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PROFILING MULTIDIMENSIONAL CLIMATE-RELATED VULNERABILITY IN SOUTH AFRICA

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Profiling Multidimensional Climate-Related Vulnerability in South Africa

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DISCLAIMER

ACKNOWLEDGEMENTS

The Transforming Social Inequalities Through Inclusive Climate Action (TSITICA) project investigates how climate change action can be socially transformative in three contrasting African countries: Ghana, Kenya and South Africa. The research agenda addresses the nexus between climate change, sustainable livelihoods and multidimensional poverty and inequality to tackle the overall question: how can climate actions be deliberately targeted to improve livelihoods and lead to equitable benefits for the most vulnerable and poor – especially for women and youth? With the goal of inspiring climate actions that also reduce poverty and inequality, based on evidence and insights from the research, TSITICA aims to contribute the Agenda 2030 ambition of leaving no one behind.

The full project team comprises researchers from two African Research Universities Alliance (ARUA) Centres of Excellence hosted by the University of Cape Town (UCT); researchers from the centres' regional nodes at universities in Ghana and Kenya; and collaborators from four universities in the United Kingdom:

- African Centre of Excellence for Inequality Research, hosted by UCT's Southern Africa Labour and Development Research Unit, School of Economics
- ARUA Centre of Excellence in Climate and Development, hosted by UCT's African Climate and Development Institute
- ARUA-CD and ACEIR nodes convened respectively by the Institute for Environment and Sanitation Studies and the Institute of Statistical, Social and Economic Research, University of Ghana
- ARUA-CD and ACEIR nodes convened respectively by the Institute for Climate Change and Adaptation and the School of Economics, University of Nairobi
- Grantham Research Institute on the Environment and Climate Change, London School of Economics and Political Science
- Townsend Centre for International Poverty Research, University of Bristol
- International Inequalities Institute, London School of Economics and Political Science
- Tyndall Centre for Climate Change Research, University of East Anglia
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Abstract

We use survey data from the National Income Dynamics Study and the Community Survey to examine inequalities and trends in multidimensional climate-related vulnerability in South Africa. We assess multidimensional climate-related vulnerability along four dimensions: demographic, economic, housing conditions, and nutrition. Overall, the findings show that there has been progress in reducing multidimensional climate-related vulnerability over time. Despite these gains, a sizable portion of the population remained vulnerable due to a lack of safe drinking water and sanitation, as well as food insecurity. Furthermore, the degree of multidimensional climate-related vulnerability varies greatly by population group, income, and location. We also find evidence that some areas with a relatively high level of multidimensionally vulnerable population are also more likely to experience climate-related hazards.

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Introduction

Although climate change is a pressing challenge that is affecting the global society and the environment, the impacts of climate change on social outcomes can vary across countries, sectors, and population groups within countries. Climate change-related weather variability and extreme events has been more frequent in developing countries with significant adverse social impacts (FAO, 2021). In particular, the most vulnerable people and systems are seen to be disproportionately affected by climate change impacts across sectors and regions, according to a recent report from the Intergovernmental Panel on Climate Change (IPCC, 2022). The objective of this paper is to analyses climate change-relate multidimensional vulnerability in South Africa, where climate change and its consequences pose a significant challenge, as it is throughout Africa (Mambo et al., 2017).

Vulnerability is a multidimensional phenomenon that is broadly defined as the state of being predisposed to be negatively affected by stresses associated with environmental and social change, as well as a lack of ability to cope and adapt (Brooks et al., 2005; Adger, 2006; IPCC, 2022). However, there are various conceptualisations and approaches for assessing climate change-related vulnerability. Over the past few decades, the methodologies for analysing and assessing climate-related vulnerability have evolved, and more recent assessments of vulnerability are increasingly taking into account the significance of social and contextual determinants of vulnerability (see IPCC, 2022). Our vulnerability assessment focuses on analysing contextual vulnerability, which seeks to understand the underlying social and contextual determinants of climate-related vulnerability. Such an analysis is useful to understand existing inequalities in the extent of vulnerability of various communities and population groups to climate-related impacts.

Recognizing and understanding disparities in capacities and constraints across people, households, and communities requires understanding the interplay of various intersecting social determinants of vulnerability (IPCC, 2022). Existing vulnerability assessments in South Africa or elsewhere are largely spatial unit level of analysis (e.g., Bourne et al., 2012; Le Roux et al., 2015; Mambo et al., 2017; Le Roux et al., 2017; Hahn et al., 2009). Roux et al. (2017), for example, used ward level data from the 2011 censuses to examine social vulnerability in urban settlements in South Africa. Place-based analyses of vulnerability are useful for identifying vulnerable areas and communities. However, even when faced with the same level of hazard and exposure, there are disparities in vulnerability within spatial units based on gender or other social factors. Therefore, spatial level analysis may underestimate the extent of inequalities across spatial units because it does not capture individual level variations. Furthermore, households within a spatial unit may be vulnerable to varying degrees in more than one dimension, which can be captured using multidimensional measures at the individual or household levels. In this study, we created a multidimensional vulnerability index to identify various and intersecting factors that may influence individuals' vulnerability to climate-related adverse effects.

Although vulnerability varies according to the context and type of hazards to which a system is exposed, certain characteristics such as poverty, livelihood strategies, and institutions can influence a system's susceptibility and ability to cope with a wide range of climate change-related impacts or other shocks (Brooks et al., 2005). In this paper, we conceptualize vulnerability to climate change-related impacts as a phenomenon that is independent of any specific type of hazard but relevant to multiple hazards. Thus, we aim to analysis what are known as "generic" vulnerability determinants, which are factors that are not necessarily associated with a specific context or hazard type (Brooks et al., 2005: pp152-153). The proposed climate-related vulnerability dimensions and indicators used in this paper are useful for analysing the extent of social vulnerability across spatial units as well as within a given spatial unit in various country contexts. Thus, our climate-related vulnerability index is primarily useful for identifying households/social groups that are multidimensionally vulnerable to the effects of climate change.

We also investigate whether areas or communities with a high proportion of multidimensionally vulnerable people are also more likely to be exposed to climate-related hazards compared to better off areas. There is evidence suggesting that the poor and marginalised social groups are more likely to live in hazard-prone areas, increasing their exposure and vulnerability (see Hallegatte et al., 2020; IPCC, 2022). We use data from the Emergency Events Database (EM-DAT) to map climate-related hazards in South Africa. This database contains information on natural disasters and estimated economic costs from around the world.

In the next section, we discuss an overview of the methods used to assess climate change-related vulnerability. Following that, we describe the data, as well as the domains and indicators used to assess climate change-related vulnerability in South Africa. The results and summary of findings are then discussed in the following sections.

Measuring climate change-related vulnerability

There are competing conceptualizations and interpretations of climate change-related vulnerability, as well as various methodologies for assessing it (see Brooks, 2003; Eakina & Luers, 2006; O'Brien et al., 2007; Hinkel et al., 2011; Fellmann, 2012; Bedeke, 2023; Estoque et al., 2023). In general, there are two main interpretations of climate change-related vulnerability: outcome (endpoint) vulnerability and contextual (starting point) vulnerability (Kelly & Adger, 2000; O'Brien et al., 2007; Füssel, 2007). Outcome vulnerability is the (expected) net effects of a given level of climate change, after accounting for feasible adaptation measures. This perspective considers vulnerability to be the residual output after any mitigation measures have been implemented. Thus, from the perspective of outcome vulnerability, reducing vulnerability entails lowering exposure through climate change mitigation or developing adaptations to limit negative outcomes.

In contrast, according to the contextual vulnerability interpretation, climate change-related vulnerability represents a system's current inability to cope with changing climate conditions (O'Brien et al., 2007 p.84; Füssel, 2007; Fellmann, 2012). Therefore, from the standpoint of contextual vulnerability, reducing vulnerability entails adjusting the context in which climate change occurs, so that people and communities are better prepared to deal with changing circumstances (O'Brien et al.,2007: pp.75-76). To reduce vulnerability, in addition to adaptation policy, broader social development is required. Therefore, by increasing adaptive capacity and decreasing susceptibility of the affected community, it is possible to reduce vulnerability to climate change-related impacts and the adverse impact of some mitigation and adaptation measures.

The two interpretations of vulnerabilities differ in terms of scale, timeframes, and approaches used to inform climate adaption policy, although there are also some overlaps (see Fellmann, 2012 for details). Irrespective of the two interpretations of vulnerability, different frameworks have been proposed to assess climate change-related vulnerability in the literature. The vulnerability framework proposed by the IPCC is the most widely used (See IPCC, 2022; Feldmeyer et al., 2021; Estoque et al., 2023). According to the recent IPCC report, vulnerability is a component of risk and defined as "The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt." (IPCC, 2022: 2927). And risk is defined as "The potential for adverse consequences for human or ecological systems, recognising the diversity of values and objectives associated with such systems (IPCC, 2022: 2921). Figure 1 shows the components of climate-related risk according to this framework.

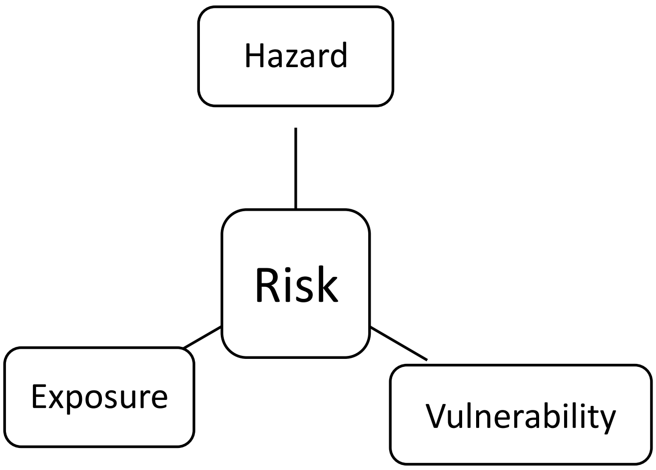


Figure 1: Components of climate-related Risk (IPCC, 2022).

Vulnerability, according to the above framework, has two components: sensitivity and coping and adaptive capacity. The sensitivity component denotes "the extent to which a system or species is affected, either negatively or positively, by climate variability or change" (IPCC, 2022; 2922). While Coping capacity refers to "the ability of people, institutions, organisations, and systems to address, manage, and overcome adverse conditions in the short to medium term" (IPCC, 2022;2904), adaptive capacity refers to "the ability of systems, institutions, humans, and other organisms to adjust to potential damage, take advantage of opportunities, or respond to consequences" (IPCC, 2022;2904).

The Hazard component in Figure 1 denotes "the potential occurrence of a natural or human-induced physical event or trend that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources" (IPCC, 2022:2911).

The exposure component indicates "The presence of people; livelihoods; species or ecosystems; environmental functions, services, and resources; infrastructure; or economic, social, or cultural assets in places and settings that could be adversely affected" (IPCC, 2022: 2908). Exposure can include, for example, people living near coastal areas and those involved in certain livelihood activities (e.g., agriculture).

The two components of vulnerability reflect the fact that, even when subjected to the same hazard and exposure, the cost and damage can differ across social groups and underlying conditions. The elderly, for example, are more vulnerable than other population groups during heat waves. Similarly, poor and marginalised people are more likely to live in flood-prone areas with inadequate infrastructure, making dealing with climate-related hazards difficult. This suggests that exposure and vulnerability are influenced by pre-existing socioeconomic conditions as well as the presence of hazards.

The use of indicators is one method for operationalizing theoretical concepts such as risk and vulnerability. This method has been widely used in the literature to investigate climate-related risk and vulnerability (Hinkel, 2011; Welle & Birkmann, 2015). The indicators used for vulnerability assessment are chosen based on the theory and conceptual framework used to define vulnerability and its components, the context and purpose of the analysis, the availability of data, and expert judgement (see O'Brien et al.,2004; Brooks et al., 2005; Hinkel, 2011; O'Brien et al., 2007; Siders, 2019). As a result, the indicators used to measure vulnerability differ depending on the spatial/institutional unit assessed (i.e. households, institutions, community, and national levels), temporal references (e.g. current vs future), and sectors (e.g. agriculture vs other sectors). Therefore, given the dynamic and context-specific nature of vulnerability, there is no agreement about which indicators should be used to assess climate change-related vulnerability.

There is a lack of agreement in defining and measuring even components of vulnerability, such as adaptive capacity (see Siders, 2019). This is because coping and adaptive capacities are highly hazard and context specific, as well as associated with significant uncertainty (Adger & Vincent, 2005; Brooks et al., 2005; Smit & Wandel, 2006). As a result, developing a set of indicators that can be used to assess coping and adaptive capacity in various contexts is extremely difficult. Furthermore, measuring adaptive capacity as defined above is difficult even within a specific context because it requires capturing systems' ability of long-term planning and learning process (see Bohensky et al., 2010).

Despite the fact that vulnerability determinants are dynamic and are determined by the context and type of hazards to which a system is exposed, certain undelaying factors that can influence a system's susceptibility and ability to cope with a wide range of climate-related impacts or other shocks have been identified (Adger & Vincent, 2005; Brooks et al., 2005). Poverty and food insecurity, livelihood strategies, demographic factors, health status, and institutional resources and effectiveness are among the undelaying factors that determine individual/household vulnerability (see Cutter et al., 2003; Eakin & Bojórquez-Tapia, 2008; Hahn et al., 2009; IPCC, 2022; Le Roux et al., 2017; Jeggle & Boggero, 2018; Thomas et al.,2019; EPA ,2021). These are known as "generic" vulnerability determinants because they are not linked to a specific context or hazard type (Brooks et al., 2005: pp152-153). Social vulnerability analysis, in this context, is concerned with assessing the unequal sensitivity and coping and adaptive capacity of social groups to plan for, respond to, and recover from hazards, regardless of the type and source of the hazards (Emrich & Cutter, 2011: p.194; EPA ,2021).

We took a similar approach in this paper, conceptualising vulnerability to climate change-related impacts as a phenomenon that is independent of any specific type of hazard but relevant to multiple hazards. As a result, we intend to investigate "generic" vulnerability determinants, which are factors that are not necessarily associated with a specific context or hazard type (Brooks et al., 2005: pp152-153). Therefore, our climate-related vulnerability indicators are primarily useful for identifying households/social groups that are likely to be susceptible to the effects of climate change in various contexts. The dimensions and indicators used to assess climate change-related vulnerability are discussed in the following section, which are identified in the literature as factors that are likely to increase individuals' climate-related vulnerability.

Dimensions and indicators

This section discusses the dimensions and indicators used to assess multidimensional climate-related vulnerability in South Africa. We consider four dimensions to assess climate change-related vulnerability: demographic, economic, housing, and nutrition status. These indicators are primarily concerned with factors that influence people's susceptibility and coping ability. The climate-related vulnerability dimensions and indicators proposed in this paper can be used in various contexts to assess the extent of social vulnerability across spatial units as well as within a given spatial unit.

1. Demographic

There is evidence that certain demographic factors make people more vulnerable to various types of climate-related hazards. The very young and old, pregnant women, and people with disabilities, for example, are more vulnerable to the effects of climate change, such as extreme heat waves and flooding. This domain is measured using four indicators. These indicators included being younger (less than 10 years old), older (>60 years old), pregnant, and disabled.

2. Economic

Livelihood strategies are important in determining susceptibility and vulnerability. People who rely mainly on primary economic activities such as agriculture and fishing are more vulnerable to the effects of climate change. Households that rely on rain-fed agriculture, for example, may be particularly vulnerable to the effects of rainfall variability. Similarly, people working in mining and quarrying, construction and other elementary occupations are more vulnerable to climate-related shocks such as heat waves and flooding. We consider individuals working in any of these jobs as susceptible to climate-related shocks.

3. Nutrition

Individuals with poor nutrition and health outcomes are more vulnerable to the effects of climate change. Children with poor health, in particular, are more vulnerable to infections and vector-borne diseases during climate-related shocks. Similarly, households that are already experiencing food insecurity will be more susceptible and vulnerable to the effects of climate change. Poor nutrition and food insecurity reflect such individuals' or households' limited ability to cope with economic and other shocks.

Individual nutrition status is measured using two indicators: anthropometric failure and food insecurity. Anthropometric failure indicates whether a child under the age of five was stunted, wasted, or underweight (Z scores less than two standard deviations from those of a healthy child of similar age and gender).

Individuals' food insecurity is measured by whether their monthly per capita household expenditure is less than the food poverty line. Given that we used data from 2008 and 2017, we estimate food poverty using an inflation-adjusted poverty line. In 2008, the inflation-adjusted food poverty line was R274, and in 2017, it was R531 (Statistics South Africa, 2019). The food poverty lines were calculated using a daily energy requirement of 2100 calories per person per day.

4. Housing conditions

Indicators of living conditions are also important indicators of vulnerability. People who live in areas where there is no safe drinking water, sanitation, or proper sewage and drainage systems are more vulnerable to the effects of climate change. Living in poor informal settlements, for example, and not having access to such basic services may increase the likelihood of negative health outcomes due to contamination of local water sources. Furthermore, residents of informal settlements are frequently more vulnerable to climate-related hazards such as flooding and landslides. People in low-income areas also lack access to information, making it difficult for households to learn about early warning systems for hazards.

We use four indicators to assess living conditions: access to safe water, sanitation, information, and type of dwelling. A lack of safe water indicates a lack of piped water in a household or yard, or within 200 meters. The sanitation indicator indicates a lack of access to an improved toilet facility. Household dwelling conditions are measured using an indicator that indicates whether the household is in an informal settlement (shack). Access to information is measured by whether a person has access to a television, radio, or the internet.

We use the Alkire-Foster method (2011) to combine the 11 indicators into a single index with equal weighting in order to measure individual level multidimensional vulnerability. As a result, each dimension (and each indicator within a given dimension) is weighted equally. The vulnerability index has a minimum of zero and a maximum of one. In addition, to assess the intensity of vulnerability, we used a counting approach to aggregate the 11 indicators for each individual. The level of vulnerability ranges from zero (vulnerability in none of the indicators) to eleven (vulnerability in all indicators).

The dimensions and indicators used in this paper may overlap with those used to measure poverty. As a result, we anticipate a strong relationship between climate-related vulnerability and poverty estimates. The two concepts, however, are not synonymous, and poverty is one of the causes and consequences of climate-related vulnerability. In general, the poor and non-poor differ in terms of exposure and copying capacity, with the poor having less coping capacity than the non-poor do (Hallegatte et al., 2020).

Data description

We use survey data from the National Income Dynamics Study (NIDS), a national representative longitudinal survey of individuals (see Brophy et al., 2018 for details). The NIDS survey collects data on the socioeconomic status of households and individuals. The first survey was carried out in 2008, and the remaining four waves were carried out every two or three years (2010, 2012, 2015, and 2017). Given that panel attrition rates were high in waves 2–4, particularly among White, Indian/Asian, and high-income persons, a top-up sample was added at Wave 5 to boost sample representivity (Brophy et al., 2018: p. 10). In this paper, we use data from wave 1 and wave 5. In the 2008 wave, 28,226 individuals were interviewed while 47,055 people were interviewed during wave 5.

We use data from the 2016 Community Survey (CS) to assess multidimensional vulnerability at the province and community level (i.e. local municipalities) because the NIDS is not representative provincially or beyond the province level. The 2016 CS is a nationally representative sample of 1 370 809 dwelling units. The CS collects data on various socioeconomic conditions of households and individuals, allowing estimates to be generated at the local municipality level. However, the 2016 CS does not include all of the indicators discussed above.

We do not have data on consumption or anthropometric failure measures in the 2016 CS. As a result, we measure the nutrition dimension using self-assessed perception indicators of food insecurity. The food insecurity indicator is based on survey respondents' responses to two questions: In the past 12 months, did this household run out of money to buy food?", and "In the past 12 months, did this household skip any meal(s) because there was not enough food for the household? Food insecure households are those who answered yes to either of the two questions.

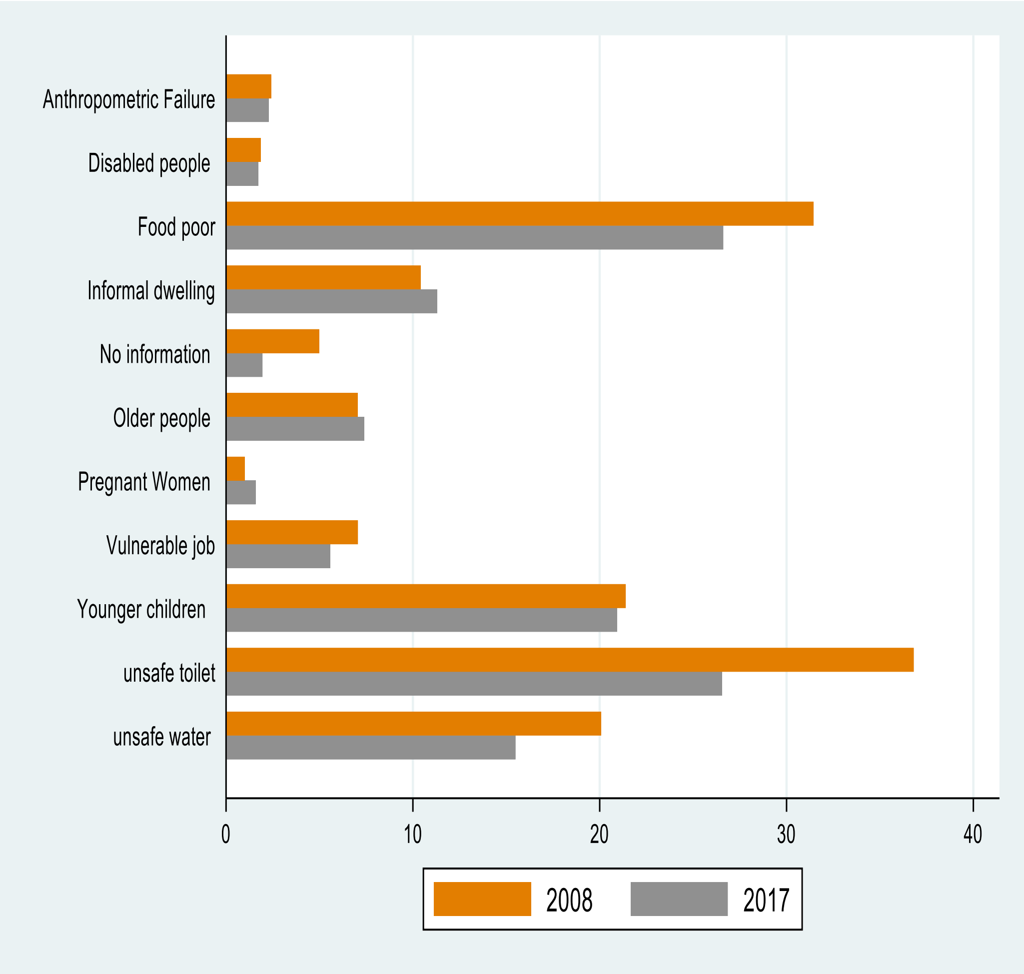
The 2016 CS lacks detailed information on employment status and employment sectors. We only have information on whether or not a household engaged in agricultural activities. As a result, we use an indicator of whether a household participated in agricultural activities and a lack of irrigation to assess economic vulnerability. The remaining domains and indicators were measured in the same manner using data from the 2016 CS and the NIDS. Thus, based on the 2016 CS, we assess multidimensional vulnerability by measuring the four domains with ten indicators. When vulnerability estimates from the two data sources are compared, they show similar patterns of vulnerability across spatial units and population groups (more on this later).

Results and Discussions

Distribution of the vulnerability indicators

Figure 2 depicts the distribution of climate-related vulnerability indicators from the 2008 to 2017 survey years. With the exception of older people, pregnant women, and informal dwelling indicators, climate-related vulnerability has decreased over time. The proportion of people living in food poverty, for example, fell from 31.5 percent in 2008 to 26.6 percent in 2017. During the same time, the proportion of the population without access to safe drinking water decreased from 20 percent to 15.5 percent, while the proportion of those without access to safe toilets decreased from 36.8 percent to 26.6 percent. In terms of the economic dimension, the proportion of people vulnerable due to vulnerable jobs fell from 7 percent in 2008 to 5.6 percent in 2017. Despite these gains, a large proportion of the population remained vulnerable in 2017 due to a lack of safe drinking water, sanitation, and food insecurity.

Figure 2: Proportion of the population per vulnerability indicator (2008 & 2017)

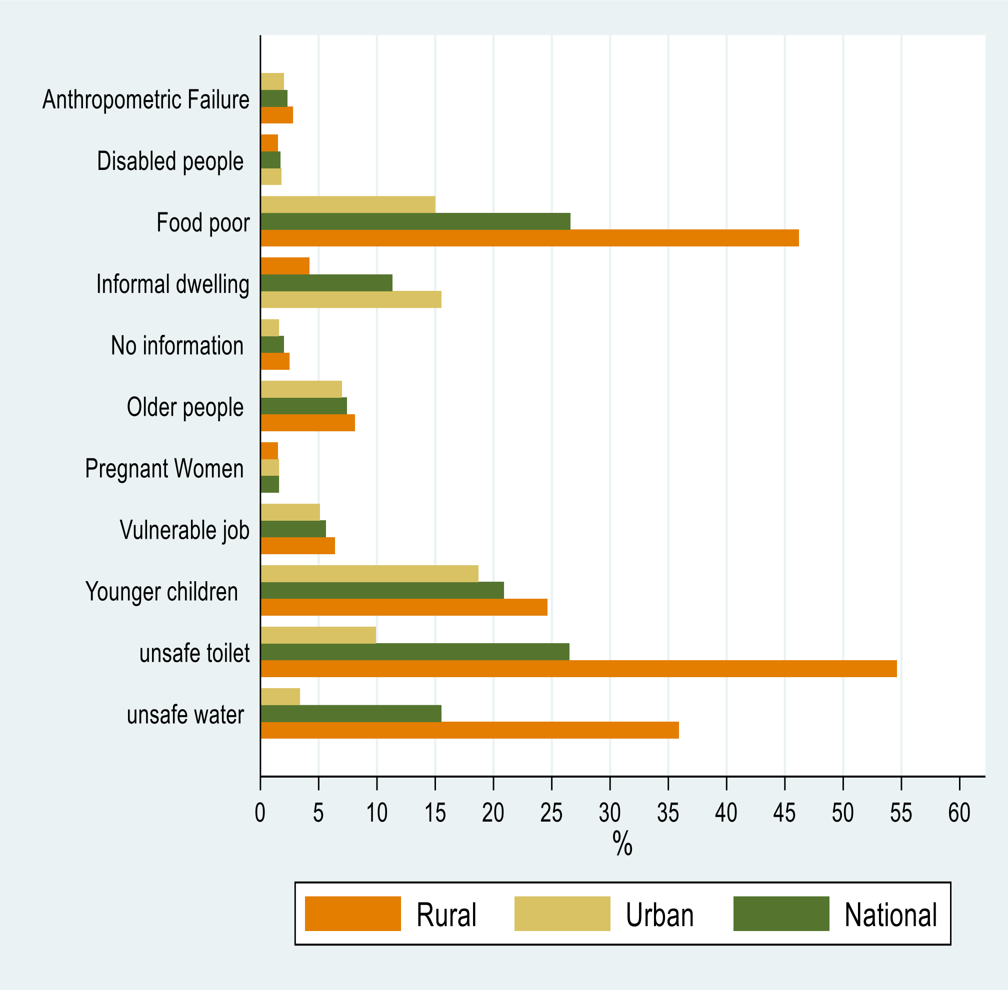


Source: Authors' calculation using NIDS (2008 & 2017).

Vulnerability due to pregnancy is one of the indicators that has increased significantly between 2008 and 2017. The proportion of the population at risk due to pregnancy has increased by 58.5 percent (from 1% to 1.6%). However, it is unclear why there is such a large difference between the two survey years. However, given the low prevalence of pregnancy-related vulnerability, the overall picture suggests that vulnerability has decreased between 2008 and 2017.

Next, we examine the distribution of the vulnerability indicators by location and income groups using the latest survey year (2017). Figure 3 provides the distribution of the vulnerability indicators by rural and urban areas. We find large rural-urban gaps based on the indicators of food poverty, access to safe water and sanitation. In general, except for the informal dwelling, pregnant women, and disability indicators, vulnerability in rural areas is relatively higher than in urban areas. For example, the percentage of the population without access to safe toilet was 54.6 percent in rural areas, while the estimate was 9.9 percent in urban areas. Similarly, the proportion of the population without access to safe water was 35.9 percent in rural areas but only 3.4 percent in urban areas. In contrast, while about 16 percent of individuals lived in informal dwelling in urban areas the estimate was only 4 percent in rural areas.

Figure 3: Proportion of the population per vulnerability indicator by location (2017)

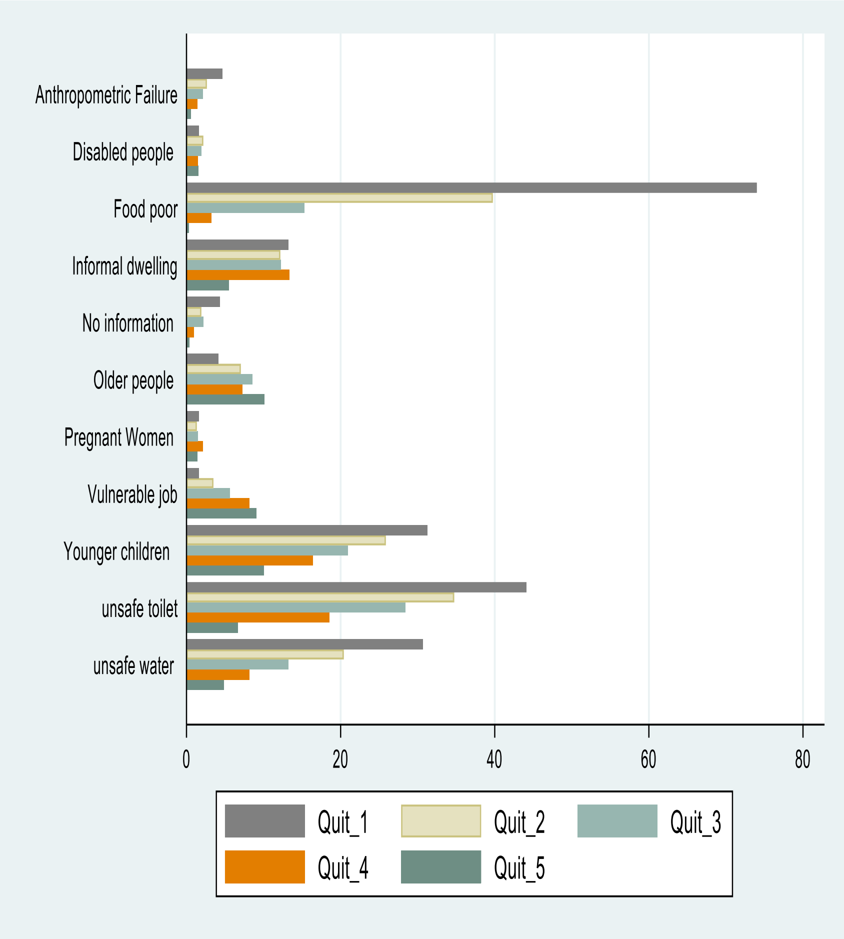


Source: Authors' calculation using NIDS (2017).

In terms of nutrition, while 15 percent of the urban population was food insecure, 46.2 percent of the rural population was. On the other hand, we find a relatively small rural-urban gap using the anthropometric failure indicator. Based on food poverty, access to safe water, and sanitation indicators, the results in Figure 3 show a relatively large rural-urban divide. We find similar rural-urban gaps Based on 2016 CS estimates, (see Figure A1 in the Appendix).

Figure 4 depicts the indicators of vulnerability by income quintile. The findings reveal significant disparities in vulnerability by income quintile for indicators of access to safe water, toilet facilities, food poverty, and younger children. For example, the proportion of people living in food poverty was 74 percent in the first income quintile, 40 percent in the second income quintile, and 3.2 percent in the fourth income quintile.

Figure 4: Proportion of the population per vulnerability indicator by income quintiles (2017)



Source: Authors' calculation using NIDS (2017).

Vulnerability due to a lack of access to safe drinking water and toilet facilities decreases as we move from the first to higher income quintiles. For example, the proportion of the population without access to safe water ranges from 30.6 percent in the first income quintile to 8.15 percent and 4.9 percent in the fourth and fifth income quintiles, respectively. Similarly, while the proportion of the population without access to safe toilet facilities was 44 percent in the first income quintile, it was 18.5 percent and 6.7 percent in the fourth and fifth income quintiles, respectively. The proportion of the population living in informal housing ranges from 13.2 percent in the first income quintile to 5.5 percent in the fifth income quintile.

When it comes to the economic dimension, we find that the proportion of the population that was vulnerable due to vulnerable jobs increases with income. The proportion of the population vulnerable due to vulnerable jobs was 1.6 percent and 3.5 percent among those in the lowest 2 income quintiles, respectively, while the corresponding estimates ranges between 8 and 9 percent for those in the richest two income quintiles. This can make sense in the context to South Africa because people in the lowest income quintiles are more likely to be unemployed.

In terms of the demographic dimension, the proportion of younger people decreases as we move from the first to the fifth income quintile, while the percentage of older people decreases as we move from the fifth to the first income quintile. This indicates that lower-income households are more likely to have younger children than higher-income households, while they are less likely to have older people.

Inequalities in Multidimensional climate-related vulnerability

In this section, we present vulnerability estimates based on the multidimensional climate-related vulnerability index and the intensity of vulnerability measures. Figure 5 depicts the average vulnerability scores and the intensity of vulnerability indicators for 2008 and 2017. We multiplied the climate-related vulnerability index by 100 for readability. The intensity of vulnerability measure indicates the proportion of the population that was not vulnerable in none of the indicators, vulnerable in one of the indicators, two of the indicators, three of the indicators, and vulnerable in four and more indicators.

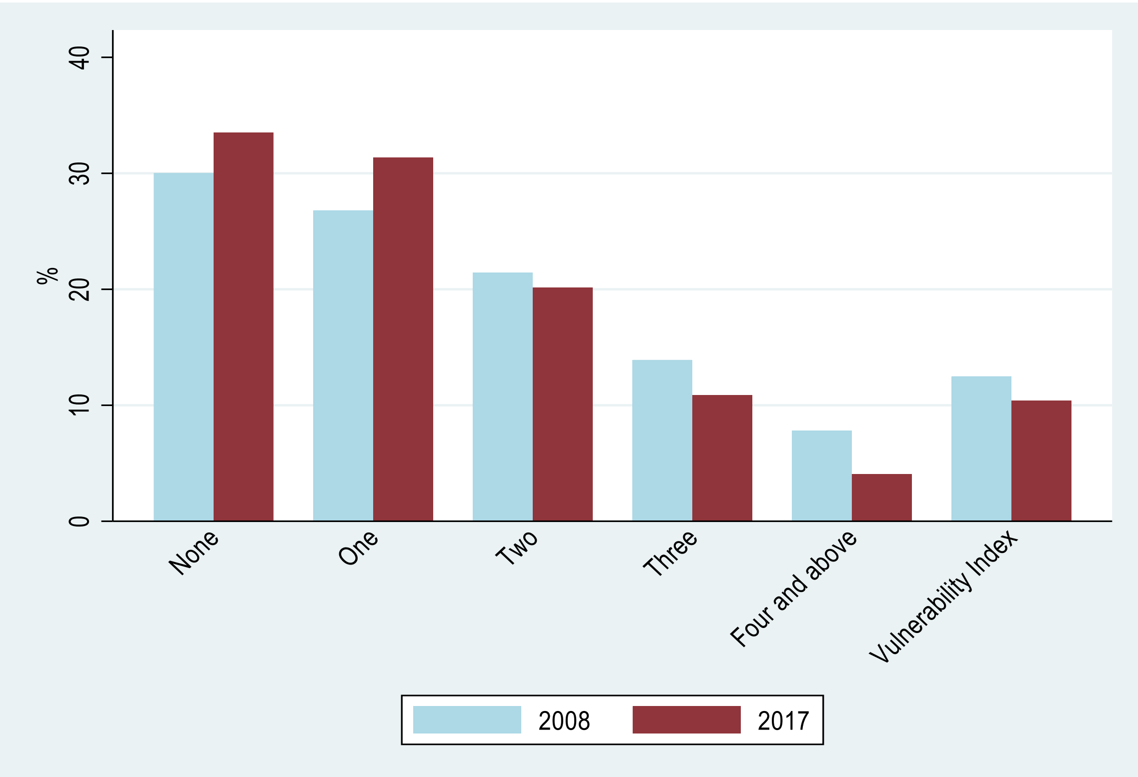


Figure 5: Multidimensional climate-related vulnerability over time (2008 & 2017)
Source: Authors' calculation using NIDS (2008 & 2017).

Both multidimensional measures indicate a decrease in multidimensional climate-related vulnerability between 2008 and 2017. While the proportion of the population vulnerable in only one of the indicators increased over time, the estimate for those vulnerable in two or more indicators decreased. Likewise, the average vulnerability index decreased from 12.5 percent in 2008 to 10.4 percent in 2017. The decline in average vulnerability index is largely due to a decline in vulnerability due to the household condition indicators and the economic dimension.

Figure 6 depicts the average multidimensional climate-related vulnerability scores by population groups, location, and income groups based on the 2017 survey. The results of the intensity of vulnerability measurer are presented in Appendix Figure A2. Rural areas outperformed urban areas and the national average in terms of multidimensional vulnerability. In terms of the intensity indicator, the proportion of the population vulnerable due to two or more indicators was higher in rural areas than in urban areas. Blacks have higher average multidimensional vulnerability scores than other race groups when multidimensional vulnerability measures are compared by race.

When multidimensional vulnerability by income quintile was examined, the poorest quintile had a relatively higher average vulnerability. For example, the proportion of the population vulnerable in two of the indicators was 32 percent and 26 percent for those in the poorest two income quintiles, respectively, while 14.2 percent and 6.8 percent were estimated for those in the richest two income quintiles.

Overall, the estimates show that the degree of multidimensional climate-related vulnerability varies significantly by population group, income, and location. However, we do not find a significant gender gap. This could be because indicators of household characteristics and poverty are measured at the household level, and everyone in the household has the same levels of vulnerability. Furthermore, a large proportion of the population was vulnerable due to a lack of safe drinking water and sanitation, as well as food poverty, and disparities between population groups are largely explained by inequalities in these indicators. As a result, comparing vulnerability by gender may not be that informative.

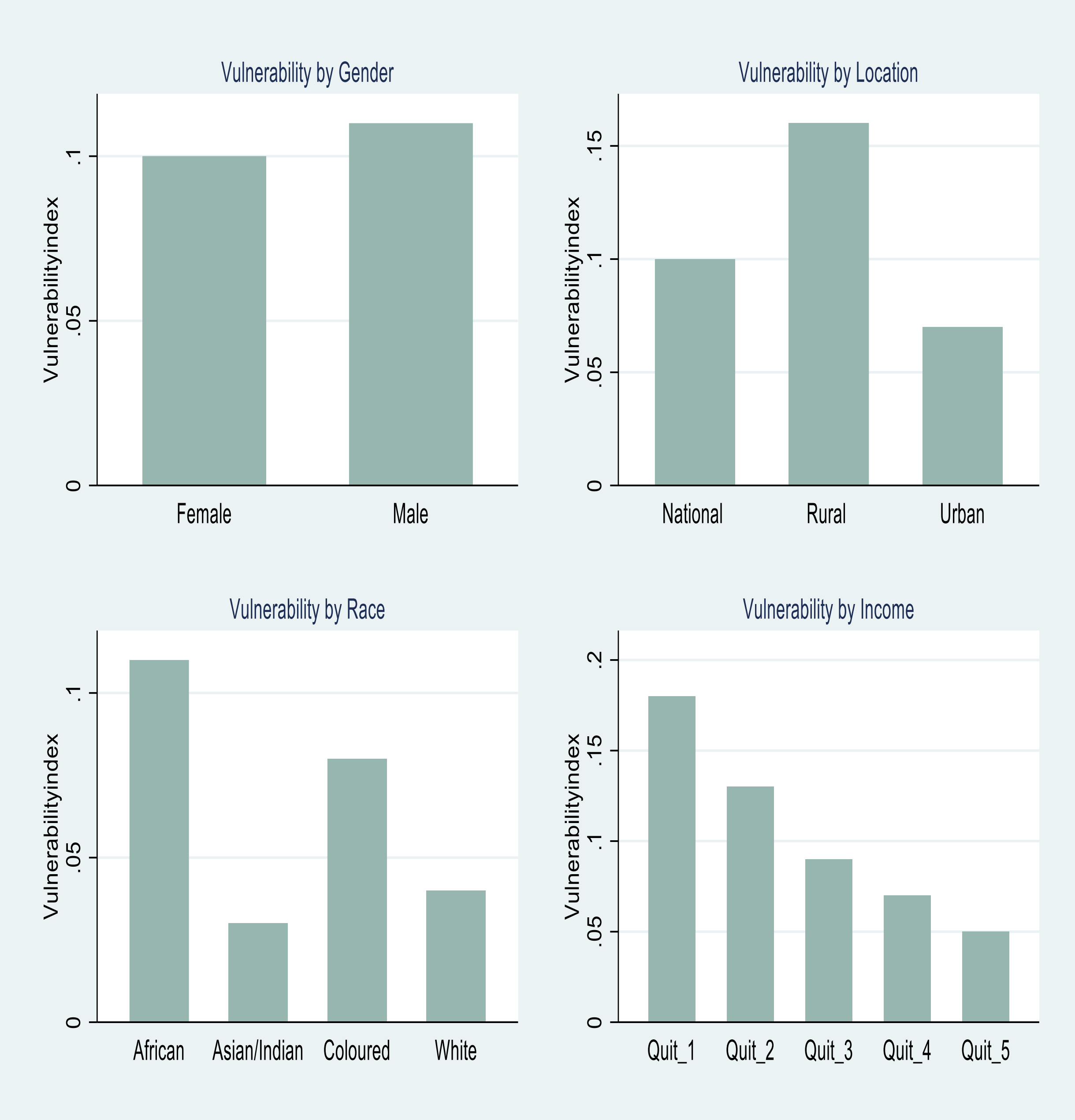


Figure 6: Multidimensional climate-related vulnerability by location, population and income groups
Source: Authors' calculation using NIDS (2007).

Spatial inequalities

Given that the NIDS is not representative at the province or local municipality levels, we provide vulnerability analysis at lower spatial unit levels using the 2016 CS. Figures A3 and A4 in the Appendix show the distribution of each vulnerability indicator at the provincial and local municipality levels. According to the findings, there are significant spatial differences between provinces and municipalities. Figure 7 depicts the average multidimensional vulnerability index and vulnerability intensity by province. The Eastern Cape had the highest average vulnerability index, followed by KwaZulu-Natal, Limpopo, and Northwest, while Gauteng and Western Cape provinces had the lowest. These disparities are largely the result of differences in the degree of vulnerability in food insecurity, as well as a lack of access to safe water and improved toilet facilities (See Figure A3).

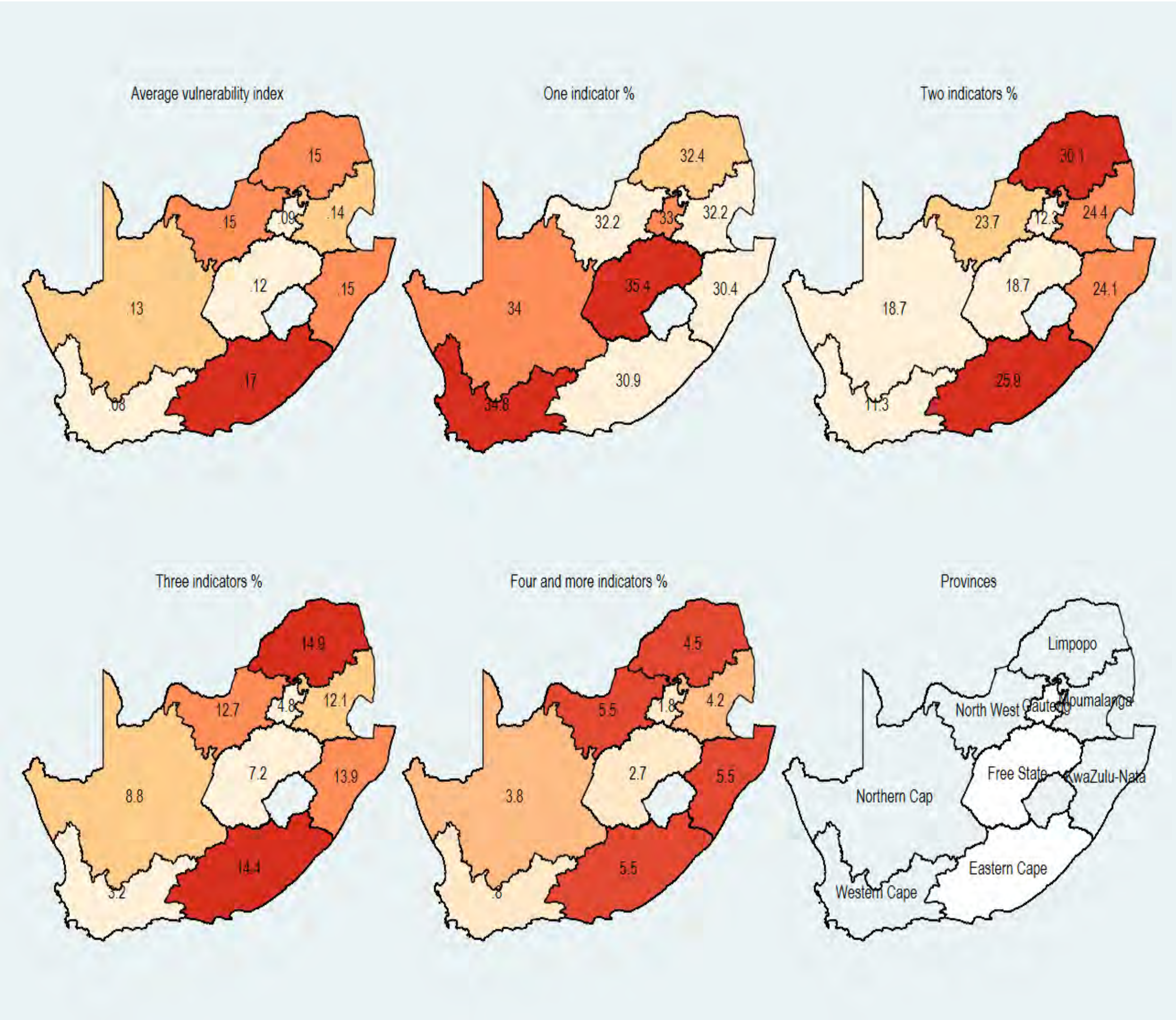


Figure 7: Multidimensional climate-related vulnerability by province (2016 CS)
Source: Authors' calculation using CS (2016).

Figure 8 depicts the average multidimensional climate-related vulnerability index by local municipality, and Table A1 in the Appendix lists the 20 most vulnerable and 20 least vulnerable local municipalities. The most vulnerable local municipalities are concentrated in the Eastern Cape and KwaZulu-Natal provinces, while the least vulnerable local municipalities are concentrated in the Western Cape Province. These disparities across local municipalities are largely the result of differences in the extent to which households participate in subsistence farming, food insecurity, and access to safe water and improved toilet facilities. For example, the proportion of the population living in a household that involved in subsistence farming ranges from 15 to 31 percent in six of the ten most vulnerable municipalities, while it ranges from zero to seven percent among the ten least vulnerable municipalities. Similarly, food insecurity ranges from 30 to 59 percent among the ten most vulnerable municipalities, while it ranges from 5 to 16 percent among the ten least vulnerable municipalities. The proportion of the population without access to safe water ranges from 40 to 90 percent among the most ten most vulnerable municipalities, while it ranges from 1 to 8 percent among the ten least vulnerable municipalities. The key dimensions and indicators that contribute to the multidimensional vulnerability index may vary across spatial units.

Figure 8: Multidimensional climate-related vulnerability by local municipality

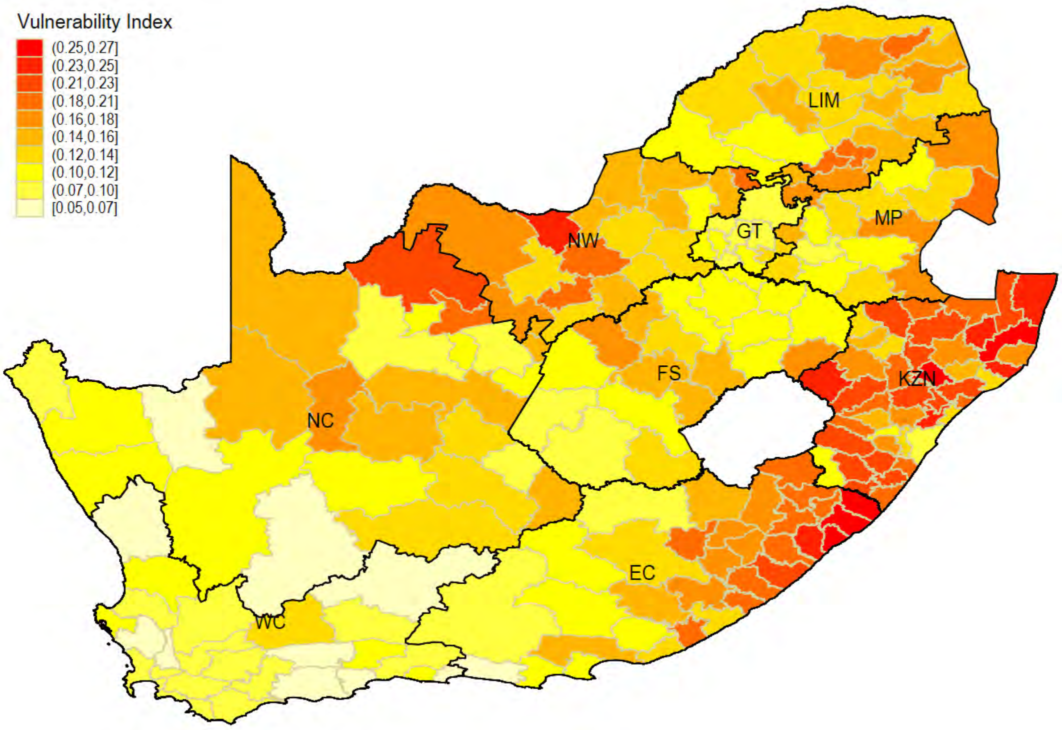


Figure 8: Multidimensional climate-related vulnerability by local municipality

Source: Authors' calculation using CS (2016).

Although Figure 8 above highlights the extent of inequalities in multidimensional climate-related vulnerability across South African local municipalities, we also find significant inequalities within each local municipality. Figure 9 shows the Gini coefficient estimates of the climate-related multidimensional vulnerability index for each local municipality. We find that areas with relativity lower average level of multidimensional climate-related vulnerability scores have higher within spatial unit inequalities. Local municipalities with a relatively higher level of inequality are mostly concentrated in the Western Cape, Northern Cape, Gauteng, and Free State provinces. On the other hand, the extent of inequality is relatively lower among the most vulnerable local municipalities, which are largely located in KwaZulu-Natal and parts of the Eastern Cape provinces. For example, the Gini coefficient estimate for Matzikama local municipality in the

Western Cape Province is 0.70, while the estimate for Mbizana local municipality in the Eastern Cape Province is 0.38. Looking at the distribution of multidimensional climate-related vulnerably scores, we find that the median multidimensional climate-related vulnerably index for Matzikama local municipality is 0.0625, while the corresponding figure for Mbizana is 0.3125. These figures show that local municipalities with relatively lower levels of inequalities have a relatively large share of their population that is less multidimensionally vulnerable, whereas marginalised groups experience higher multidimensional climate-related vulnerability. On the other hand, in areas that are worse off in terms of average vulnerability scores and have a lower inequality index, a relatively large share of their population is multidimensionally vulnerable, implying that they are "equally" vulnerable.

Figure 9: Inequalities in multidimensional climate-related vulnerability by local municipality

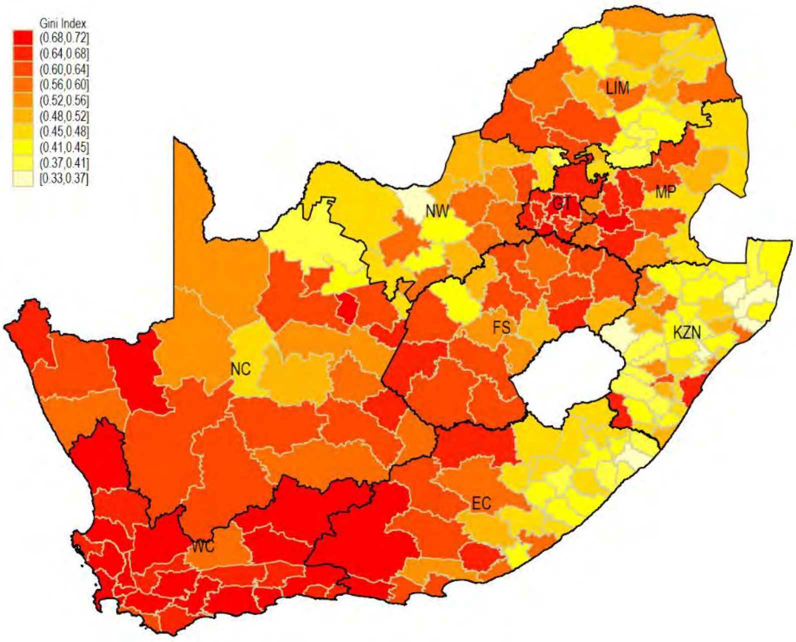


Figure 9: Inequalities in multidimensional climate-related vulnerability by local municipality

Source: Authors' calculation using CS (2016).

Multidimensional climate-related vulnerability and exposure to climate-related Hazards

In this section, we examine whether areas with relatively high proportion of climate-related multidimensionally vulnerable population are also exposed to climate-related hazards. The 2016 CS is the only survey that can be used to measure climate-related multidimensional vulnerability at lower-level spatial units. Data on exposure to climate-related hazards like flooding and storms is frequently quantified at large spatial units rather than smaller area levels. For this reason, analysing the relationship between the occurrence and intensity of climate-related hazards and climate-related vulnerability at disaggregated spatial units is difficult.

In this paper, we use the Emergency Events Database (EM-DAT) from the Centre for Research on the Epidemiology of Disasters (CRED)[3] to examine the association between climate-related disasters and our multidimensional vulnerability measures. According to CRED, a disaster is defined based on one or more of the following criteria:

- 10 or more people dead
- 100 or more people affected
- The declaration of a state of emergency
- A call for international assistance

EM-DAT provides data on natural disasters and estimated economic costs at the country level in each country since 1960. More recently, the GDIS (Geocoded Disasters) database has geocoded the EM-DAT disaster data between 1960 and 2018 to subnational level in each country (see Rosvold & Buhaug, 2021). The GDIS dataset provides spatial geometries in the form of GIS polygons as well as centroid latitude and longitude coordinates for each administrative entity listed as a disaster location in the EM-DAT database.

Disaster data for South Africa is available beginning in 1964, and geocoded disaster data is available between 1968 and 2014. A large proportion of natural disasters (around 38 percent) occurred before the year 2000. Because we want to link vulnerability estimates to recent disasters, we limit our sample to disasters that occurred since 2000. In particular, we focus on natural disasters that occurred within five years of the 2016 community survey data collection (i.e., 2010-2014).

However, there are some difficulties when attempting to link disaster data with vulnerability estimates because most disaster locations are not consistently coded. When documenting disasters, the latitude and longitude information contains a combination of different administrative levels information (i.e. provinces, districts, local municipalities, and towns). For example, for some disasters, we may only have the province name, such as "Western Cape," whereas in other cases, the location information is more specific, such as "City of Cape Town," or locations within City of Cape Town, such as "Parow" or "Cape Winelands." When only a province name and location is given, it is difficult to properly identify disaster locations at lower levels of spatial units such as local municipalities. As a result, if a disaster location is specified as "Western Cape," we assume that all lower-level administrative units, such as local municipalities, will be affected by the same disaster. As a result, our analysis has limitations in terms of linking disaster data with climate-related vulnerability at lower spatial unit levels.

[3] See https://www.emdat.be/

Figure A5 in the Appendix shows the total number of disasters that have occurred in each local municipality since 2000. The number of disasters varies from two to thirteen per local municipality. However, if we limit our observations to the years 2010 to 2014, this figure ranges between one and four (Figure 10). According to Figure 10, the provinces of KwaZulu-Natal and North West had the highest number of disasters, followed by Gauteng, Limpopo, and Mpumalanga.

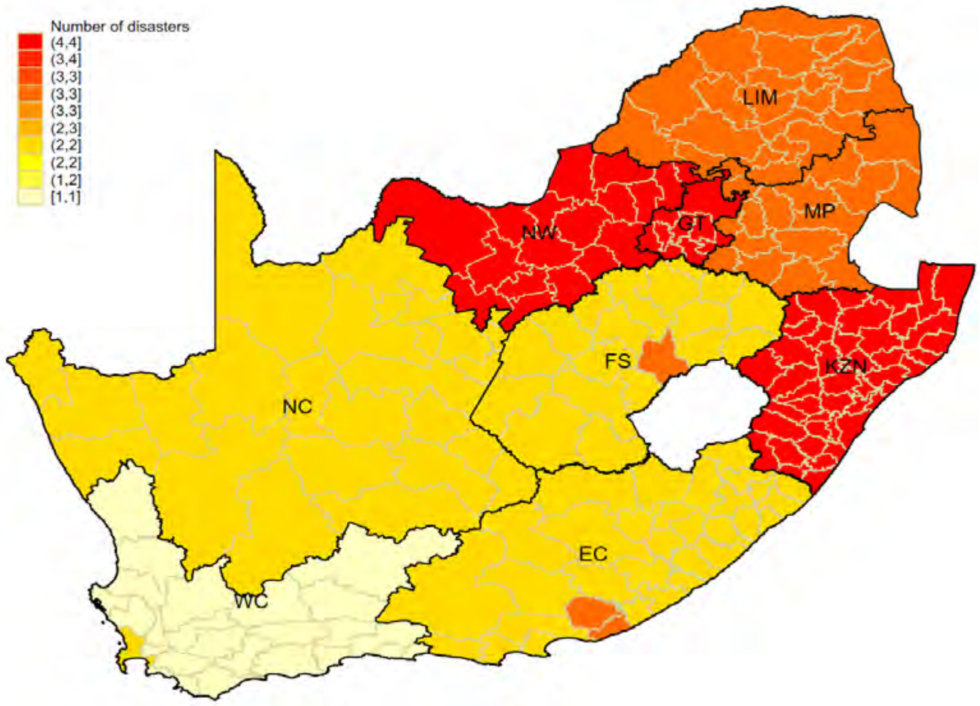


Figure 10: Number of climate-related disasters by local municipality (2010-2014)

Source: Authors elaboration using EM-DAT data.

Figure 11 provides the bivariate map of climate-related disasters that happened between 2010 and 2014 and our multidimensional vulnerability estimates at local municipality level. Figure A6 in Appendix shows the corresponding map for disasters that happened between 2000 and 2014. The graph shows that areas that had both relatively large share of vulnerable population and experienced more climate-related disasters were largely located in KwaZulu-Natal and North West provinces followed by Mpumalanga and Limpopo provinces.

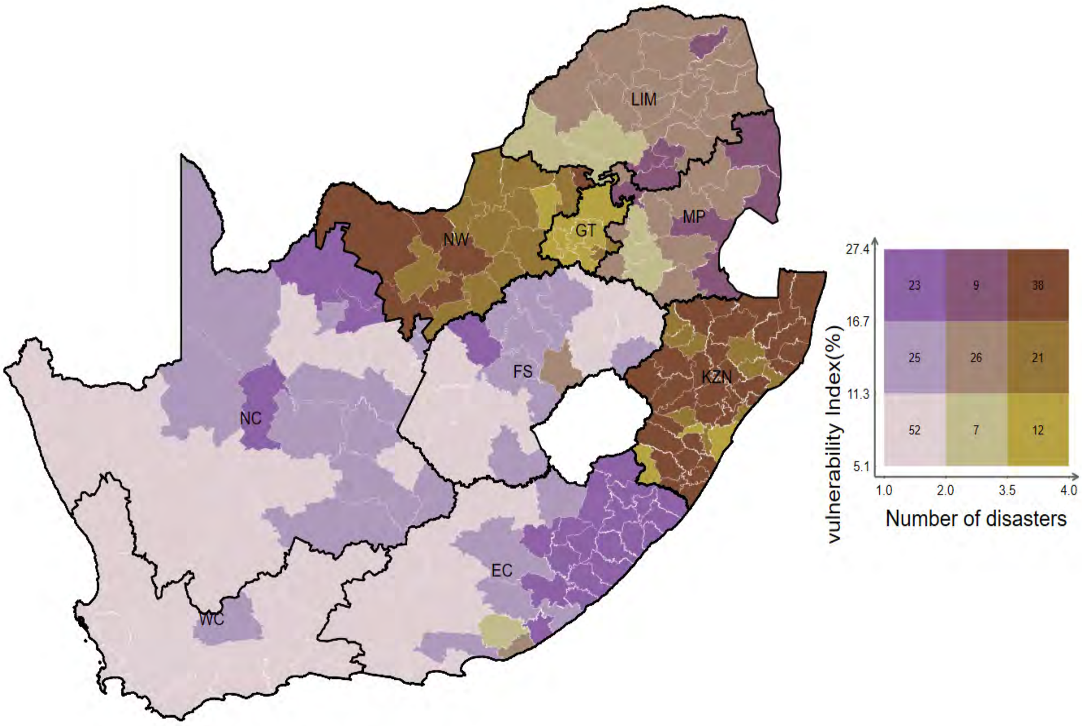


Figure 11: Relationship between number of climate-related disasters (2010-2014) and vulnerability

Source: Authors elaboration using EM-DAT data and the 2016 CS.

The majority of locations with relatively lower multidimensional vulnerability and recent disaster experiences are in the Western and Northern Cape provinces. Although provinces such as Gauteng had experienced a greater number of disasters, the extent of vulnerability is relatively small in comparison to provinces such as KwaZulu-Natal and North West. Despite the data limitations, our analysis in this section suggests that areas with relatively more multidimensionally vulnerable population are also more likely to experience climate-related hazards.

Conclusion

We examined multidimensional climate-related vulnerability in South Africa using household survey data from the 2008 and 2017 NIDS, and the 2016 CS. Our findings show that the proportion of multidimensionally vulnerable people has decreased between 2008 and 2017. However, due to a lack of safe drinking water and sanitation, as well as food insecurity, a large proportion of the population remained vulnerable.

Our findings also show that there are large disparities in the extent of multidimensional climate-related vulnerability by location, income, and social groups. Multidimensional climate-related vulnerability was higher among rural residents, those with lower incomes, and the Black population. These large spatial and social disparities are largely due to inequalities in lack of access to safe water, sanitation, informal housing, and food poverty. Policies that improve access to basic infrastructure and reduce food insecurity are important steps towards reducing social vulnerability and increasing individual coping capacity in the face of climate-related hazards.

We also find evidence that areas with a high level of multidimensional climate-related vulnerability are also vulnerable to climate-related disasters. However, at disaggregated spatial unit levels, our data on climate-related disasters has limitations. Reliable data on climate-related disasters at subnational levels can be useful in drawing correct conclusions about the relationship between climate-related hazards and vulnerability.

References

Adger, W. N. (2006). Vulnerability. *Global enviromental change* 16 (3), 268-281.

Adger, W. N., & Vincent, K. (2005). Uncertainty in adaptive capacity. *Comptes Rendus Geoscience*, *337*(4), 399-410.

Bedeke, S. B. (2023). Climate change vulnerability and adaptation of crop producers in sub-Saharan Africa: A review on concepts, approaches and methods. *Environment, Development and Sustainability*, *25*(2), 1017-1051.

Bohensky, E., Stone-Jovicich, S., Larson, S., & Marshall, N. (2010). Adaptive capacity in theory and reality: implications for governance in the Great Barrier Reef region. *Adaptive capacity and environmental governance*, 23-41.

Bourne, A., Donatti, C., Holness, S., & Midgley, G. (2012). Climate change vulnerability assessment for the Namakwa District Municipality. *Cape Town: Conservation South Africa*.

Brooks, N. (2003). Vulnerability, risk and adaptation: A conceptual framework. *Tyndall Centre for climate change research working paper*, *38*(38), 1-16.

Brooks, N., Adger, W. N., & Kelly, P. M. (2005). The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Global environmental change*, *15*(2), 151-163.

Brophy, T., Branson, N., Daniels, R.C., Leibbrandt, M., Mlatsheni, C., & Woolard, I., (2018). *National Income Dynamics Study Panel User Manual. Release 2018. Version 1*. Cape Town: Southern Africa Labour and Development Research Unit.

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social science quarterly*, *84*(2), 242-261.

Eakin, H., & Bojórquez-Tapia, L. A. (2008). Insights into the composition of household vulnerability from multicriteria decision analysis. *Global Environmental Change*, *18*(1), 112-127.

Emrich, C. T., & Cutter, S. L. (2011). Social vulnerability to climate-sensitive hazards in the southern United States. *Weather, Climate, and Society*, *3*(3), 193-208.

Engle, N. L. (2011). Adaptive capacity and its assessment. *Global environmental change*, 21(2), 647-656.

EPA. (2021). Climate Change and Social Vulnerability in the United States: A Focus on Six Impacts. U.S. Environmental Protection Agency, EPA 430-R-21-003. Available at: www.epa.gov/cira/social-vulnerability-report.

Estoque, R. C., Ishtiaque, A., Parajuli, J., Athukorala, D., Rabby, Y. W., & Ooba, M. (2023). Has the IPCC's revised vulnerability concept been well adopted?. *Ambio*, *52*(2), 376-389.

FAO (2021). FAO 2020–2021 La Niña advisory. Potential impacts on agriculture and food security in high-risk countries (revised version) Available at: https://www.fao.org/documents/card/es/c/cb2954en/

Feldmeyer, D., Birkmann, J., McMillan, J. M., Stringer, L., Leal Filho, W., Djalante, R., ... & Liwenga, E. (2021). Global vulnerability hotspots: differences and agreement between international indicator-based assessments. *Climatic change*, *169*, 1-22.

Fellmann, T. (2012). The assessment of climate change-related vulnerability in the agricultural sector: reviewing conceptual frameworks. In Alexandre M., Jussi L., Suzanne R., Nadine A., & Vincent G.(Eds), *Building resilience for adaptation to climate change in the agriculture sector* (pp. 37-61). Rome.

Füssel, H. M. (2007). Vulnerability: A generally applicable conceptual framework for climate change research. *Global environmental change*, *17*(2), 155-167.

Hahn, M. B., Riederer, A. M., & Foster, S. O. (2009). The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change—A case study in Mozambique. *Global environmental change*, *19*(1), 74-88.

Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., & Beaudet, C. (2020). From poverty to disaster and back: A review of the literature. *Economics of Disasters and Climate Change*, *4*, 223-247.

Hinkel, J. (2011). "Indicators of vulnerability and adaptive capacity": towards a clarification of the science–policy interface. *Global environmental change*, 21(1), 198-208.

IPCC (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, H.-O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (Eds.). Cambridge University Press. Cambridge, UK and New York, NY, USA., doi:10.1017/9781009325844.

Jeggle, T., & Boggero, M. (2018). Post-Disaster Needs Assessment. Available at: https://openknowledge.worldbank.org/bitstream/handle/10986/30945/130985-WP-PUBLIC-P157588-Final-PDNA-Evaluation-Report.pdf

Kelly, P. M., & Adger, W. N. (2000). Theory and practice in assessing vulnerability to climate change and Facilitating adaptation. *Climatic change*, *47*(4), 325-352.

Le Roux, A., Khuluse, S., & Naude, A. J. S. (2015). Creating a high resolution social vulnerability map in support of national decision makers in South Africa.

Le Roux, A., Mans, G., Van Huyssteen, E., & van Niekerk, W. (2017). Profiling the vulnerabilities and risks of South African settlements. Understanding the social & environmental implications of global change. Stellenbosch: African Sun Media, 26-35.

Mambo, J., & Faccer, K. (2017). South African Risk and Vulnerability Atlas: understanding the social & environmental implications of global change.

O'Brien, K., Eriksen, S., Nygaard, L. P., & Schjolden, A. N. E. (2007). Why different interpretations of vulnerability matter in climate change discourses. Climate policy, *7*(1), 73-88.

O'Brien, K., Leichenko, R., Kelkar, U., Venema, H., Aandahl, G., Tompkins, H., ... & West, J. (2004). Mapping vulnerability to multiple stressors: climate change and globalization in India. *Global environmental change*, 14(4), 303-313.

Rosvold, E. L., & Buhaug, H. (2021). GDIS, a global dataset of geocoded disaster locations. Scientific data, 8(1), 61. doi: 10.1038/s41597-021-00846-6

Siders, A. R. (2019). Adaptive capacity to climate change: A synthesis of concepts, methods, and findings in a fragmented field. *Wiley Interdisciplinary Reviews: Climate Change*, *10*(3), e573.

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global environmental change*, *16*(3), 282-292.

Statistics South Africa (2019). National Poverty Lines. Pretoria. Available at: http://www.statssa.gov.za/publications/P03101/P031012019.pdf.

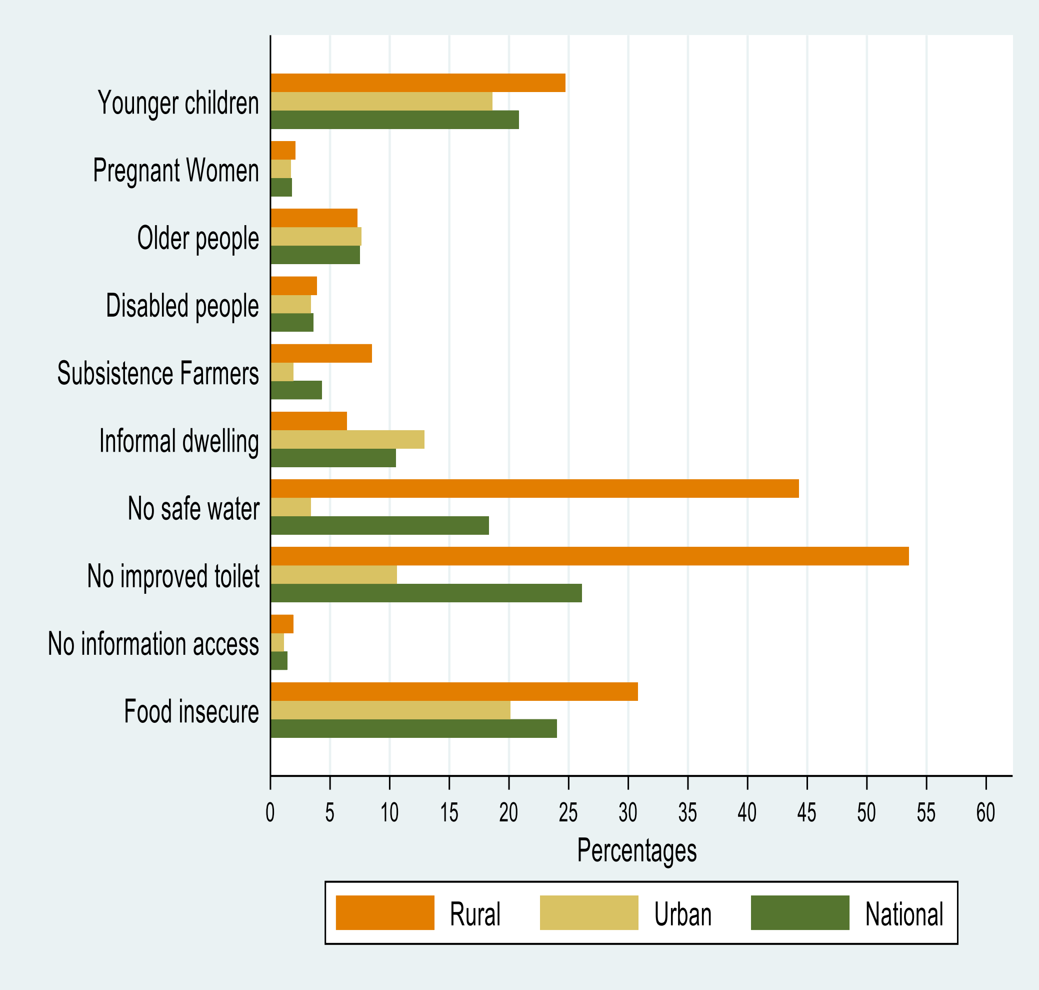
Thomas, K., Hardy, R. D., Lazrus, H., Mendez, M., Orlove, B., Rivera-Collazo, I., ... & Winthrop, R. (2019). Explaining differential vulnerability to climate change: A social science review. *Wiley Interdisciplinary Reviews: Climate Change*, *10*(2), e565.

Welle, T., & Birkmann, J. (2015). The world risk index–an approach to assess risk and vulnerability on a global scale. Journal of Extreme Events, 2(01), 1550003.

Appendices

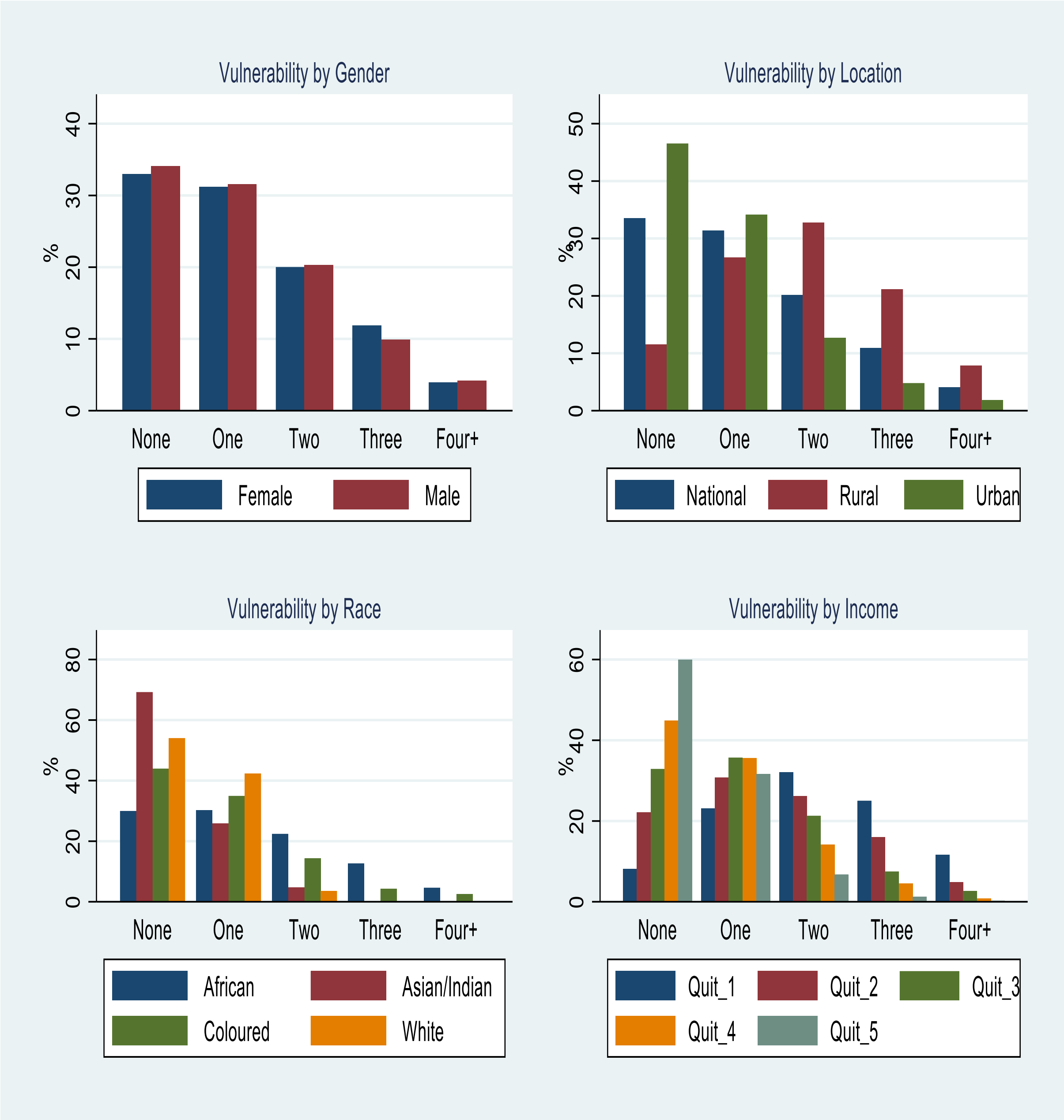
Appendix A

A1: Proportion of the population per vulnerability indicator by location, 2016 CS



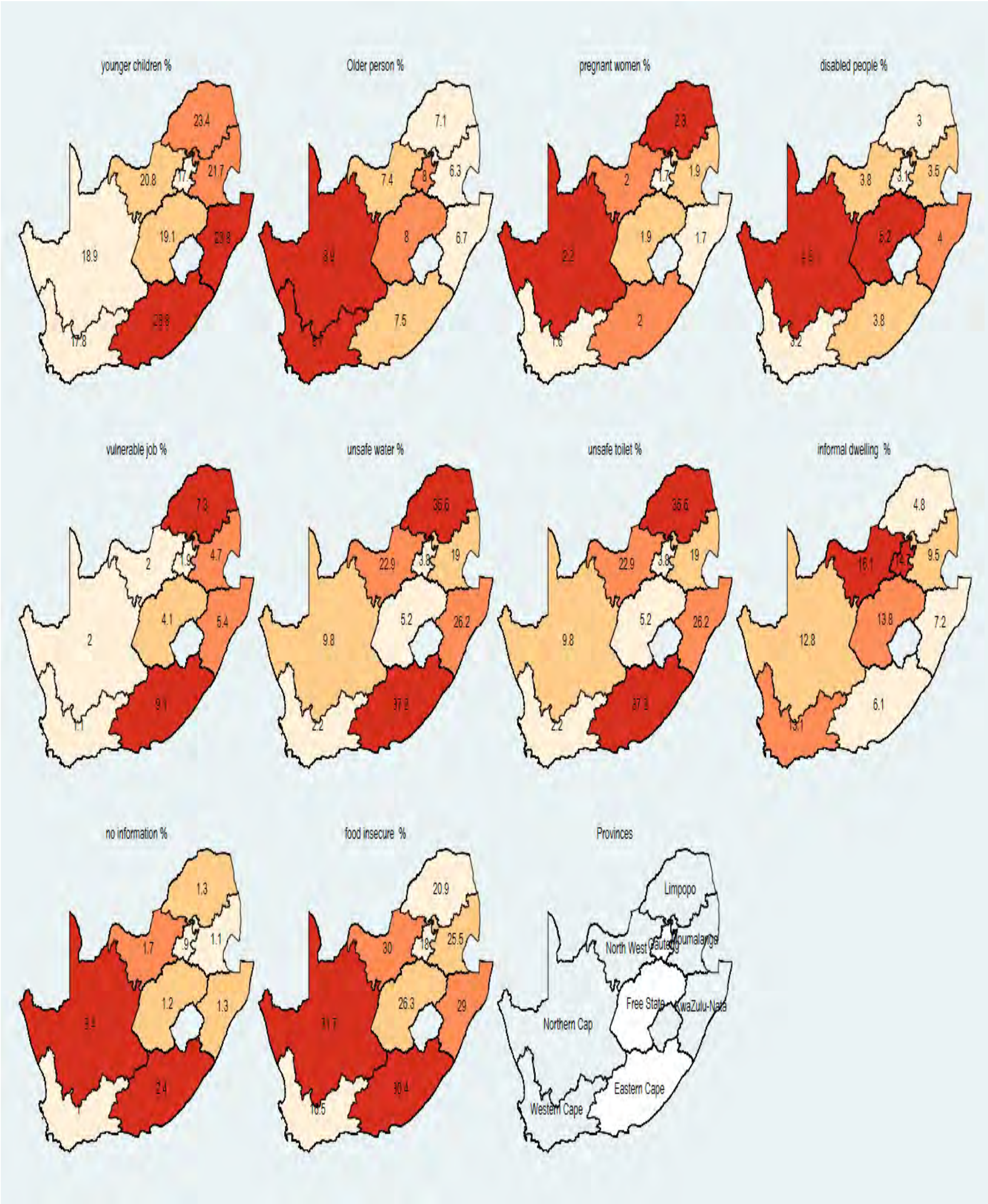
Source: Authors' calculation using CS 2016.

A2: Intensity of Multidimensional climate-related vulnerability



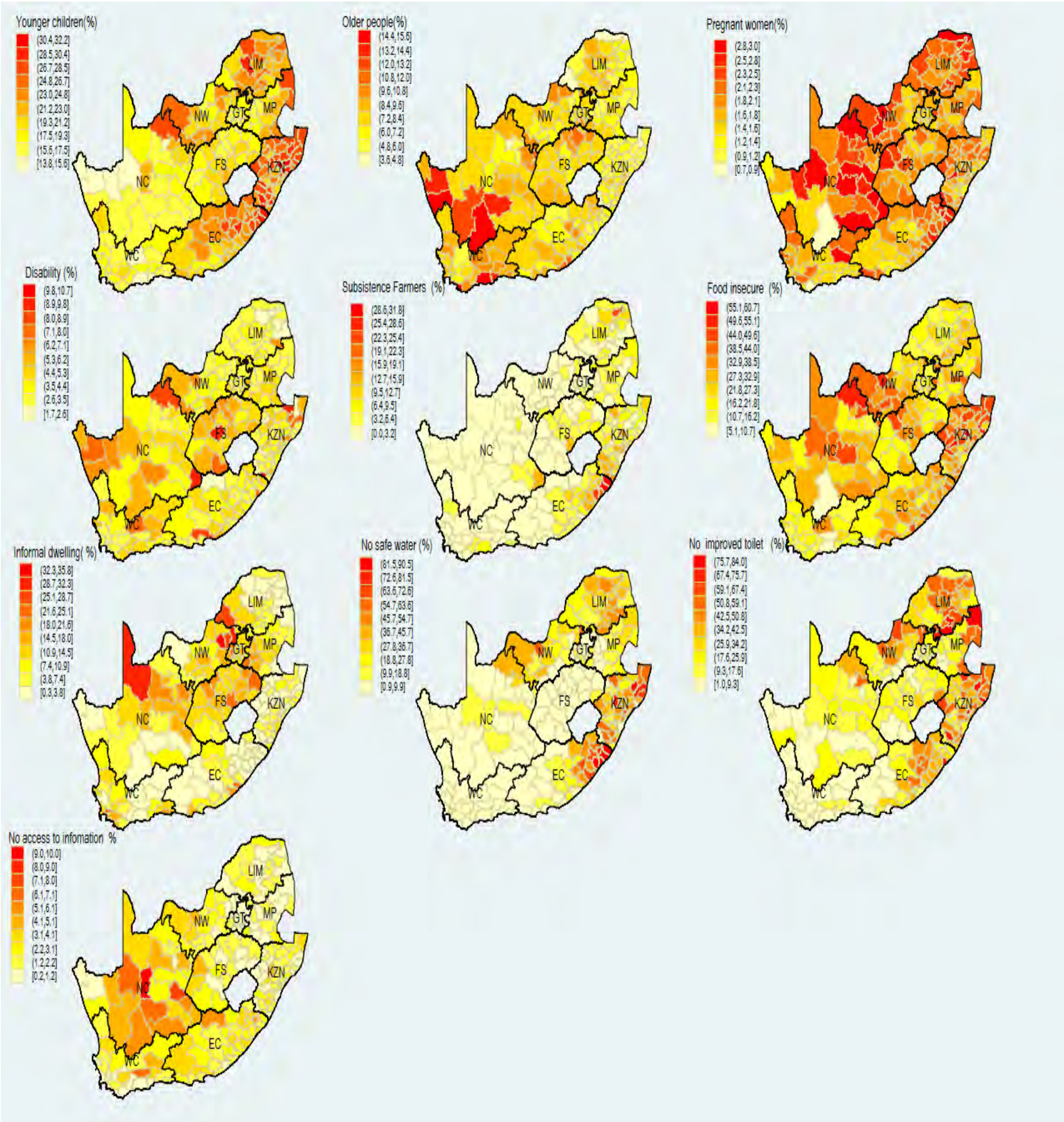
Source: Authors' calculation using NIDS.

Figure A3: Proportion of the population per vulnerability indicator by province (2016 CS)



Source: Authors' calculation using CS 2016.

Figure A4: Distribution of each vulnerability indicator by local municipality (CS,2016)



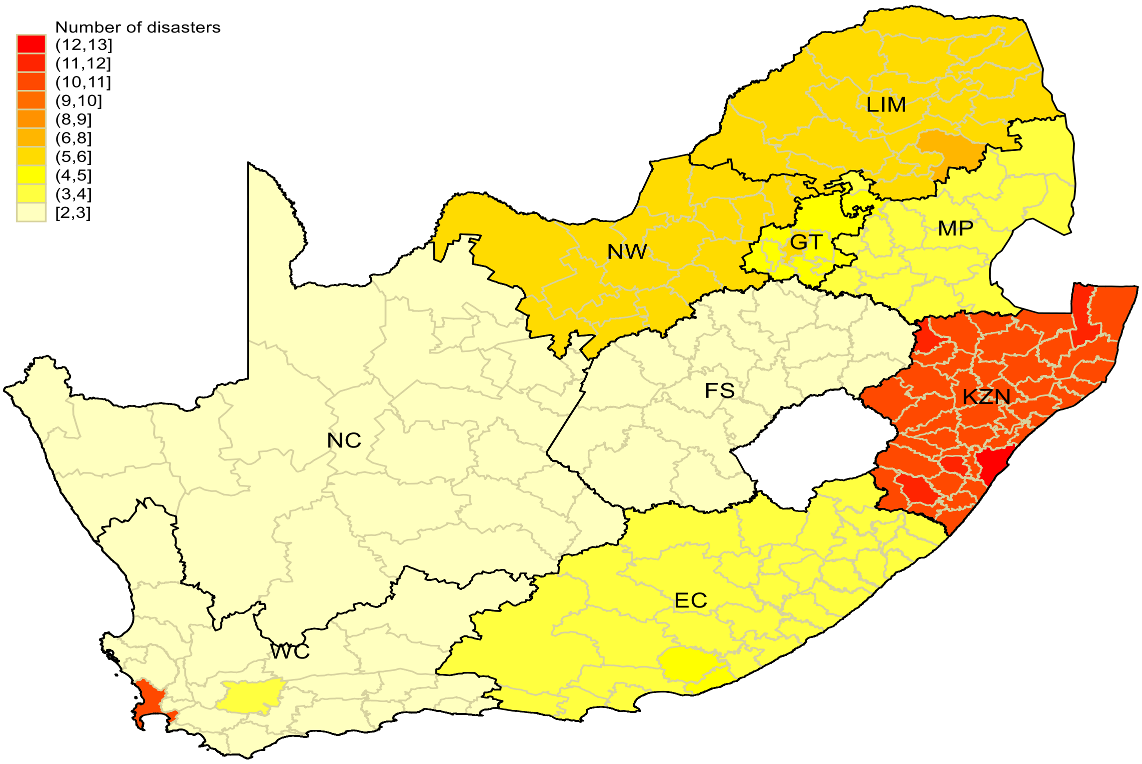
Source: Authors' calculation using CS 2016.

Table A1: The top 20 most vulnerable and bottom 20 least vulnerable municipalities

Top 20	score	Bottom 20	Score
Ngquza Hill	0.274	Cape Agulhas	0.080
Nkandla	0.263	Witzenberg	0.080
Mbizana	0.261	Stellenbosch	0.079
Port St Johns	0.260	Langeberg	0.078
Big Five Hlabis	0.254	Dr Beyers Naude	0.076
Nyandeni	0.248	City of Cape To	0.076
Nongoma	0.247	Bergrivier	0.076
Ratlou	0.247	Theewaterskloof	0.075
Mfolozi	0.247	Emfuleni	0.074
Ndwedwe	0.241	Kh I Ma	0.073
Umhlabuyalingan	0.231	Bitou	0.071
Okhahlamba	0.231	Beaufort West	0.070
Inkosi Langalib	0.229	Mossel Bay	0.069
Ubuhlebezwe	0.229	Drakenstein	0.067
Jozini	0.227	Matzikama	0.065
Umzumbe	0.227	Karoo Hoogland	0.061
Joe Morolong	0.225	Hessequa	0.060
uMlalazi	0.223	Swartland	0.060
Maphumulo	0.223	Kannaland	0.059
Dr Nkosazana Dl	0.221	Kou-Kamma	0.051

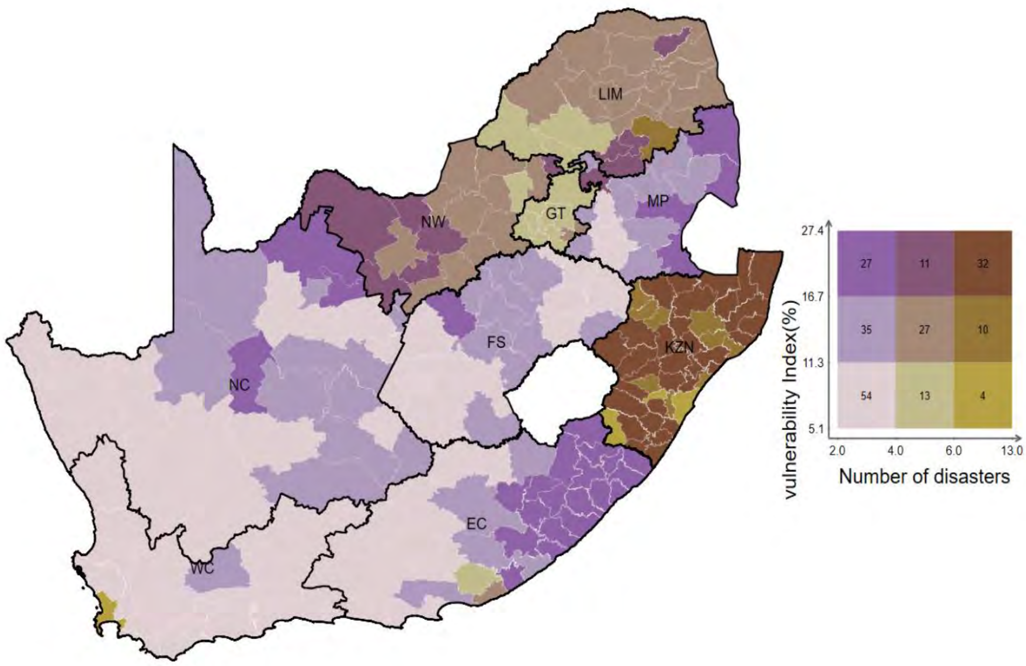
Source: Authors' calculation using CS 2016.

A5: number of climate-related disasters by local municipality (2000-2014)



Source: Authors' elaboration using EM-DAT data.

A6: Relationship between number of climate-related disasters (2000-2014) and vulnerability



Source: Authors' elaboration using EM-DAT data and the 2016 CS.