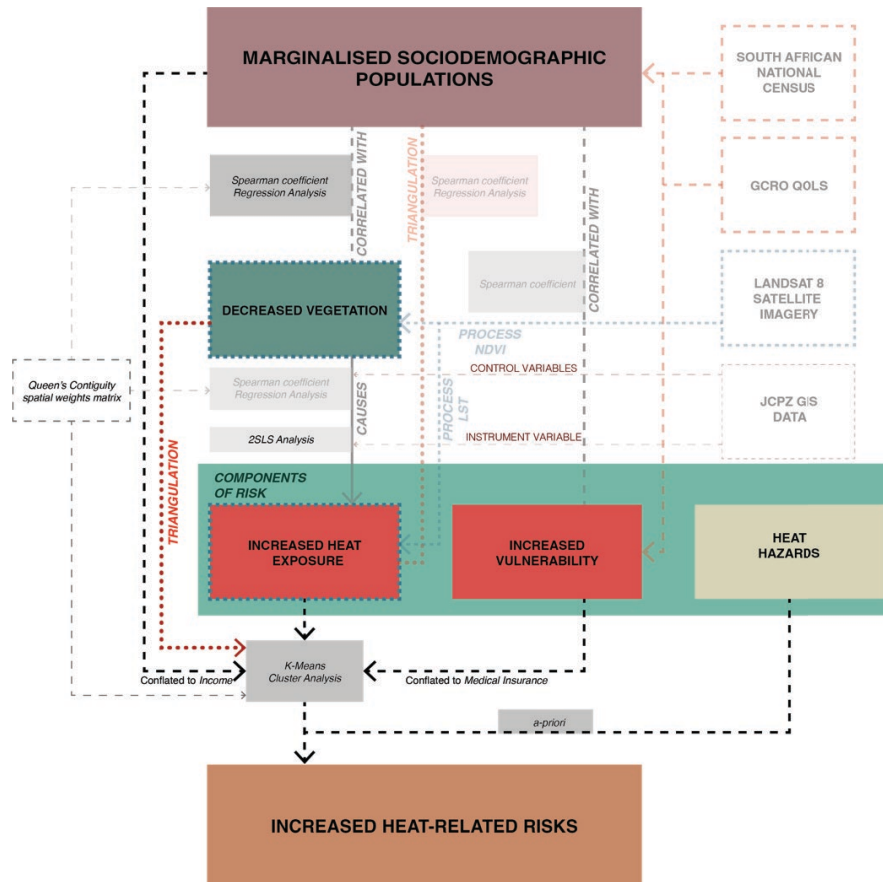


Figure 32: Combining Exposure and Vulnerability to evaluate heat risk for marginalised populations

This section addresses *RQ4: Do increased heat-exposure and vulnerability produce outsized heat-risk among socio-spatially marginalised populations within Johannesburg?*

Within highly unequal urban systems, segregated along social, economic, and racial lines, risks resulting from the impacts of environmental destruction and climate change can be conceived of as a combination of three factors – (i) *Hazards*, (ii) *Vulnerability*, and (iii) *Exposure* (Dodman et al., 2023; Oppenheimer et al., 2015). Increased levels of *Vulnerability* and *Exposure* among *Marginalised Sociodemographic Populations* has already been established above, while an increase in both current and expected future heat-*Hazards* is considered as an *a-priori* contributing risk factor, already demonstrated widely across the globe and in Johannesburg (Souverijns et al., 2022).

While increases in any one component of *Risk* (ie *Hazards*, *Exposure*, or *Vulnerability*) produces an increase in *Risk*, the overlapping increase in all three determinants within areas occupied by marginalised populations results in an outsized increase in *Risk* for these populations. In order to demonstrate these overlaps of *Marginalised Sociodemographic Populations*, *Exposure* and *Vulnerability*, the following K-Means cluster analysis shows the

spatial distributions of similar relationships between degrees of marginalisation (*Income*), *Exposure (LST)* and *Vulnerability (Medical Insurance)*.

Medical Insurance is determined as a generalised indicator of *Vulnerability*, in order to visualise these relationships. Indicators of *Vulnerability* are conflated to the single variable of *Medical Insurance* using the below Spearman coefficients, which show it to be significantly correlated with other indicators of *Vulnerability* (table 7). This is triangulated through an examination of Spearman coefficients between *Medical Insurance* and *Income* (0.83***), *NDVI* (0.66***), and *LST* (0.29***), which demonstrate the expected relationships (table 6).

Spearman's Correlation: *Vulnerability* variables, *** significant at 0.001 level, ** significant at 0.01 level, * significant at 0.05 level.

Variable	Age	Medical Insurance	Work Days Missed	Depression	TB	HIV
Age	1	-0.4019***	0.1298	0.1585	-0.0397	0.1989*
Medical Insurance	-0.4019***	1	-0.2397**	-0.4988***	-0.2703**	-0.4977***
Work Days Missed	0.1298	-0.2397**	1	0.5454***	0.2336**	0.3126***
Depression	0.1585	-0.4988***	0.5454***	1	0.3211***	0.4314***
TB	-0.0397	-0.2703**	0.2336**	0.3211***	1	0.3058***
HIV	0.1989*	-0.4977***	0.3126***	0.4314***	0.3058***	1

Table 7: Spearman's Coefficients to Conflate Vulnerability Variables

K-Means Cluster Analysis

A K-Means Cluster analysis is conducted to answer *Research Question 4: Do increased heat-exposure and vulnerability intersect to produce outsized heat-related risk among socio-spatially marginalised populations within Johannesburg?* This section aims to determine whether marginalised populations, who also live in areas with reduced vegetation and increased *Exposure*, overlap with the experience of increased *Risk* due to their being more vulnerable to the adverse effects of heat. In doing so, it identifies the extent of the disparity in *Risk*, and thus answer the overall research question of: *To what extent do marginalised sociodemographic populations experience aggravated heat risk as a result of an uneven and unequal spatial distribution of vegetation in Johannesburg?* To ensure comparable values across indicators of differing units and scale, all variables were normalised using Min-Max normalisation, with a range of 0 to 1 (with one representing the highest ward-value, and zero representing the lowest). This allows for a better understanding of the extent of disparity within the respective components of *Risk* between wards.

Following from the above Spearman coefficients and combining of variables, sociodemographic marginalisation is conflated to the variable of *Income*, while *Vulnerability* is conflated to the variable of *Medical Insurance*. *LST* remains a proxy for *Exposure*, and *NDVI* is maintained – serving as both a triangulating variable due to its established correlations with the other variables, while also remaining to provide insight for policymakers and planners on its uneven distribution within the city. Through an iterative process using GeoDa software, the number of clusters is determined to be two, as any clusters revealed small, anomalous relationships – confounding the general data trend and analysis. The following two distinct clusters were revealed, with *Marginalised Sociodemographic Populations*, *Exposure*, *Vegetation Distribution*, and *Vulnerability* levels represented on a scale of 0 to 1:

Cluster 1	Cluster 2
Increased marginalisation (<i>Income</i> : 0.05)	Decreased marginalisation (<i>Income</i> : 0.53)
Increased heat <i>Exposure</i> (<i>LST</i> : 0.53)	Decreased heat <i>Exposure</i> (<i>LST</i> : 0.32)
Decreased vegetation (<i>NDVI</i> : 0.4)	Increased vegetation (<i>NDVI</i> : 0.83)
Increased <i>Vulnerability</i> (<i>Med Insurance</i> : 0.1)	Decreased <i>Vulnerability</i> (<i>Med Insurance</i> : 0.59)

It is therefore demonstrated that **marginalised sociodemographic populations experience greater risk associated with increasing temperatures** – with 63.7% higher *LST* (as a proxy for *Exposure*), and 82.36% lower levels of *Medical Insurance* (as a conflated proxy for *Vulnerability* to the ill-effects of heat exposure). Therefore, it is seen that not only do marginalised populations experience greater heat-related *Risk* due to having increased *Exposure* (resulting from the uneven distribution of vegetation), but also that these populations have increased *Vulnerability* to the adverse effects of heat – thus further increasing *Risk*, while taking the presence of heat-related *Hazards* to be an *a priori* property of global warming (Dodman et al., 2023; Klopfer & Pfeiffer, 2023; Romanello et al., 2023; Souverijns et al., 2022). With increased levels of vegetation contributing towards decreasing temperatures, the lower levels of vegetation within wards that have greater levels of sociodemographic marginalisation can be understood to play an important role in determining greater levels of *Exposure*, and therefore greater *Risk*. Further, the potential co-benefits of access to vegetation for health outcomes is an important consideration for the reduction of co-morbidities that influence *Vulnerability* to the ill-effects of heat *Exposure*.

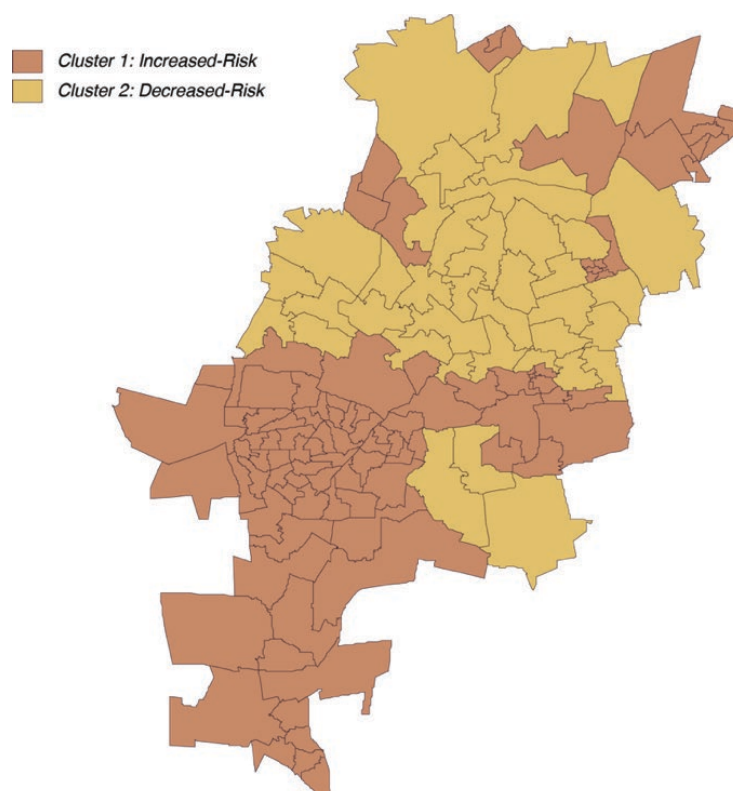


Figure 33: K-Means cluster map showing uneven distribution of Risk

4.3 Discussion

The results within this study, analysing the disproportionate heat-related *Risk* for marginalised sociodemographic populations in Johannesburg that result the uneven distribution of vegetation, and compounded by increased levels of *Vulnerability* to the ill-effects of heat.

Distribution of Vegetation and Heat Exposure for Marginalised Demographics

The results are consistent with the literature reviewed in Chapter 2, revealing that areas of CoJ occupied by marginalised populations have reduced levels of vegetation, and therefore experience greater *Exposure* to heat. These findings highlight concerns around *longue durée* and contemporary issues of socio-spatial and ecological justice – both within the context of Johannesburg (Ballard & Hamann, 2021; Blaire Howe, 2022; Pieterse & Owens, 2018) and internationally (Anguelovski et al., 2018; Dodman et al., 2023) regarding the compounding effects of inequality and climate change (Ebi et al., 2021; Romanello et al., 2023; Satterthwaite et al., 2020). For planners and policymakers, these findings provide valuable guidance on numerous fronts. Initially, the findings that marginalised populations live in areas with drastically reduced vegetation levels – and thus do not benefit from the wide range of benefits derived from ecosystem services and green infrastructure – points to the importance of integrating environmental and social justice concerns within planning and policymaking. In the case of Johannesburg, while significant investment has been made in infrastructure upgrades since the end of apartheid (Pieterse & Owens, 2018), these have not necessarily benefitted historically marginalised and underserved regions and ‘*sacrifice zones*’ (Blaire Howe, 2022) following broader global urban development trends (Anguelovski et al., 2018; Dodman et al., 2023).

The study establishes that, as expected, vegetation levels affect localised temperatures, resulting in increased heat *Exposure* within low-vegetation areas (which tend to be occupied by marginalised demographics). This finding, within the context of heat as an increasing *Risk* to population health and as temperatures rise with climate change (Cele et al., 2020; Kroeger, 2023; WHO, 2024), point to the importance of flourishing ecosystems and vegetation levels as a concern for policymakers as an important and effective preventative healthcare strategy. As a result, investments in equitable access to green infrastructure and ecosystem services is an important concern not only for socio-spatial and environmental justice, but also in reducing strain on healthcare systems (both directly through heat-related morbidity and indirectly by exacerbating the severity of co-morbidities) as well as reducing the negative impact of heat on economic productivity (Romanello et al., 2023). Finally, as increased risk to health and economic activity as a result of heat *Exposure* disproportionately affects already marginalised demographics, it contributes to a reinforcing feedback loop of inequality.

However, while the above concerns are widely acknowledged, this study furnishes these recommendations with additional detail on the nature of investments and attention to equitable green spaces and vegetation. It uncovers that while the equitable allocation of, and investment in parks and public spaces serves as an important component of improving access to green spaces, this is insufficient if there is not sufficient investment and care for the health of the vegetation within these spaces. This finding, revealed in the fact that the area of park space alone is not associated with a decrease in heat *Exposure*, holding vegetation levels constant.

Vulnerability to Heat for Marginalised Demographics

While it is established that marginalised sociodemographic populations experience increased heat exposure, it is also found that they are more vulnerable to the ill-effects of this exposure – therefore multiplying associated risk. This provides further evidence for policymakers and planners on the urgency and importance of addressing unequal distribution of vegetation, which not only reduces temperatures and exposure within these areas, but also contributes to reducing *Vulnerability* through the positive effects of green spaces on co-morbidities that are exacerbated by heat. Improvements to local air quality, reducing respiratory disease, promoting active lifestyles, improving mental health outcomes by reducing levels of depression and loneliness, and building resilience to wider climate-health concerns such as flooding are merely a few of the ways in which improved distribution of vegetation could provide co-benefits and tackle co-morbidities (Kjellén & Virgin, 2009; Romanello et al., 2023).

Heat Risk for Marginalised Demographics

Using the IPCC’s conceptualisation of *Risk* as a function of *Hazards* – taken within this research to be an *a-priori* factor both within CoJ and internationally (Africa Data Hub, 2024; Lindsey & Dahlman, 2024; Souverijns et al., 2022) – *Vulnerability*, and *Exposure* (Dodman et al., 2023), this study demonstrates that marginalised populations demonstrate both increased *Exposure* as well as increased *Vulnerability*, which interact dynamically to produce outsized levels of *Risk*. As the distribution of vegetation is established as resulting in increased *exposure*, and thus increased *risk*, and that this overlaps with increased *vulnerability* – thus multiplying the *Risk* faced by marginalised populations – unevenly distributed vegetation has a dramatic effect in multiplying heat-related *Risk* for marginalised populations. As a result, the study provides important evidence for the disproportionate and systemic impact of investments in the equitable distribution of vegetation in simultaneously addressing concerns of socio-spatial justice, environmental justice, healthcare burdens, and economic productivity.

5. Conclusions

This study explored some of the dynamics through which marginalised sociodemographic populations in Johannesburg experience increased heat-related *Risk*, as a result of unequally distributed vegetation, and having disproportionate levels of *Vulnerability* to its impacts. This research is particularly motivated by a rapidly growing concern for climate change as a risk to population health – particularly for marginalised populations in the Global South – and the potential robust medical evidence for these dynamics to motivate urgent climate action and equitable investments in resilience-enhancing ecosystems within urban systems. While the radical multilateral response to the COVID-19 pandemic illustrated the scale of action required to address health crises, climate change has received far less attention, despite representing the most critical threat to population health and healthcare systems. Strategic, targeted action is needed, by policymakers, planners, and citizens, to protect the most at-risk populations and environments. While the primary purpose of this study has been to identify some of the dynamics through which heat *Risk* affects the most marginalised populations, it also reframes the ways in which policymakers account for the impact of investments in equitable climate resilience – considering investments in nature-based, resilience-enhancing infrastructure not only in environmental terms, but as critical components preventative healthcare.

The study's findings corroborate the hypothesis that heat-related *Risk* disproportionately affects already marginalised populations, further entrenching existing inequalities by affecting health and economic activity. This lends additional weight to the interconnected and outsized impacts of addressing these risks through equitable and just spatial planning and policymaking. Finally, the study provides the groundwork for further research on the implementation of counterfactual accounting for the impact of investments in climate and heat resilience – including in the equitable distribution of vegetation and green space – to consider and account for its wide-reaching benefits across social and ecological systems.

The results are in-line with existing literature on risk, climate change, socio-spatial justice, and environmental justice, highlighting both the disproportionate risk to climate change faced by marginalised populations, as well as the role of vegetation and NbSs in addressing heat *Exposure* as one component of *Risk*. The focus on the case study of Johannesburg, both as an example of a Global South urban context and in its unique context of socio-spatial inequality, provides simultaneously transferrable findings and models for understanding the interplay between heat and resilient, equitable urban development, as well as specific contextual insights into the dynamics of heat *Risk* within the city itself. Transferring these findings to other urban contexts, variables affecting sociodemographic inequality and *Vulnerability* may be modified within the conceptual model and operationalisation, while additions of context-specific adaptive capacities, and local qualitative insights into the feedback loops and complex interplay between sociodemographic factors, investment in equitable urban planning and GI, climate change, and *Vulnerability* present promising and important lines of further research within Johannesburg and international contexts.

Recommendations

Following from the findings within this study, the following recommendations are proposed:

1. Targeted investment in equitable green infrastructure and vegetation maintenance within underserved areas – developing safe, accessible, and multifunctional green spaces. These should intentionally target and contribute towards building resilience to heat and other climate-related risks such as flooding and biodiversity, while improving populations health and wellbeing across physical and mental dimensions.
2. Development of a counterfactual accounting system for the interconnected co-benefits of climate action and investments in resilience, in order to better understand their true value and impact. This should include attention to private sector and ESG accounting for the impact of systemic and targeted investments that have widespread benefits.
3. Integration of climate risks within national healthcare policy, and in the case of South Africa, within the proposed National Health Insurance system, as a vital component of preventative healthcare.
4. Integration of environmental justice within urban planning and decision-making, reconsidering the ontological separation of human and ecological wellbeing as trade-offs, rather than mutually reinforcing and interconnected systems.
5. Improved cross-cutting vertical and horizontal collaboration between governmental departments and public sector siloes, to better understand value of resilient, equitable urban planning and policy for local and national economies and healthcare systems, as well as climate targets.
6. Improved monitoring and data collection of factors that impact risk through exposure, such as spatial data on air quality and pollution, biodiversity, and flooding, as well as factors that impact vulnerability as a component of risk, such as community networks, co-morbidities, and adaptive capacity.

Further Research Opportunities

This study intentionally serves as an entry-point to further studies which explore the potential for integrated climate and health action, as well as tackling ontologies of extractive modern narratives of development. Some potential research avenues are:

1. Understanding long-term effects of increased heat-related risk to the health outcomes of vulnerable populations.
2. Local-scale studies that build a more detailed picture of urban environmental dynamics which affect heat exposure, such as building height, materiality, the effect of air conditioning systems in producing external heat, and urban sprawl.
3. Qualitative studies on community action and adaptive capacity in building resilience and reducing vulnerability to heat exposure.
4. Development of counterfactual measuring, accounting, and reporting frameworks and to inform finance mechanisms for investments in green infrastructure and equitable resilience.
5. Adaptation and application of the conceptual and methodological model developed within this thesis to other Global South contexts, enabling comparative analyses between urban centres, and the development of risk-mitigation strategies and interventions that are both transferrable and context-specific.
6. Philosophical research into the implications of Planetary Health – the notion that climate change and environmental health represents the most critical threat to human health – on the extractive ontological distinctions between human and environmental systems that underpin modern economic narratives of growth and development.

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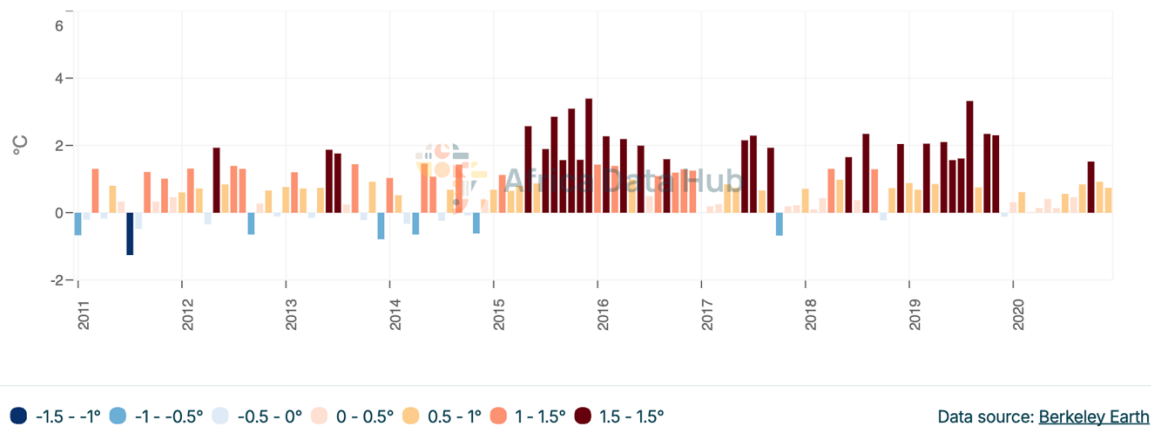
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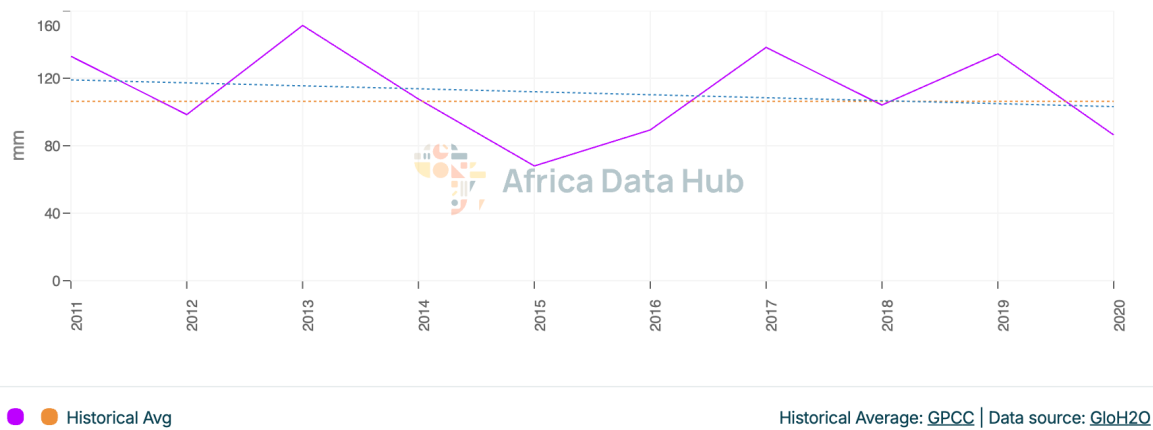
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Appendix 2: Historic CoJ Climate Data



Temperature anomalies in Johannesburg 2011-2020 (Africa Data Hub, 2024)



December rainfall in Johannesburg 2011-2020 (Africa Data Hub, 2024)

Appendix 3: Processing of Landsat 8 Satellite Data

1. Calculation of Top-of-atmosphere, using the formula:

$$TOA = MI * Q_{cal} + AI$$

2. Conversion of TOA to Brightness Temperature (BT):

$$BT = (K_2 / (\ln(K_1/L) + 1)) - 273.15$$

Where:

K_1 = Band-specific thermal conversion constant from the metadata

K_2 = Band-specific thermal conversion constant from the metadata

L = TOA

To convert the results in Celsius, the radiant temperature is adjusted by adding the absolute zero (approx. -273.15 degrees C)

3. Calculation of Normalised Difference Vegetation Index (NDVI):

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

Where:

NIR = Landsat 8 Band 4

RED = Landsat 8 Band 5

4. Calculation of Proportion of Vegetation Index (Pv):

$$P_v = \left(\frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})} \right)^2$$

5. Calculation of Emissivity (E):

$$E = 0.004 * P_v + 0.986$$

Where:

P_v = Proportion of Vegetation

6. Calculation of Land Surface Temperature (LST):

$$LST = BT / (1 + (\lambda * BT / c2) * \ln (E))$$

Where:

BT = Brightness Temperature

λ = Wavelength of emitted radiance = 10.8 (i.e. wavelength of Landsat 8 data)

$C2 = h * c / s$ (14388); h = Plank constant, s = boltzmann constant, c = velocity of light

E = Emissivity

Note: 10.8 is the wavelength of Landsat 8 data and 14388 is a constant

The results from the NDVI and LST analysis for all sample days are aggregated by ward, and represented initially as an average value per ward, per study day, and then as a total average value of the study days for each ward.

Appendix 4: Regression Analysis Results

OLS Regression Analysis of *NDVI* on *LST*, with *Elevation* and *Park Area* as control variables (Regressions 1a; 1b; 1c)

```

REGRESSION
-----
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set      : ShapeFile Only
Dependent Variable : LST      Number of Observations: 130
Mean dependent var : 0.486174 Number of Variables   : 2
S.D. dependent var : 0.19355  Degrees of Freedom    : 128

R-squared      : 0.166256  F-statistic      : 25.5243
Adjusted R-squared : 0.159742 Prob(F-statistic) : 1.47165e-06
Sum squared residual: 4.06033  Log likelihood    : 40.8455
Sigma-square    : 0.0317213 Akaike info criterion : -77.691
S.E. of regression : 0.178105 Schwarz criterion  : -71.956
Sigma-square ML  : 0.0312333
S.E of regression ML: 0.17673

-----
Variable      Coefficient    Std.Error    t-Statistic    Probability
-----
CONSTANT      0.655798      0.0370305    17.7097        0.00000
NDVI          -0.31369      0.0620903    -5.05216       0.00000
-----

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER 4.519933
TEST ON NORMALITY OF ERRORS
TEST      DF      VALUE      PROB
Jarque-Bera 2      11.6484    0.00296

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST      DF      VALUE      PROB
Breusch-Pagan test 1      6.2314    0.01255
Koenker-Bassett test 1      3.6357    0.05655
===== END OF REPORT =====

REGRESSION
-----
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set      : ShapeFile Only
Dependent Variable : LST      Number of Observations: 130
Mean dependent var : 0.486174 Number of Variables   : 3
S.D. dependent var : 0.19355  Degrees of Freedom    : 127

R-squared      : 0.180805  F-statistic      : 14.0152
Adjusted R-squared : 0.167905 Prob(F-statistic) : 3.16288e-06
Sum squared residual: 3.98948  Log likelihood    : 41.9898
Sigma-square    : 0.0314132 Akaike info criterion : -77.9797
S.E. of regression : 0.177238 Schwarz criterion  : -69.3771
Sigma-square ML  : 0.0306883
S.E of regression ML: 0.175181

-----
Variable      Coefficient    Std.Error    t-Statistic    Probability
-----
CONSTANT      0.661401      0.0370386    17.8571        0.00000
NDVI          -0.356062      0.0679242    -5.24204       0.00000
Park Area     0.189716      0.126319     1.50188        0.13561
-----

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER 5.343006
TEST ON NORMALITY OF ERRORS
TEST      DF      VALUE      PROB
Jarque-Bera 2      13.7849    0.00102

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST      DF      VALUE      PROB
Breusch-Pagan test 2      7.6567    0.02175
Koenker-Bassett test 2      4.3011    0.11642
===== END OF REPORT =====

REGRESSION
-----
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set      : ShapeFile Only
Dependent Variable : LST      Number of Observations: 130
Mean dependent var : 0.486174 Number of Variables   : 4
S.D. dependent var : 0.19355  Degrees of Freedom    : 126

R-squared      : 0.233502  F-statistic      : 12.7946
Adjusted R-squared : 0.215252 Prob(F-statistic) : 2.36476e-07
Sum squared residual: 3.73284  Log likelihood    : 46.3117
Sigma-square    : 0.0296257 Akaike info criterion : -84.6233
S.E. of regression : 0.172121 Schwarz criterion  : -73.1532
Sigma-square ML  : 0.0287142
S.E of regression ML: 0.169453

-----
Variable      Coefficient    Std.Error    t-Statistic    Probability
-----
CONSTANT      0.825319      0.0662992    12.4484        0.00000
NDVI          -0.398233      0.0675017    -5.8996        0.00000
Park Area     0.205958      0.122797     1.67723        0.09598
Elevation     -0.238732      0.0811129    -2.9432        0.00387
-----

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER 9.961650
TEST ON NORMALITY OF ERRORS
TEST      DF      VALUE      PROB
Jarque-Bera 2      5.5726    0.06165

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST      DF      VALUE      PROB
Breusch-Pagan test 3      7.2476    0.06441
Koenker-Bassett test 3      4.8109    0.18618
===== END OF REPORT =====

```

SEM Regression Analysis of *NDVI* on *LST*, with *Elevation* and *Park Area* as control variables (Regressions 2a; 2b; 2c)

```

REGRESSION
-----
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set      : ShapeFile_Only
Spatial Weight : Weights
Dependent Variable : LST      Number of Observations: 130
Mean dependent var : 0.486174 Number of Variables : 2
S.D. dependent var : 0.193550 Degrees of Freedom : 128
Lag coeff. (Lambda) : 0.835537

R-squared      : 0.753508 R-squared (BUSE) : -
Sq. Correlation : -      Log likelihood : 106.510736
Sigma-square    : 0.00923397 Akaike info criterion : -209.021
S.E of regression : 0.0960935 Schwarz criterion : -203.286

-----
Variable      Coefficient      Std.Error      z-value      Probability
-----
CONSTANT      0.611527      0.0476988      12.8206      0.00000
NDVI          -0.259793      0.0552733      -4.70016     0.00000
LAMBDA        0.835537      0.0486122      17.1878     0.00000
-----

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST      DF      VALUE      PROB
Breusch-Pagan test      1      8.4947      0.00356

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : Weights
TEST      DF      VALUE      PROB
Likelihood Ratio Test    1      131.3304      0.00000
===== END OF REPORT =====

REGRESSION
-----
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set      : ShapeFile_Only
Spatial Weight : Weights
Dependent Variable : LST      Number of Observations: 130
Mean dependent var : 0.486174 Number of Variables : 3
S.D. dependent var : 0.193550 Degrees of Freedom : 127
Lag coeff. (Lambda) : 0.834439

R-squared      : 0.754788 R-squared (BUSE) : -
Sq. Correlation : -      Log likelihood : 106.904055
Sigma-square    : 0.009186 Akaike info criterion : -207.808
S.E of regression : 0.0958436 Schwarz criterion : -199.206

-----
Variable      Coefficient      Std.Error      z-value      Probability
-----
CONSTANT      0.612386      0.0474442      12.9075      0.00000
NDVI          -0.267794      0.0558245      -4.79707     0.00000
Park Area     0.0582965      0.0656036      0.888617     0.37421
LAMBDA        0.834439      0.0488331      17.0876     0.00000
-----

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST      DF      VALUE      PROB
Breusch-Pagan test      2      8.9876      0.01118

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : Weights
TEST      DF      VALUE      PROB
Likelihood Ratio Test    1      129.8284      0.00000
===== END OF REPORT =====

REGRESSION
-----
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set      : ShapeFile_Only
Spatial Weight : Weights
Dependent Variable : LST      Number of Observations: 130
Mean dependent var : 0.486174 Number of Variables : 4
S.D. dependent var : 0.193550 Degrees of Freedom : 126
Lag coeff. (Lambda) : 0.824930

R-squared      : 0.757309 R-squared (BUSE) : -
Sq. Correlation : -      Log likelihood : 108.038991
Sigma-square    : 0.00909159 Akaike info criterion : -208.078
S.E of regression : 0.0953498 Schwarz criterion : -196.608

-----
Variable      Coefficient      Std.Error      z-value      Probability
-----
CONSTANT      0.714569      0.0807615      8.84789      0.00000
NDVI          -0.279819      0.0558127      -5.01354     0.00000
Park Area     0.0383739      0.0667419      0.57496      0.56532
Elevation     -0.177149      0.115912      -1.5283      0.12644
LAMBDA        0.82493      0.0507231      16.2634      0.00000
-----

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST      DF      VALUE      PROB
Breusch-Pagan test      3      10.1660      0.01721

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : Weights
TEST      DF      VALUE      PROB
Likelihood Ratio Test    1      123.4547      0.00000
===== END OF REPORT =====

```

Two-Stage Lease Squares Regression using Instrumental Variable

```
. reg ndvi_average_mean park_area_pct elev_mean q5_14_13_walk_park
```

Source	SS	df	MS	Number of obs	=	130
Model	.224899007	3	.074966336	F(3, 126)	=	21.01
Residual	.449547897	126	.00356784	Prob > F	=	0.0000
				R-squared	=	0.3335
				Adj R-squared	=	0.3176
Total	.674446904	129	.005228271	Root MSE	=	.05973

ndvi_average_mean	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
park_area_pct	-.0012639	.0002213	-5.71	0.000	-.0017018	-.000826
elev_mean	.0086153	.0276775	0.31	0.756	-.0461576	.0633883
q5_14_13_walk_park	.0097522	.00226	4.32	0.000	.0052797	.0142247
_cons	.3293145	.0182659	18.03	0.000	.2931668	.3654623

```
. ivregress 2sls lst_average_mean (ndvi_average_mean = park_area_pct) elev_mean
```

```
Instrumental variables 2SLS regression
```

Number of obs	=	130
Wald chi2(2)	=	8.47
Prob > chi2	=	0.0145
R-squared	=	0.1765
Root MSE	=	1.4842

lst_average_mean	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
ndvi_average_mean	-9.214941	3.747198	-2.46	0.014	-16.55931	-1.870567
elev_mean	.8933798	.6858013	1.30	0.193	-.4507661	2.237526
_cons	37.04748	1.365485	27.13	0.000	34.37118	39.72379

Endogenous: ndvi_average_mean

Exogenous: elev_mean park_area_pct

Regression Analysis of Marginalised Demographics Distribution of Vegetation (Regressions 3a; 3b)

REGRESSION

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

```
Data set      : Ward JHB only
Dependent Variable : NDVI      Number of Observations: 130
Mean dependent var : 0.540385  Number of Variables   : 2
S.D. dependent var : 0.252045  Degrees of Freedom    : 128

R-squared      : 0.533116  F-statistic       : 146.158
Adjusted R-squared : 0.529469  Prob(F-statistic) : 6.46476e-23
Sum squared residual: 3.85575  Log likelihood    : 44.206
Sigma-square     : 0.030123  Akaike info criterion : -84.4119
S.E. of regression : 0.17356  Schwarz criterion  : -78.6769
Sigma-square ML   : 0.0296596
S.E of regression ML: 0.17222
```

Variable	Coefficient	Std.Error	t-Statistic	Probability
CONSTANT	0.400908	0.0191002	20.9897	0.00000
income	0.72132	0.0596645	12.0896	0.00000

REGRESSION DIAGNOSTICS

MULTICOLLINEARITY CONDITION NUMBER 2.012659

TEST ON NORMALITY OF ERRORS

TEST	DF	VALUE	PROB
Jarque-Bera	2	1.7015	0.42709

DIAGNOSTICS FOR HETEROSKEDASTICITY

RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	1	1.6870	0.19399
Koenker-Bassett test	1	1.9321	0.16453

===== END OF REPORT =====

```

REGRESSION
-----
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set      : Ward JHB only
Spatial Weight : Weights
Dependent Variable : NDVI Number of Observations: 130
Mean dependent var : 0.540385 Number of Variables : 2
S.D. dependent var : 0.252045 Degrees of Freedom : 128
Lag coeff. (Lambda) : 0.686252

R-squared      : 0.694684 R-squared (BUSE) : -
Sq. Correlation : - Log likelihood : 63.953334
Sigma-square    : 0.0193957 Akaike info criterion : -123.907
S.E of regression : 0.139269 Schwarz criterion : -118.172

-----
Variable      Coefficient      Std.Error      z-value      Probability
-----
CONSTANT      0.39261      0.0389211      10.0873      0.00000
income        0.642536      0.0876107      7.33399      0.00000
LAMBDA        0.686252      0.0746992      9.18688      0.00000
-----

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST
Breusch-Pagan test      DF      VALUE      PROB
                        1      3.1490      0.07597

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : Weights
TEST
Likelihood Ratio Test    DF      VALUE      PROB
                        1      39.4947      0.00000
===== END OF REPORT =====

```

Regression Analysis of Marginalised Demographics, Distribution of Vegetation, and Heat Exposure (Regressions 4a; 4b)

```

REGRESSION
-----
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set      : Ward JHB only
Dependent Variable : LST Number of Observations: 130
Mean dependent var : 0.486154 Number of Variables : 2
S.D. dependent var : 0.19346 Degrees of Freedom : 128

R-squared      : 0.336931 F-statistic      : 65.0416
Adjusted R-squared : 0.331750 Prob(F-statistic) : 4.54097e-13
Sum squared residual: 3.22615 Log likelihood : 55.7939
Sigma-square    : 0.0252043 Akaike info criterion : -107.588
S.E. of regression : 0.158759 Schwarz criterion : -101.853
Sigma-square ML : 0.0248165
S.E of regression ML: 0.157533

-----
Variable      Coefficient      Std.Error      t-Statistic      Probability
-----
CONSTANT      0.571263      0.0174713      32.6972      0.00000
income        -0.440149      0.0545763      -8.06484      0.00000
-----

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER 2.012659
TEST ON NORMALITY OF ERRORS
TEST
Jarque-Bera      DF      VALUE      PROB
                2      11.1962      0.00370

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST
Breusch-Pagan test 1      7.5034      0.00616
Koenker-Bassett test 1      4.5605      0.03272
===== END OF REPORT =====

```

```

REGRESSION
-----
SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set      : Ward JHB only
Spatial Weight : Weights
Dependent Variable : LST      Number of Observations: 130
Mean dependent var : 0.486154 Number of Variables   : 2
S.D. dependent var : 0.193460 Degrees of Freedom    : 128
Lag coeff. (Lambda) : 0.793197

R-squared      : 0.729673 R-squared (BUSE)      : -
Sq. Correlation : -      Log likelihood        : 102.510998
Sigma-square    : 0.0101174 Akaike info criterion : -201.022
S.E of regression : 0.100585 Schwarz criterion   : -195.287

-----
Variable      Coefficient    Std.Error    z-value      Probability
-----
CONSTANT      0.527369      0.0377995    13.9517      0.00000
income        -0.267635     0.0697847    -3.83515     0.00013
LAMBDA        0.793197      0.0567652    13.9733      0.00000
-----

REGRESSION DIAGNOSTICS
DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST          DF      VALUE      PROB
Breusch-Pagan test      1      6.3743     0.01158

DIAGNOSTICS FOR SPATIAL DEPENDENCE
SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : Weights
TEST          DF      VALUE      PROB
Likelihood Ratio Test    1     93.4341     0.00000
===== END OF REPORT =====

```

