



# **Unravelling the spatial dynamics of unemployment rates in district municipalities in South Africa: A disaggregated analysis for informed policymaking**

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# Unravelling the spatial dynamics of unemployment rates in district municipalities in South Africa: A disaggregated analysis for informed policymaking

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## Abstract

Statistics South Africa is vital in providing national and provincial data, offering quarterly employment indicators for the country. However, accurately estimating district (sub-national) unemployment rates presents significant challenges due to high sampling variability in the Quarterly Labour Force Survey (QLFS) within smaller areas. To tackle these issues, this study employs a spatiotemporal small area estimation (SAE) technique that integrates both spatial and temporal dimensions. This study uses data from the QLFS (Q1 2022 to Q1 2024) along with auxiliary variables from the 2016 Community Survey to produce robust quarterly estimates of unemployment rates for all 52 district municipalities. Our analysis indicates a statistically robust and consistently observable spatial inequality in unemployment rates between metropolitan and non-metropolitan districts. Specifically, metropolitan districts tend to exhibit lower and more stable unemployment rates, primarily attributed to the diversity of their economic activities across various sectors. In contrast, non-metropolitan districts experience higher and less stable rates, mainly due to limited industrial diversity and a dependence on seasonal jobs. Our robust methodology also highlights practical implications by identifying specific geographic hotspots of youth unemployment, particularly among the 15–24 and 25–34 age groups. Additionally, we observe distinct gender disparities, with women facing greater barriers to employment than men. The primary contribution of our study is methodological, as it provides a robust tool for informing evidence-based interventions in local workforce monitoring. Our findings offer valuable evidence for prioritising place-based development initiatives and emphasise the necessity of moving beyond a one-size-fits-all approach in national policies to effectively address South Africa's deeply entrenched spatial inequities.

*Keywords:* Unemployment rate; small area estimation; spatiotemporal; Metropolitan cities

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## 1. Introduction

Unemployment has significant social and economic consequences. It can lead to reduced productivity, decreased demand, and increased public deficits, affecting a country's economy. Additionally, it can result in social issues such as psychological and discriminatory effects (Bugallo et al., 2024). In essence, the unemployment rate is a vital indicator of a country's

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economic health and its impact on people's quality of life. A low unemployment rate indicates a strong economy with fewer social issues, while a high unemployment rate suggests a weak economy with more social conflicts (Chand et al., 2017; Davidescu et al., 2021). Therefore, monitoring and addressing unemployment rates is crucial for ensuring the well-being of the population.

The historical racial divisions in the South African job market stem from the legacy of apartheid, which enforced systemic discrimination against the majority population. Although affirmative action policies have been implemented since the end of apartheid in 1994, significant disparities in employment opportunities persist.

Key elements of these historical divisions include the Job Preservation Act of 1926, which aimed to prioritize employment for white individuals during a period of economic instability. This legislation systematically excluded Black, Coloured, and Indian workers from skilled and semi-skilled positions (Carrim et al., 2022). Moreover, the apartheid regime institutionalized racial capitalism, exploiting the labour of Black, Coloured, and Indian individuals while fostering a sense of racial superiority among white workers (Motaung, 2021).

Since the conclusion of apartheid, there has been an increase in employment opportunities for Black, Coloured, and Indian individuals. However, these groups still disproportionately occupy low-skilled, low-paying jobs. Occupational segregation remains a significant challenge, with less than one-third of this segregation explained by educational disparities among different racial groups (Gradín, 2019).

The unemployment rate in South Africa varies significantly between urban and rural areas. According to Coetzee et al. (2022), urban municipalities exhibit distinct unemployment patterns, and the gap between unemployed and employed individuals in these regions has decreased since 1991. Research indicates that factors such as population growth rate, population density, and the size of the informal sector are linked to lower unemployment rates in specific locations (Weir-Smith, 2018). Furthermore, higher levels of education and a more substantial presence in key sectors such as mining, manufacturing, construction, and trade have been associated with lower unemployment rates (Weir-Smith, 2014). These findings highlight the considerable influence of local economies and labour markets on unemployment levels in South African cities and towns (Viljoen, 2015). Therefore, it is essential to separately estimate the unemployment rate for urban and rural areas across different age groups and genders, as well as to monitor how urbanization affects these rates.

Statistics South Africa (Stats SA) releases quarterly unemployment estimates at the national and provincial levels; however, estimates for lower administrative levels, such as districts and local municipalities, as well as specific demographic groups like age, gender, or minorities, are not available due to small sample sizes and high sampling variability of the Quarterly Labour Force Survey (QLFS). Understanding these national and provincial rates is crucial for effective policymaking, while analysing district-level unemployment rates by gender and age groups is essential for developing targeted local interventions. Using this information, district government officials can implement initiatives for job creation and provide entrepreneurial training to address unemployment better.

Analyzing disaggregated unemployment rates can provide valuable insights into socioeconomic disparities. This approach enables the examination of regional unemployment rate variations, which are commonly used to gauge regional economic inequality (Bayer and Jüssen, 2007; Hotchkiss, 1991). Estimating disaggregated unemployment rates allows for a comprehensive understanding of the dynamics and interdependencies among different regions (Bayer and Jüssen, 2007). This information is essential for formulating effective regional policies to address unemployment disparities (Enrique and Elisabet, 2011). This is why modern states require precise data to monitor and make decisions to mitigate these issues. Consequently, governments are interested in mapping labour force indicators, such

as the proportion of employees or unemployment rates, at a sufficiently disaggregated level (Bugallo et al., 2024).

This study aims to analyse the distribution of the unemployment rate across the district municipalities of South Africa, focusing on variations by gender and age groups. It employs spatiotemporal small area estimation (SAE) techniques, which are especially useful when direct survey data is limited (Rao and Molina, 2015). This study generates reliable estimates by combining information from community surveys with historical data from the Quarterly Labour Force Survey (QLFS). The goal is to provide accurate estimates of unemployment rates for the 52 district municipalities, resulting in 104 domains for gender and 208 domains for age groups.

This research makes several key contributions to the literature and enhances our understanding of labour dynamics in South Africa. Firstly, it employs a novel spatiotemporal SAE approach. This method combines spatial and temporal dimensions, using quarterly data from the QLFS (Quarter 1 of 2022 to Quarter 1 of 2024) and auxiliary variables from the 2016 Community Survey. The approach aims to improve the accuracy of unemployment estimates at the district level, addressing the significant issue of unreliable and high-frequency unemployment rate estimates that result from high sampling variability in direct survey estimates from the QLFS. The SAE framework increases data granularity without requiring additional field data and integrates multiple data sources effectively. Secondly, the study employs this robust spatiotemporal SAE technique to deliver the first high-resolution (detailed) quarterly unemployment rate estimates for the 52 districts of South Africa, covering the period from Q1 2022 to Q1 2024. This pioneering approach offers valuable longitudinal insights into micro (sub-national) labour market dynamics in the post-pandemic recovery phase. Furthermore, recognising the importance of detailed estimates is crucial for moving beyond national and provincial averages to provide actionable policy insights. These estimates highlight spatial disparities between metropolitan and non-metropolitan economies and identify priority districts for targeted interventions in youth and gender employment. This information can help develop effective policies, target specific population groups, and monitor existing programs. By aligning these findings with initiatives like the Presidential Youth Employment Intervention (PYEI) (Department of Basic Education, 2025), this study shifts from a statistical exercise to a strong evidence base for targeted and effective policymaking that promotes equitable growth.

The research will address the following questions:

1. Are there disparities in unemployment rates between men and women in district municipalities?
2. What are the differences in unemployment rates among various age groups, particularly youth aged 15–24 and 25–34, in district municipalities?
3. Are there disparities in unemployment rates between metropolitan municipalities (cities) and non-metropolitan district municipalities?

These research questions align with the global framework of indicators for monitoring the Sustainable Development Goals (SDGs). This framework highlights the need to disaggregate information by geographical location, income group, gender, age, race, ethnicity, immigration status, and disability status (Molina, 2022). More detailed statistics can help target policies and interventions more effectively by identifying specific subgroups within the population that may not benefit from development efforts.

The remainder of the paper is organised as follows: Section 2 reviews employment indicators and the implementation of the spatiotemporal SAE. Section 3 covers the methodology

and data sources, Section 4 presents the results, Section 5 discusses the findings, Section 6 explores policy implications and recommendations, and Section 7 concludes.

## 2. Literature review

### 2.1. Overview of employment indicators in South Africa

The employment situation in South Africa is influenced by a range of socioeconomic indicators that reflect the country's economic conditions, labour market dynamics, and social challenges. Through relevant literature, this section explores vital employment indicators, such as unemployment rates, labour force participation, youth employment, and sectoral employment trends.

**Unemployment rate.** The unemployment rate has been a significant challenge and concern for South Africa for many years. Recent reports indicate that the unemployment rate is 33.5% for the second quarter of 2024. This marks a third consecutive quarterly increase, up from 32.9% in the first quarter of 2024, due to a further rise in the number of unemployed individuals. It is one of the highest rates in the world. The high unemployment rate is attributed to several factors, including: (i) *Economic slowdown:* The high unemployment rate in South Africa is a complex issue mainly caused by slow economic growth, which has greatly limited job creation. Since the country transitioned to democracy in 1994, South Africa's economic growth has been disappointing. There has been a significant decrease in the non-mineral tradable sector, especially in export-oriented manufacturing, which has hindered job creation (Rodrik, 2008). (ii) *Structural issues:* The persistent unemployment is partly due to the mismatch between skills and job requirements. Furthermore, historical policies from the apartheid era have led to a spatially segregated workforce, resulting in low absorption rates of black people in the labour market (Mncayi and Shuping, 2021). Moreover, high wage levels in certain sectors hinder employment growth as businesses struggle to absorb the available labour (Rodrik, 2008). (iii) *The COVID-19 pandemic impact:* The COVID-19 pandemic has had a significant impact on South Africa's unemployment rate, presenting a major challenge and concern. Sectors such as tourism and accommodation have seen unprecedented job losses and salary reductions, leading to many businesses being unable to maintain their workforce (Sucheran, 2024). Furthermore, the construction sector has also experienced workforce reductions, with over 43% of companies reporting significant losses, especially in skilled labour. This has resulted in project delays and further contributed to unemployment (Chabalala et al., 2024).

**Youth employment.** South Africa wrestles with high youth unemployment rates despite significant investments in Active Labour Market Programs by the government, private sector, and civil society (De Lannoy et al., 2020). The challenges faced by young people include:

- **Impact of COVID-19:** The National Planning Commission (2023) reports a rise in unemployment from 25.4% to 27.7% between 2012 and 2018, worsened by the pandemic. Ranchhod and Daniels (2021) noted that during the April 2020 lockdown, about one in three employed individuals lost their jobs or faced unpaid work. Meanwhile, Bassier et al. (2023) highlighted a 40% drop in employment from February to April 2020, with job losses disproportionately affecting vulnerable groups such as women, Black individuals, youth, and those with lower education levels.
- **The Matric Paradox: High Pass Rates but Low Employment Opportunities**
  - Between 2020 and 2023, more students achieved National Senior Certificate (NSC) passes than in the previous five years (Wills et al., 2024). However, a Davie (2025) report reveals that many of South Africa's 2024 matriculants will face a challenging job

market. Although 48% earned a bachelor's pass, fewer than 15% are expected to attend university, leaving most to seek employment. The report also criticizes the education system and notes that labour laws restrict small and medium-sized enterprises (SMEs) from hiring inexperienced school leavers.

- **Spatial Mismatch Limits Access:** South African cities, although covering only a small fraction of the country's land, are vital to the economy, accounting for nearly 60% of formal employment through major metros like Johannesburg, Cape Town, Tshwane, eThekweni, and Ekurhuleni (Turok and Visagie, 2025). Weir-Smith and Dlamini (2024) found that increased urbanization correlates with higher labour absorption rates. Machebele and Weir-Smith (2024) highlighted that job opportunities are predominantly located in well-developed areas, leaving impoverished regions distant from employment. Crankshaw (2022) examined urban inequality in Johannesburg, revealing that labour market changes have mostly benefitted well-educated workers, while economic decentralization in wealthy Sandton has worsened spatial inequality and unemployment in the southern suburbs, emphasizing a significant north-south economic divide.
- **Focus on Supply-Side Factors:** De Lannoy et al. (2020) thoroughly reviewed evidence from 1994 to 2018 on factors related to this complex issue and found that most efforts have concentrated on supply-side labour market factors, with little attention to employer behavior or the gender dynamics affecting youth.
- **Inadequate Training:** Young individuals often lack access to quality education and training, resulting in insufficient work experience and skills, making them less attractive to employers (Beginina, 2023; Somerville et al., 2022; Harvey, 2014).
- **Economic Disparities:** Geographic and economic differences limit job opportunities for young people in rural areas compared to urban centers (Mlatsheni and Rospabé, 2002).
- **Limited Job Opportunities:** Not enough entry-level positions are available, making it hard for youth to find work (Harvey, 2014).

***Sectoral employment trends.*** Although agriculture and mining remain significant sources of employment, they have faced various challenges and job losses (Fedderke, 2018). Mining projects, which were once essential for many small towns in South Africa, have significantly declined due to resource depletion, weak community engagement, a lack of trust, poor collaboration, and shortcomings in policy. As a result, the sector has experienced considerable job losses, leading to a dramatic decrease in employment over recent decades (Meggersee and Guvuro, 2023). Similarly, while agriculture continues to create job opportunities amidst high unemployment rates, it is becoming increasingly precarious due to climate change, drought, and pressures from global markets (Ramakgasha et al., 2024). In contrast, the manufacturing sector still plays a crucial role in stimulating demand in other industries through strong backward linkages (Tregenna, 2008). On the other hand, the services sector—particularly finance and business services—has shown resilience and growth, emerging as a primary source of employment (Tregenna, 2008; Mkhize, 2019). This shift reflects the changing structure of the economy, with employment transitioning from primary to tertiary sectors (Mkhize, 2019). Overall, the trend indicates a movement toward a more capital-intensive economy, resulting in an increasing demand for highly skilled workers, at the expense of unskilled labour (Mkhize, 2019).

**labour force participation.** South Africa is grappling with ongoing challenges in its labour market, which is marked by low absorption rates and high levels of discouragement among job seekers. For instance, in the first quarter of 2024, the labour force participation rate rose by 0.7 percentage points to 60.7%, but the absorption rate fell by 0.1 percentage points to 40.7% (Statistics South Africa, 2024). The high number of discouraged job seekers further highlights the deteriorating health of the labour market. At the beginning of this study (Q1:2022), approximately 3.8 million individuals were classified as discouraged and not actively seeking work due to discouragement reasons (Statistics South Africa, 2022). This number has gradually decreased, reaching about 3 million at the final period of this study (Q1:2024), suggesting a slight improvement in labour market inclusion (Statistics South Africa, 2024).

Several factors contribute to the challenges in the labour market, including a mismatch between skills and job opportunities, ineffective job search methods, and structural inequalities (Mncayi and Shuping, 2021). Demographic variables such as age, race, and geographic location significantly influence labour market outcomes, with women and Black Africans encountering greater difficulties in securing employment (Nkhumeleni, 2022).

To address these challenges, it is essential to implement strategies that focus on skill development, promote economic growth, and specifically target interventions for youth. These measures are critical for generating more job opportunities and alleviating the country's high unemployment rates. Additionally, increasing youth labour force participation is vital for reducing the number of discouraged job seekers and fostering economic growth (Nkhumeleni, 2022).

## *2.2. Spatiotemporal SAE for accurate socioeconomic indicator estimation*

Spatiotemporal SAE techniques are valuable for estimating various socioeconomic indicators at a small area level. These indicators include unemployment rates, poverty measures, health applications, forest variables, and so on. Researchers, such as Kim et al. (2023), have utilised spatiotemporal SAE models that consider both spatial and temporal random effects. These models can improve the accuracy of estimates of undernutrition indicators. These methods have also been employed to estimate forest variables across large geographic areas and long periods, providing reliable estimates at a higher spatial and temporal resolution. Studies conducted by Wakefield et al. (2020) and Stanke et al. (2022) have demonstrated the effectiveness of these techniques in estimating forest variables.

There are different ways to implement these models. One way is to use Gaussian processes, which capture correlation structures across space and time and enable efficient statistical inference (Vogt et al., 2023). Another way is to use Bayesian spatial models, which incorporate spatial autocorrelation to enhance the accuracy of regional and local estimates (Semenova et al., 2021).

Overall, spatiotemporal SAE techniques offer improved precision and efficiency in estimating characteristics of interest for small domains, which is critical as these estimates are often used as a basis for political decision-making that impacts our daily lives. For example, SAE techniques are used by the World Bank to create poverty maps in both developing and developed countries and by the United States Census Bureau to estimate income, poverty, and the proportion of school-age children living in poverty (Molina, 2022).

Spatiotemporal SAE techniques offer several advantages. One of the main benefits is the ability to enhance the accuracy of estimates for small geographic regions by utilising information from other sub-populations (Bocci et al., 2020). These techniques are instrumental when analysing continuous variables with a strong spatial structure and skewed distribution (Sugasawa and Kubokawa, 2023). Another advantage is that spatiotemporal models can capture the spatial correlation between small areas, which is crucial in cases where neighbouring

regions are likely to be correlated (Salvati et al., 2006).

### 3. Data sources and labour force indicators

While Statistics South Africa (Stats SA) regularly disseminates quarterly labour force statistics at national and provincial levels, there is a growing need for more detailed official statistics at a more specific level (e.g., domain level). This involves breaking down data within district municipalities by demographic factors such as gender and age groups. To address this, this study utilizes the SAE methodology and a spatiotemporal linear mixed model at the local level to estimate unemployment rates for South African district municipalities, disaggregated by age groups and gender. The study utilizes data from two major surveys: the QLFS conducted between the first quarter of 2022 (2022Q1) and the first quarter of 2024 (2024Q1) and the 2016 community survey. These datasets are freely available on the Stats SA website (<https://www.statssa.gov.za>).

#### 3.1. A brief description of the QLFS

The QLFS, conducted by Statistics South Africa, offers information on employment, unemployment, and other related indicators. The QLFS survey, however, had a high level of sampling variability, and it was not intended to generate reliable direct estimates at the micro-level (disaggregated) due to its small sample sizes.

For instance, in the first quarter of 2024 (QLFS24Q1), the anonymized QLFS data file records 66,879 individuals, including 31,894 males and 34,985 females. In this research, the population of interest,  $U$ , encompasses individuals aged 15 and above ( $\text{age} \geq 15$ ) in South Africa. Respondents under 15 years old are excluded as they are below the minimum South African working age. Consequently, the survey data file size decreases to approximately 47,872 working-age respondents, with 22,341 males and 25,531 females. Subsequently, respondents were categorized based on their district municipality of residence and sex (1: male, 2: female). Additionally, the age variable was then used to group people into four categories: 15–24, 25–34, 35–49, and 50 and above, based on their age in years.

Figure 1 presents the employment patterns over time, analysed by age and gender. These plots illustrate the trends in the number of individuals across various employment statuses: Unemployed, Employed, and Inactive. Additionally, we have included a breakdown of employment status by age groups and gender.

Table A.6 in the Appendix shows the distribution of respondents by employment status, sex, and age group. The active population is mostly found in the second and third age groups, while inactivity rises significantly from age 50 and in the 15–24 age group. Additionally, younger respondents and women experience higher rates of unemployment and inactivity.

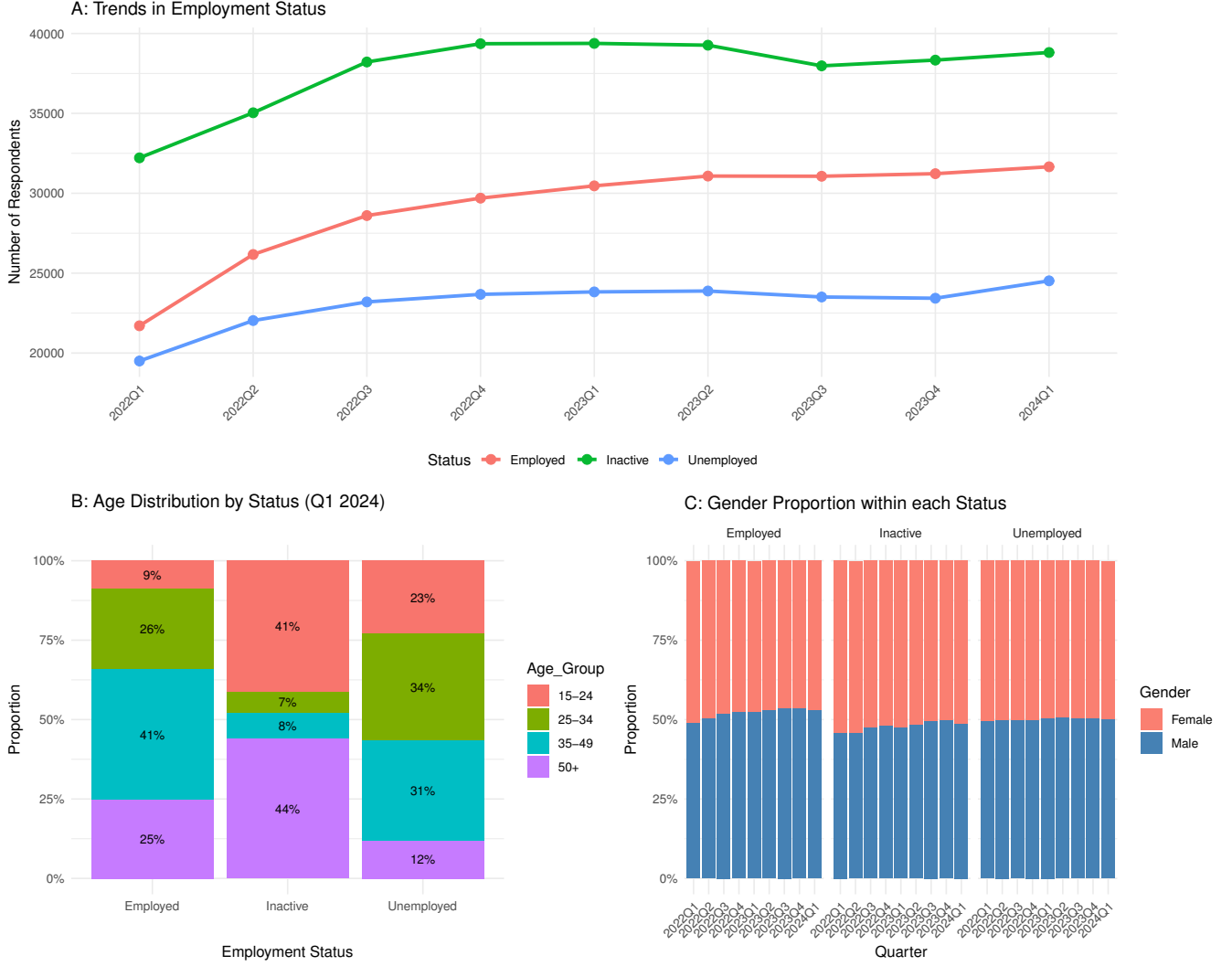


Figure 1: Employment patterns over time: analysis by age and gender

### 3.2. Design-based direct estimators

Survey samples offer valuable insights into a population, eliminating the need for time-consuming and expensive censuses. Sampling theory involves methodologies and procedures for drawing inferences from finite populations. Estimators of parameters for the overall population can be adapted to estimate domain parameters by treating domains as independent populations. This approach yields design-based direct estimators for SAE (Morales et al., 2021). For a total of  $n$  working-age respondents, and for each individual  $j$  in the domain  $d$ , the binary target variables  $y_{dj}$ ,  $z_{dj}$ , and  $t_{dj}$  represent whether the individual is unemployed, employed, or inactive, respectively. These variables are defined as follows:

$$y_{dj} = \begin{cases} 1 & \text{if } j \text{ is unemployed} \\ 0 & \text{otherwise} \end{cases}$$

$$z_{dj} = \begin{cases} 1 & \text{if } j \text{ is employed} \\ 0 & \text{otherwise} \end{cases}$$

$$t_{dj} = \begin{cases} 1 & \text{if } j \text{ is inactive} \\ 0 & \text{otherwise} \end{cases}$$

In this context, the total number of unemployed people, employed people, and the total number of inactive people are denoted by  $Y_d = \sum_{j \in S_d} w_{dj} y_{dj}$ ,  $Z_d = \sum_{j \in S_d} w_{dj} z_{dj}$ , and  $T_d = \sum_{j \in S_d} w_{dj} t_{dj}$ , respectively. We compute the widely-used design-based estimator, which relies solely on data within the domain and does not use any auxiliary variables as the direct estimator. When working with a stratified random sampling design, this estimator (in this case, the unemployment rate) can be calculated as follows:

$$\hat{R}_d^{dir} = \frac{Y_d}{Y_d + Z_d}.$$

By using Taylor linearization, one can estimate the design-based variance of ( $\hat{R}_d^{dir}$ ):

$$\begin{aligned} \widehat{\text{Var}}\left(\hat{R}_d^{dir}\right) &= \frac{Z_d^2}{(Z_d + Y_d)^4} \widehat{\text{Var}}\left(\hat{Y}_d\right) + \frac{Y_d^2}{(Z_d + Y_d)^4} \widehat{\text{Var}}\left(\hat{Z}_d\right) \\ &\quad - 2 \frac{Y_d Z_d}{(Z_d + Y_d)^4} \text{Cov}(Y_d, Z_d). \end{aligned}$$

The design based variances are

$$\begin{aligned} \widehat{\text{Var}}\left(\hat{Y}_d\right) &= \sum_{j \in S_d} w_{dj} (w_{dj} - 1) (Y_{dj} - \hat{Y}_d)^2 \\ \widehat{\text{Var}}\left(\hat{Z}_d\right) &= \sum_{j \in S_d} w_{dj} (w_{dj} - 1) (Z_{dj} - \hat{Z}_d)^2. \end{aligned}$$

Additionally, the design-based covariance is

$$\text{Cov}(Y_d, Z_d) = \sum_{j \in S_d} w_{dj} (w_{dj} - 1) (Y_{dj} - \hat{Y}_d) (Z_{dj} - \hat{Z}_d), \quad d = 1, \dots, D,$$

where  $\hat{Y}_d = Y_d/N_d = \sum_{j \in S_d} w_{dj} y_{dj} / \sum_{j \in S_d} w_{dj}$  and  $\hat{Z}_d = Z_d/N_d = \sum_{j \in S_d} w_{dj} z_{dj} / \sum_{j \in S_d} w_{dj}$ ,  $N_d = \sum_{j \in S_d} w_{dj}$  is the size of area d (López-Vizcaíno et al., 2013). The information regarding the design-based direct estimators is taken from (Morales et al., 2021).

### 3.3. Selection of auxiliary variables

In area-level models, the dependent variables are usually direct estimators of means or totals of population domains. However, these estimators may not be sufficiently reliable due to the small sample size. Therefore, in area-level models, we describe the behavior of the direct estimators, taking into account the relationships with aggregate auxiliary variables, the interdependencies of the data from different domains, and the possible temporal or spatial correlation structures. These models consider relationships with auxiliary variables and interdependencies of data from different domains (Morales et al., 2021).

In many applications of SAE, it is common to use auxiliary variables derived from population censuses and community surveys. In this study, the auxiliary variables are derived from the 2016 South African community survey conducted by Stats SA. This survey collects information on demographics, migration patterns, households, and socio-economic factors. When using auxiliary variables and leveraging cross-sectional data or time and spatial correlation to generate more accurate estimates, it is crucial to identify a subset of these variables that can help build a more concise model and effectively predict the outcome variable. To accomplish this, this study employed cross-validation to randomly divide the data into training and test samples. A model was fitted using the training sample, and prediction errors

were estimated using the test sample (Dobson and Barnett, 2018). The estimated coefficients were obtained from a subset of the data (i.e., the first  $m$  observations) as follows

$$\hat{\boldsymbol{\beta}}^* = (\mathbf{X}_{1:m}^T \mathbf{X}_{1:m})^{-1} \mathbf{X}_{1:m}^T \mathbf{y}_{1:m}$$

The estimated prediction errors for the observations, which are determined using the test sample, are as follows:

$$\hat{e}_i^* = y_i - \sum_{j=0}^p \hat{\beta}_j^* x_i, \quad i = m+1, \dots, n$$

The root mean square prediction error (RMSE) is calculated as

$$\text{RMSE} = \sqrt{\sum_i (\hat{e}_i^*)^2 / (n - m)}, \quad i = m+1, \dots, n.$$

Additionally, the Mean Absolute Error (MAE) is given by:

$$\text{MAE} = \frac{1}{n - m} \sum_{i=m+1}^n |\hat{e}_i^*|,$$

where  $|\hat{e}_i^*| = \left| y_i - \sum_{j=0}^p \hat{\beta}_j^* x_i \right|$ ,  $i = m+1, \dots, n$ .

### 3.4. Area-level spatiotemporal linear mixed model

In this section, we introduce an extension of the Fay-Herriot model that takes into account the spatial correlation between neighboring areas and utilizes data from multiple time points to enhance small area estimation at the current time point. In this context, for each area (in this study, district municipalities are crossed by both genders and four distinct age groups) (denoted by  $d = 1, \dots, D$ ) and time point (denoted by  $t = 1, \dots, T$ ), let  $\boldsymbol{\theta}_{dt}$  be the target area characteristic,  $y_{dt}$  represents the direct estimate, while  $\mathbf{x}_{dt}$  is a vector containing aggregated values of  $p$  auxiliary variables. Here, the indices  $d$  and  $t$  correspond to domains and temporal instances, respectively. The extended spatiotemporal Fay-Herriot model consists of two levels and is formally defined as follows:

**Sampling model:**

$$y_{dt} = \boldsymbol{\theta}_{dt} + e_{dt}, \quad e_{dt} \stackrel{iid}{\sim} N[\boldsymbol{\theta}_{dt}, \sigma_{dt}^2], \quad d = 1, \dots, D, \quad t = 1, \dots, T, \quad (1)$$

where the variances  $\sigma_{dt}^2$  is assumed to be known for all  $d$  and  $t$ .

**Linking model (Area-Level model):**

$$\boldsymbol{\theta}_{dt} = \mathbf{x}_{dt} \boldsymbol{\beta} + u_{1d} + u_{2dt}, \quad d = 1, \dots, D, \quad t = 1, \dots, T, \quad (2)$$

**Area-time random effects assumption (AR(1) structure):** Consider the scenario where the vectors of area-time effects, denoted as  $(u_{2d1}, \dots, u_{2dT})'$ , are independently and identically distributed (i.i.d.) for each area  $d$ . These follow an autoregressive process of the first order (AR(1)) characterized by an autocorrelation parameter  $\rho_2$ , that is,

$$u_{2dt} = \rho_2 u_{2d,t-1} + \eta_{2dt}, \quad |\rho_2| < 1, \quad \eta_{2dt} \stackrel{iid}{\sim} N[0, \sigma_\eta^2], \quad (3)$$

where  $\rho_2$  is the autoregressive parameter, capturing the correlation between consecutive time points within the same domain.

Finally, the vector of area effects, denoted as  $(u_{11}, \dots, u_{1D})'$ , adheres to a Spatial Autoregressive (SAR(1)) process characterized by a variance parameter  $\sigma_1^2$ , spatial autocorrelation coefficient  $\rho_1$ , and a row-standardized proximity matrix  $\mathbf{W} = (w_{d,\ell})$ , that is:

$$u_{1d} = \rho_1 \sum_{l \neq d} w_{d,l} u_{1,l} + \epsilon_{1d}, \quad |\rho_1| < 1, \quad \epsilon_{1d} \stackrel{i.i.d.}{\sim} N(0, \sigma_1^2), \quad d = 1, \dots, D. \quad (4)$$

Combining Equations 1, 2, 3 and 4 provides the spatiotemporal Fay-Herriot model, as follows:

$$y_{dt} = \mathbf{x}_{dt} \boldsymbol{\beta} + u_{1d} + u_{2dt} + e_{dt}, \quad \text{for } d = 1, \dots, D, \quad t = 1, \dots, T. \quad (5)$$

Alternatively, Equation (5) can be reformulated as

$$\mathbf{y} = \mathbf{X} \boldsymbol{\beta} + \mathbf{Z}_1 \mathbf{u}_1 + \mathbf{Z}_2 \mathbf{u}_2 + \mathbf{e}, \quad (6)$$

where

$$\begin{aligned} \mathbf{y} &= \text{col}_{1 \leq d \leq D} \left( \text{col}_{1 \leq t \leq T} (y_{dt}) \right), \quad \mathbf{e} = \text{col}_{1 \leq d \leq D} \left( \text{col}_{1 \leq t \leq T} (e_{dt}) \right), \\ \mathbf{u}_1 &= \text{col}_{1 \leq d \leq D} (u_{1d}), \quad \mathbf{u}_2 = \text{col}_{1 \leq d \leq D} (\mathbf{u}_{2d}), \quad \mathbf{u}_{2d} = \text{col}_{1 \leq t \leq T} (u_{2dt}), \\ \mathbf{X} &= \text{col}_{1 \leq d \leq D} \left( \text{col}_{1 \leq t \leq T} (\mathbf{x}_{dt}) \right), \quad \mathbf{x}_{dt} = \text{col}'_{1 \leq j \leq p} (x_{dtj}), \end{aligned}$$

The random vectors  $\mathbf{u}_1$  and  $\mathbf{u}_2$ , as well as the error vector  $\mathbf{e}$ , are independently distributed and follow multivariate normal distributions with covariance matrices  $\mathbf{V}_{u_1}$ ,  $\mathbf{V}_{u_2}$ , and  $\mathbf{V}_e$ , respectively. The covariance matrix  $\mathbf{V}_{u_1}$  is defined as a function of the parameter  $\rho_1$  and takes the form  $\mathbf{V}_{u_1} = \sigma_1^2 \Omega_1(\rho_1)$ . In this expression,  $\Omega_1(\rho_1)$  is a matrix that depends on the proximity matrix  $\mathbf{W}$  and the parameter  $\rho_1$ . It is explicitly defined as  $[(\mathbf{I}_D - \rho_1 \mathbf{W})'(\mathbf{I}_D - \rho_1 \mathbf{W})]^{-1}$ , which is also represented as  $\mathbf{C}^{-1}(\rho_1)$ .

The covariance matrix  $\mathbf{V}_{u_2}$  is defined as  $\mathbf{V}_{u_2} = \sigma_2^2 \Omega_2(\rho_2)$ , where  $\Omega_2(\rho_2)$  is a diagonal matrix that depends on the parameter  $\rho_2$ . It is defined as  $\Omega_2(\rho_2) = \text{diag}_{1 \leq d \leq D}(\Omega_{2d}(\rho_2))$ , where  $\Omega_{2d}(\rho_2)$  is a  $T \times T$  matrix that depends on  $\rho_2$ , and is defined as

$$\Omega_{2d}(\rho_2) = \frac{1}{1 - \rho_2^2} \begin{bmatrix} 1 & \rho_2 & \dots & \rho_2^{T-2} & \rho_2^{T-1} \\ \rho_2 & 1 & \ddots & & \rho_2^{T-2} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \rho_2^{T-2} & & \ddots & 1 & \rho_2 \\ \rho_2^{T-1} & \rho_2^{T-2} & \dots & \rho_2 & 1 \end{bmatrix}$$

To find the Empirical Best Linear Unbiased Predictor (EBLUP here after) for  $\mu_{dt}$ , we can use the estimated variance components  $\hat{\boldsymbol{\theta}}$ . The EBLUP is calculated as follows:

$$\hat{\mu}_{dt} = \tilde{\mu}_{dt}(\hat{\boldsymbol{\theta}}) = \mathbf{x}_{dt} \hat{\boldsymbol{\beta}} + \hat{u}_{1d} + \hat{u}_{2dt}. \quad (7)$$

Here,  $\hat{\boldsymbol{\beta}}$ ,  $\hat{u}_{1d}$ , and  $\hat{u}_{2dt}$  represent the estimated coefficients for the fixed effects, the unit-specific random effects, and the time-specific random effects, respectively. This information is based on the spatiotemporal SAE descriptions from the sources (Morales et al., 2021; Marhuenda et al., 2013).

The EBLUPs are calculated using the model provided in Equation 7, and a parametric bootstrap procedure is recommended for estimating the mean squared error of the small area estimators. This procedure is described in the study by (Morales et al., 2021; Marhuenda et al., 2013).

## 4. Results

Table 1 presents the results of a cross-validation analysis, showcasing model performance metrics such as RMSE and MAE for both the null and full models across various demographic groups. The RMSE and MAE were calculated using 10-fold cross-validation to enhance the robustness of the results. The null model demonstrates higher error values, with an RMSE of 13.321 and an MAE of 10.508 across all groups. In contrast, the full model, which incorporates auxiliary variables from the 2016 Community Survey, shows improved performance with lower RMSE and MAE values across different age groups and genders.

The use of auxiliary variables from the 2016 Community Survey is crucial for enhancing small area estimates by “borrowing strength” from neighbouring districts. Our model integrates this auxiliary information to help mitigate sparse or missing data at the district level (Asian Development Bank, 2020). The QLFS leverages the extensive coverage of the 2016 Community Survey, producing reliable estimates even for smaller areas. This survey provides valuable demographic, migration, household, and socio-economic information that serves as strong proxies for stable economic factors influencing unemployment.

As a result, our spatiotemporal framework generates less volatile and more robust estimates than direct QLFS estimates. Additionally, the temporal autoregressive component of our model effectively captures the economic changes that have occurred since 2016. These findings underscore the importance of using auxiliary variables to reduce prediction errors (Dobson and Barnett, 2018).

Our spatiotemporal framework is effective; however, its success relies on several key factors. Firstly, the auxiliary data must be reliable and available at the district municipality level. The 2016 Community Survey is ideal for South Africa in this context. The approach becomes less applicable if the data is outdated or unreliable, as the effectiveness of SAE relies heavily on the quality of the auxiliary variables. Secondly, the availability of estimates from the QLFS and their corresponding variances is crucial. Our model requires direct estimates for each district across nine quarters, along with their variances, to enable effective comparison with model-based estimates. Without these measures of uncertainty, the model cannot be utilized. Finally, it is essential to have strong correlations between the auxiliary variables and the target variables (in this case, unemployment rates) for various demographic groups. Poor predictors can significantly limit the improvements in precision. When these criteria are met, as demonstrated in this study, our approach provides a robust framework for producing reliable and accurate district-level estimates. This is evident through lower RMSE and MAE across different age groups and genders, which are essential for implementing targeted policy interventions.

Table 1: Model performance metrics (RMSE and MAE)

<b>Model</b>	<b>Age Group/Gender</b>	<b>RMSE</b>	<b>MAE</b>
<b>Null model</b>	All Groups	13.321	10.508
<b>Full model</b>	Age 15-24	10.203	7.310
	Age 25-34	10.229	7.338
	Age 35-49	9.690	7.106
	Age $\geq$ 50	9.759	7.141
	Male	9.413	6.713
	Female	9.398	6.975

As described in the methods section, we fitted two variations of the spatio-temporal Fay–Herriot model: one with uncorrelated time effects (independent model) and another with AR(1)-correlated time effects (AR(1) model). Table 2 provides the goodness-of-fit

measures for both models across four age groups and genders, including log-likelihood, AIC, and BIC values. Generally, models with lower AIC and BIC values are preferred, as they indicate a better fit with appropriate complexity for all age groups and genders. For instance, the uncorrelated spatio-temporal SAE model demonstrates slightly better performance for the 25–34 and 50+ age groups as well as for females.

In contrast, the correlated model is slightly more suitable for the 15-24 age group and for males. For instance, the AR(1) model is particularly effective for the 15-24 age group due to the volatility of youth unemployment rates when compared to other age brackets. This volatility largely stems from the prevalence of young individuals working in seasonal, informal, and temporary sectors, such as hospitality, retail, and services, which are especially vulnerable to economic fluctuations. Consequently, young workers are often regarded as the “last hired, first fired,” during economic downturns, resulting in greater job insecurity.

Shocks to the youth unemployment rate at the district municipality level—such as the conclusion of the holiday season or broader economic downturns—can have lasting effects in the subsequent quarters. This persistence creates a significant temporal correlation that traditional independent models may struggle to identify. The autoregressive model of order one (AR(1)) predicts the unemployment rate in a district municipality at time  $t$  by directly referencing its rate at time  $t-1$ , making it well-suited to capture this high level of inertia and state dependence. Several studies in the literature document mechanisms such as benefit eligibility rules, temporary contracts, and higher separation hazards, which all contribute to the last-hired, first-fired outcomes for youth. Most of this evidence relies on transition hazards, retrospective trajectories, and aggregate panel contrasts (Xu and Couch, 2017; Verd et al., 2019).

Table 2: Goodness-of-fit for spatiotemporal SAE model by different demographic groups

Category	Model	Log-Likelihood	AIC	BIC
Age 15–24	Uncorrelated	221.08	-414.15	-356.08
	Correlated	222.26	-414.51	-352.29
Age 25–34	Uncorrelated	61.46	-96.93	-43.00
	Correlated	61.55	-95.11	-37.03
Age 35–49	Uncorrelated	-1.76	31.53	89.61
	Correlated	-7.88	41.76	95.69
Age $\geq$ 50	Uncorrelated	-102.10	232.20	290.28
	Correlated	-101.87	233.74	295.96
Male	Uncorrelated	115.29	-202.58	-144.50
	Correlated	116.82	-203.64	-141.41
Female	Uncorrelated	128.51	-229.02	-170.94
	Correlated	128.80	-227.61	-165.38

Tables 3 and 4 illustrate the trends in unemployment rates across various quarters for specific demographic groups, including those aged 15–24, as well as females and males. In the first quarter of 2024, the unemployment rate for the 15–24 age group shows considerable variation, ranging from 47.76% in the DC2 districts to 93.07% in the DC39 districts. The average unemployment rate for this age group is 73.65%, while the median rate is 75.12%.

In the first quarter of 2024, the unemployment rate for women ranges from 25.37% in the DC2 districts to 70.54% in the DC24 districts. The mean unemployment rate for women is 48.73%, while the median is 48.88%. Similarly, in the first quarter of 2024, the unemployment rate for men ranges from 23.06% to 66.96%. The mean unemployment rate is 42.90%, while the median rate is 42.55%.

Figures 3 and 4 show the model-based estimates of unemployment rates for each district

Table 3: Unemployment rate trends for age group 15-24 across quarters

Statistic	2024 Q1	2023 Q4	2023 Q3	2023 Q2	2023 Q1	2022 Q4	2022 Q3	2022 Q2	2022 Q1
Min	47.76	50.57	50.33	51.46	51.48	52.59	55.28	56.21	56.3
1st Qu	69.35	67.40	66.35	67.23	67.93	69.73	66.94	68.77	71.57
Median	75.12	72.71	72.02	73.58	74.50	73.78	75.16	77.03	77.76
Mean	73.65	72.65	71.43	72.42	73.39	74.10	73.74	74.81	77.70
3rd Qu	79.32	78.93	77.99	77.55	80.33	81.21	80.23	79.63	83.88
Max	93.07	93.85	89.77	93.65	90.61	96.87	89.47	91.83	96.05

Table 4: Unemployment rate trends for women across quarters

Statistic	2024 Q1	2023 Q4	2023 Q3	2023 Q2	2023 Q1	2022 Q4	2022 Q3	2022 Q2	2022 Q1
Females									
Min	25.37	27.09	28.20	27.67	25.97	28.31	30.46	28.75	29.59
1st Qu	41.53	41.49	40.68	41.78	40.52	42.28	41.01	42.98	43.24
Median	48.88	47.54	48.07	52.06	49.63	50.51	51.51	51.47	50.82
Mean	48.73	47.96	47.53	49.64	49.33	49.85	50.12	49.95	50.91
3rd Qu	56.86	55.82	54.37	55.38	55.55	57.72	56.70	57.29	58.21
Max	70.54	67.60	67.45	76.57	83.39	82.05	74.63	70.18	72.83
Males									
Min	23.06	23.35	24.19	22.62	22.99	22.9	26.9	29.01	29.06
1st Qu	35.6	35.57	36.17	34.83	34.88	35.06	35.36	35.85	37.88
Median	42.55	40.26	40.91	42.14	41.31	43.45	41.96	42.12	44.29
Mean	42.9	41.98	42.21	42.98	43.33	43.84	44.04	45.39	46.05
3rd Qu	47.93	47.82	48.18	50.39	50.81	51.69	49.55	53.72	51.79
Max	66.96	67.09	67.87	69.49	72.08	75.13	75.3	79.44	73.36

across the nine provinces of South Africa, categorized by 52 districts and presented separately for females (Figure 3) and for individuals aged 15-24 (Figure 4) over the period from the first quarter of 2022 to the first quarter of 2024. Both figures evaluate and compare the performance of metropolitan municipalities against their neighbouring non-metropolitan district municipalities across all nine provinces over nine quarters. From Figure 3, we can draw significant conclusions regarding the female unemployment rate: Metropolitan districts, such as Buffalo City (BUF), Nelson Mandela Bay (NMA), Mangaung (MAN), Ekurhuleni (EKU), Johannesburg (JHB), Tshwane (TSH), eThekweni (ETH), and Cape Town (CPT), generally have lower unemployment rates compared to non-metropolitan districts within their provinces. For instance, the metropolitan districts in Gauteng and the Western Cape exhibit more stable and consistently lower unemployment trends than the non-metropolitan districts in those same provinces, while non-metropolitan districts in provinces such as the Eastern Cape, Limpopo, and Northern Cape experience higher unemployment rates. In the Eastern Cape, the BUF and NMA metropolitan districts consistently show lower unemployment rates than surrounding non-metropolitan districts like DC12, DC15, and DC44. Similarly, in KwaZulu-Natal, ETH demonstrates lower and more stable unemployment rates compared to the non-metropolitan districts DC22, DC26, and DC27. Furthermore, CPT also exhibits lower and more stable unemployment rates in the Western Cape than its non-metropolitan neighbours. Lastly, unemployment rates in metropolitan districts fluctuate less over the quarters, indicating a more stable economic environment and better access to job opportunities compared to non-metropolitan districts.

Figure 4 provides important insights into the youth unemployment rate for individuals aged 15 to 24. It highlights a notable difference in youth unemployment rates between metropolitan and non-metropolitan district municipalities. For instance, in provinces like the Eastern Cape and North West, non-metropolitan district municipalities exhibit notably high youth unemployment rates. Additionally, the figure indicates that youth unemployment rates in several non-metropolitan areas are more variable, showing significant fluctuations across different quarters.

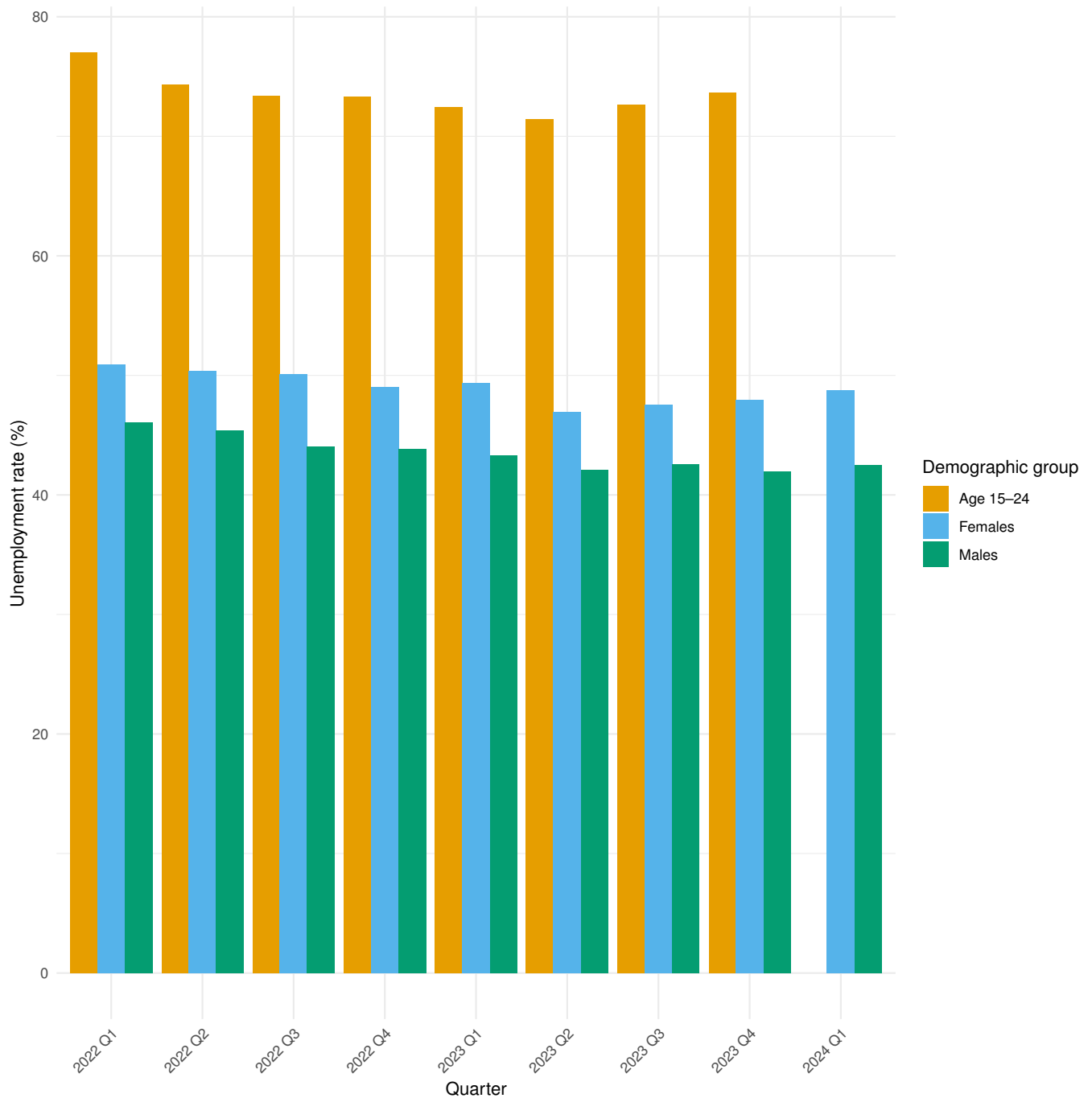


Figure 2: The distributions of the model-based unemployment rate estimates for each district municipality across the nine provinces in South Africa for females: 2022Q1 – 2024Q1.

Additionally, Figure 5 presents model-based estimates of unemployment rates for all 52 districts across six demographic groups for each quarter from 2022Q1 to 2024Q1. This figure provides several key insights:

- (i) It shows that young individuals and females experience higher unemployment rates, highlighting challenges in entering the labour market and underscoring gender disparities in employment opportunities, particularly among young and middle-aged workers.
- (ii) Many non-metropolitan district municipalities face high unemployment rates, highlighting ongoing economic challenges that need practical solutions. Specifically, DC48

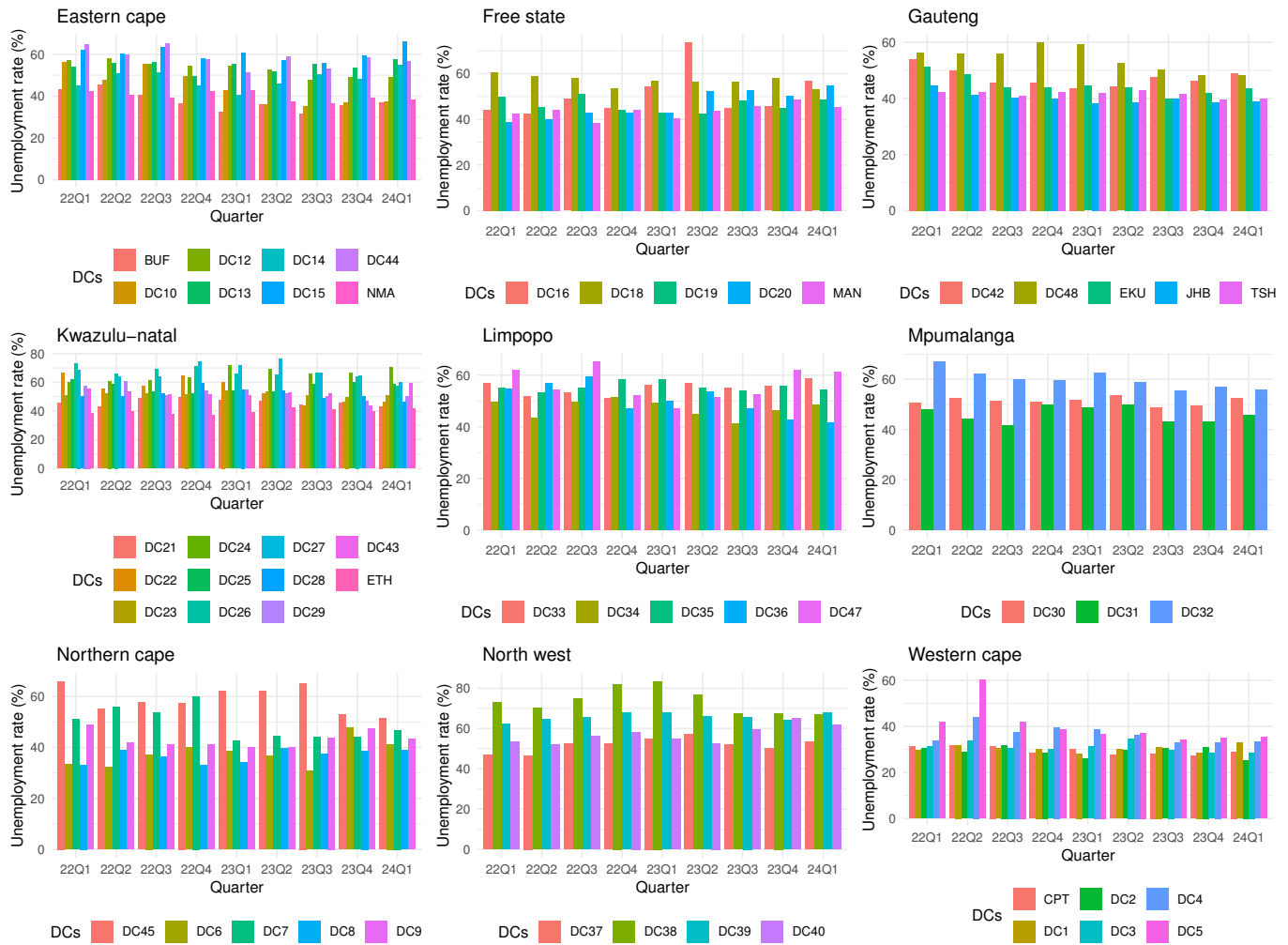


Figure 3: The distributions of the model-based unemployment rate estimates for each district municipality across the nine provinces in South Africa for females: 2022Q1 – 2024Q1.

in Gauteng, DC15 in Eastern Cape, DC45 in Northern Cape, DC38 in North West, and DC32 in Mpumalanga show particularly high unemployment rates across all quarters, especially among young people aged 15 to 24.

- (iii) In 2022 and 2024, unemployment rates remained stable across all quarters in nearly all districts and provinces, showing no significant improvements or declines. This consistency indicates that unemployment is a persistent issue in most areas, necessitating ongoing interventions.

Table 5 showcases the highest estimates of unemployment rates for females (over 60%) and for individuals aged 15-24 (over 80%), along with their 95% confidence intervals (CIs). These municipalities are situated in the North West, Eastern Cape, Limpopo, KwaZulu-Natal, and Mpumalanga provinces. For instance, the unemployment rate for females in DC 24 is 70.54% (95% CI = 70.43, 70.66), while for individuals aged 15–24, it stands at 90.62% (95% CI = 90.52, 90.71). This table highlights districts that need urgent attention from policymakers.

#### 4.1. Validation of the reliability of the model-based estimates

The study employed bias diagnostics, goodness-of-fit metrics, coefficients of variation (CV), and root mean square error (RMSE) to validate the reliability of the model-based

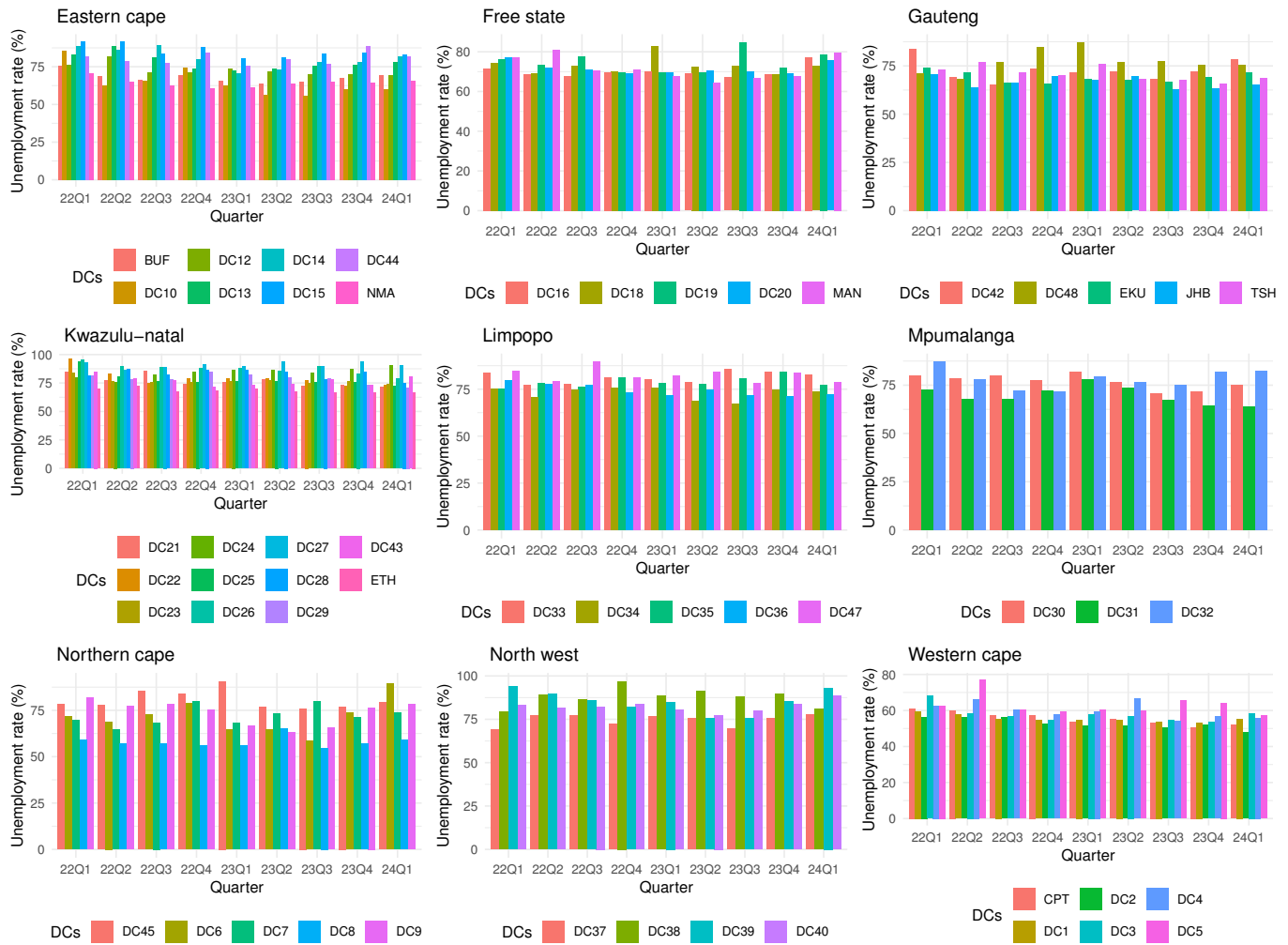


Figure 4: The distributions of the model-based unemployment rate estimates for each district municipality across the nine provinces in South Africa for Age 15–24: 2022Q1 – 2024Q1.

estimates, thereby ensuring the robustness of the statistical inferences drawn from the estimates.

#### 4.1.1. RMSE estimates

In Figure 4, we can see a comparison of the estimated root mean squared errors (MSEs) of the EBLUPs based on the spatio-temporal SAE models, obtained using the bootstrap procedure, and the root MSEs of direct estimators for all district municipalities. The domains are sorted in ascending order based on the coefficient of variation for unemployment rates for various age groups. This figure shows that model-based estimators are generally more efficient in terms of RMSE than direct estimators for most district municipalities, especially those with higher coefficients of variation. This is because minimizing the model-based RMSE is a characteristic of the class of model-based unbiased linear predictors (Rao and Molina, 2015).

#### 4.1.2. Coefficients of variation (CV)

To compare the precision of the EBLUP estimates and direct survey estimates, we calculated the coefficient of variation (CV). The CV quantifies sampling variability as a percentage of the estimate (Rao and Molina, 2015). Figure 7 displays the CVs of the model-based estimates alongside the CVs for the corresponding direct estimators of unemployment rates.

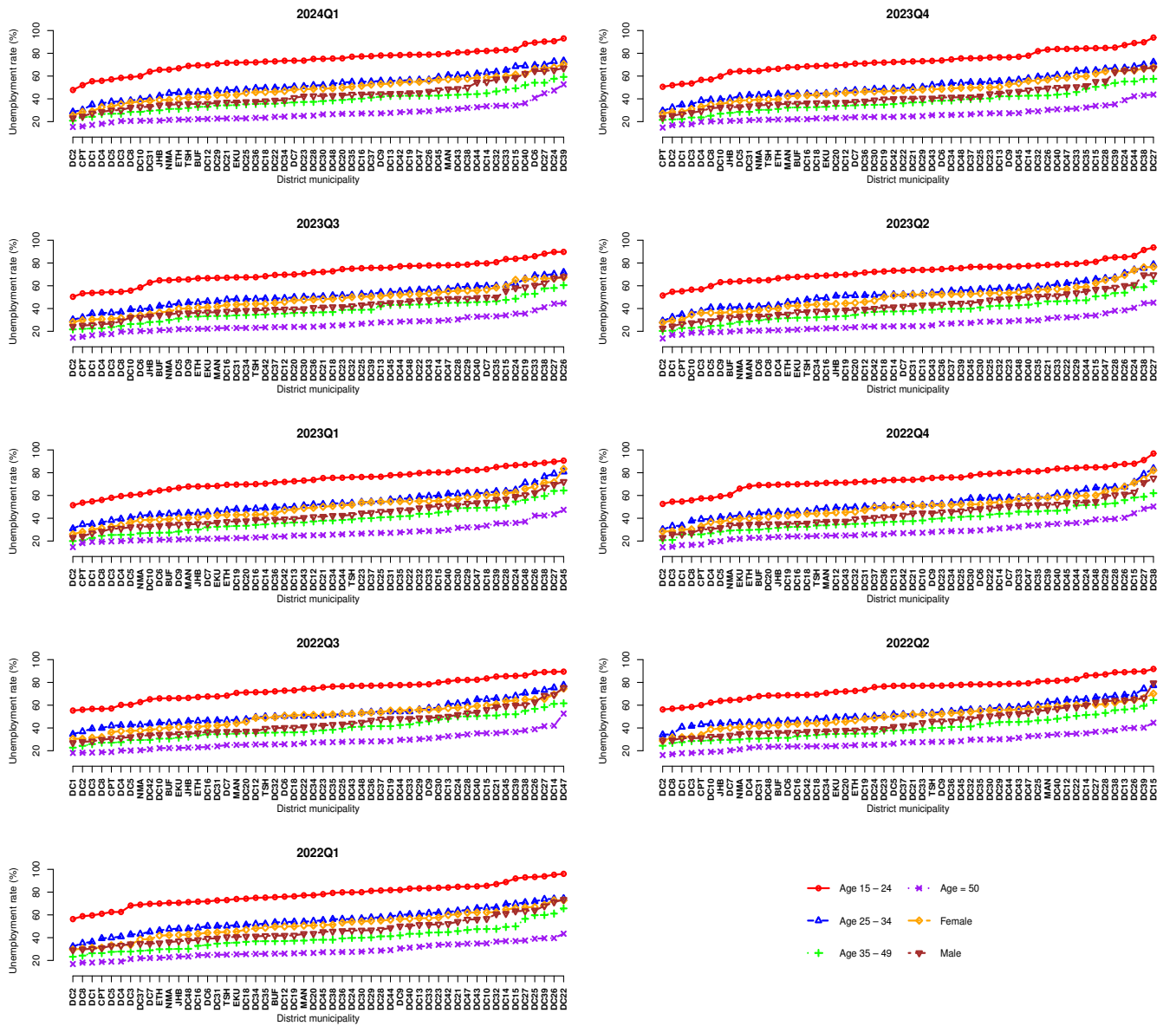


Figure 5: The model-based estimates of unemployment rate for each metropolitan municipalities in South Africa: 2021Q1 – 2024Q1

Notably, the model-based estimators consistently exhibited lower CVs than the direct estimators across most districts. This discrepancy underscores the superiority of model-based small-area estimates over traditional survey-based estimates in terms of precision. This improvement in accuracy, attributed to the application of FH and spatial FH models, is supported by findings in the existing literature (Rao and Molina, 2015; Shiferaw, 2020).

#### 4.1.3. Bias diagnostics

Figure 8 shows the EBLUPs of the unemployment rate for South African district municipalities, which were obtained from the spatiotemporal SAE model. These EBLUPs are compared with their corresponding direct estimates. In most district municipalities, the EBLUPs closely align along the  $y = x$  line (blue line), indicating that the EBLUP estimates are approximately unbiased since they are similar to the direct estimates (Marhuenda et al., 2013; Rao and Molina, 2015). This suggests that model-based estimators share the unbiased property of design-based estimators (Esteban et al., 2020).

Table 5: The direct and EBLUP estimates of the unemployment rates, as well as the coefficients of variation of the direct and EBLUP estimators (multiplied by 100). Additionally, the 95% confidence intervals of EBLUP estimates for South African district municipalities with the highest unemployment rates for females (greater than 60) and the age group 15 – 24 (greater than 80). The lower and upper limits of the confidence interval for  $\theta_i$  based on the EBLUP estimate is obtained as:  $(L_i, U_i)$ , where  $L_i = \hat{\theta}_i^{\text{EB}} - Z_{\alpha/2} \sqrt{\widehat{\text{MSE}}(\hat{\theta}_i^{\text{EB}})}$  and  $U_i = \hat{\theta}_i^{\text{EB}} + Z_{\alpha/2} \sqrt{\widehat{\text{MSE}}(\hat{\theta}_i^{\text{EB}})}$ .

Province	DC	Estimate		RMSE		CV		Confidence interval (CI)	
		Direct	EBLUP	Direct	EBLUP	Direct	EBLUP	Lower ( $L_i$ )	Upper ( $U_i$ )
Females: unemployment rate (%) > 60%									
Limpopo	DC47	62.16	61.34	0.05	0.05	1.20	1.13	61.25	61.43
North west	DC40	64.29	61.85	0.06	0.06	1.52	1.53	61.73	61.98
Eastern cape	DC15	66.41	66.31	0.06	0.05	1.44	1.26	66.21	66.41
North west	DC38	68.07	66.71	0.05	0.04	1.21	1.01	66.63	66.80
North west	DC39	69.21	67.67	0.07	0.06	1.66	1.46	67.55	67.79
Kwazulu-natal	DC24	71.72	70.54	0.06	0.06	1.33	1.39	70.43	70.66
Age 15 – 24: unemployment rate (%) > 80%									
Kwazulu-natal	DC43	82.02	80.82	0.08	0.06	1.83	1.47	80.69	80.95
North west	DC38	82.93	80.88	0.06	0.06	1.32	1.25	80.77	80.99
Eastern cape	DC44	81.87	81.86	0.07	0.04	1.51	0.99	81.77	81.94
Eastern cape	DC14	88.01	82.07	0.10	0.07	2.17	1.49	81.94	82.19
Mpumalanga	DC32	83.11	82.60	0.04	0.04	0.83	0.88	82.52	82.67
Limpopo	DC33	83.69	82.95	0.06	0.03	1.25	0.74	82.88	83.01
Eastern cape	DC15	83.54	83.27	0.07	0.06	1.68	1.44	83.15	83.39
North west	DC40	90.45	88.38	0.04	0.04	0.87	0.91	88.30	88.46
Northern cape	DC6	95.13	89.42	0.05	0.04	1.11	1.00	89.33	89.51
Kwazulu-natal	DC27	90.95	90.31	0.06	0.04	1.25	0.87	90.24	90.39
Kwazulu-natal	DC24	92.49	90.62	0.05	0.05	1.02	1.10	90.52	90.71
North west	DC39	94.57	93.07	0.03	0.04	0.74	0.96	92.99	93.16

Additionally, a red line representing the fitted line of the linear model has been included to show the relationship between the direct and EBLUP estimates based on the data. In general, the red line closely follows the  $y = x$  line (blue line) for most district municipalities, except for a few points in the age groups 15-24 and 50+, indicating substantial agreement between the EBLUP estimates and the direct estimates for most district municipalities. However, in some municipalities, a few points diverge from the lines, particularly for the age groups 15-24 and 50+. This divergence may be due to notable differences between the direct and EBLUP estimates, possibly caused by underlying data variations such as small sample size or missing covariates in the model that could account for their values (Marhuenda et al., 2013).

#### 4.2. Unemployment rate maps

Figure 9 illustrates the unemployment rates for individuals aged 15 to 24 across the 52 district municipalities of South Africa. The figure presents model-based unemployment rates (i.e., EBLUP) derived from the spatiotemporal SAE approach, covering the period from the first quarter of 2022 to the first quarter of 2024. The maps highlight significant geographical variations in unemployment rates among the district municipalities.

Certain districts consistently exhibit higher unemployment rates across various provinces, as highlighted by darker shades of orange and red on the map. This pattern suggests a persistent issue of high unemployment among young people. Based on these trends, the following district municipalities are likely to be classified as hotspots:

- **Limpopo Province:** Mopani (DC33), Sekhukhune (DC47), Waterberg (DC36), and Vhembe (DC34)

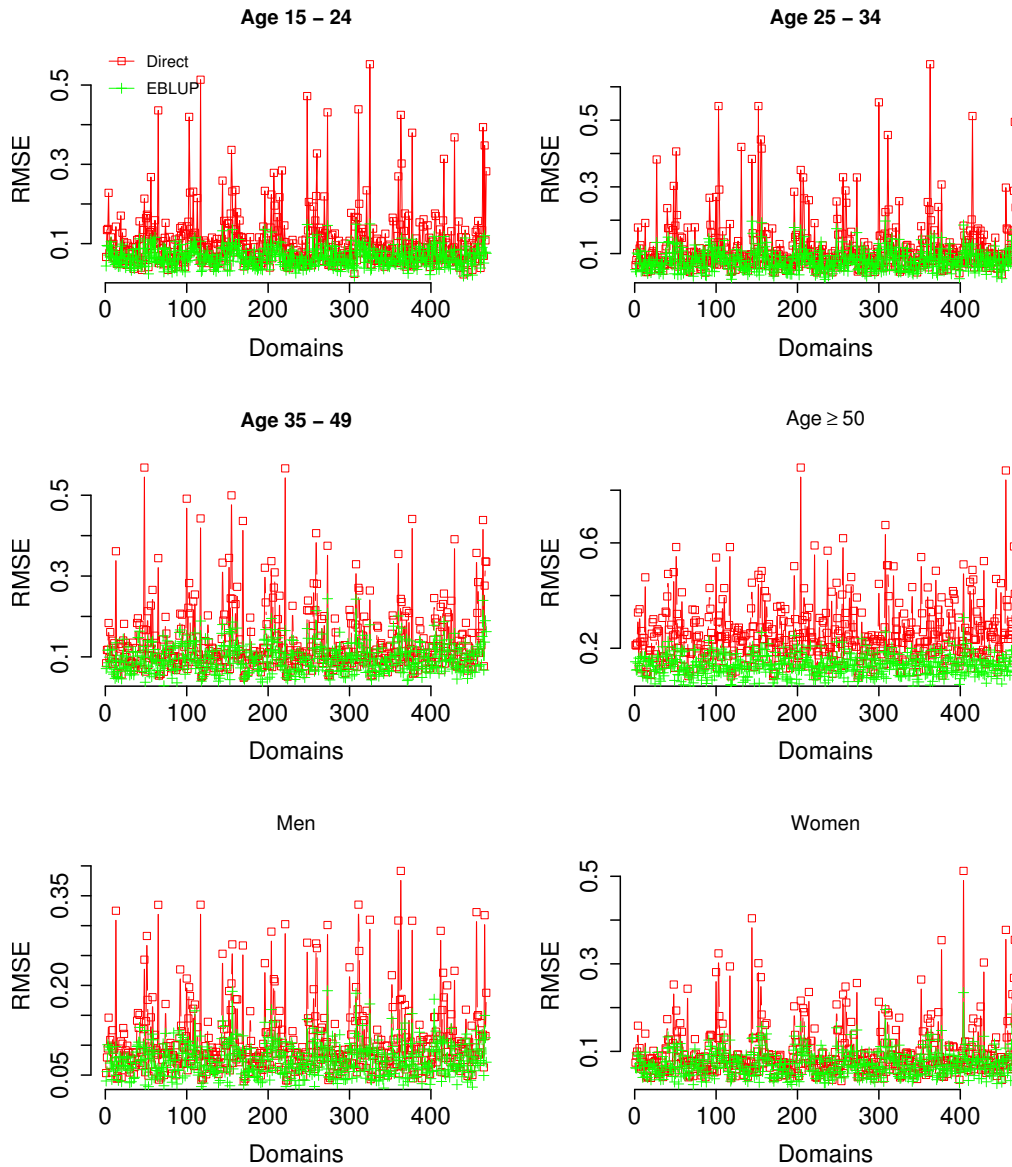


Figure 6: The root MSEs of direct and model-based estimates for each metropolitan and nonmetropolitan municipality in South Africa across various age groups: 2022Q1 – 2024Q1

- **Mpumalanga Province:** Ehlanzeni (DC32), Nkangala (DC31), and Gert Sibande (DC30)
- **KwaZulu-Natal Province:** Uthukela (DC23), Amajuba (DC25), and Ugu (DC21)
- **Free State Province:** Lejweleputswa (DC18)

These areas may require targeted interventions to address youth unemployment.

The lighter shaded areas on the map represent district municipalities with lower unemployment rates. These areas may include the following from the Western Cape province: City of Cape Town (CPT), West Coast (DC1), Cape Winelands (DC2), Overberg (DC3), and Central Karoo (DC5). Additionally, districts in the Northern Cape province may include Namakwa (DC6), Pixley ka Seme (DC7), Frances Baard (DC9), and Taolo Gaetsewe (DC45).

Over time, few districts experience fluctuations in unemployment rates. For example, some districts display worsening unemployment rates over time, transitioning from lighter

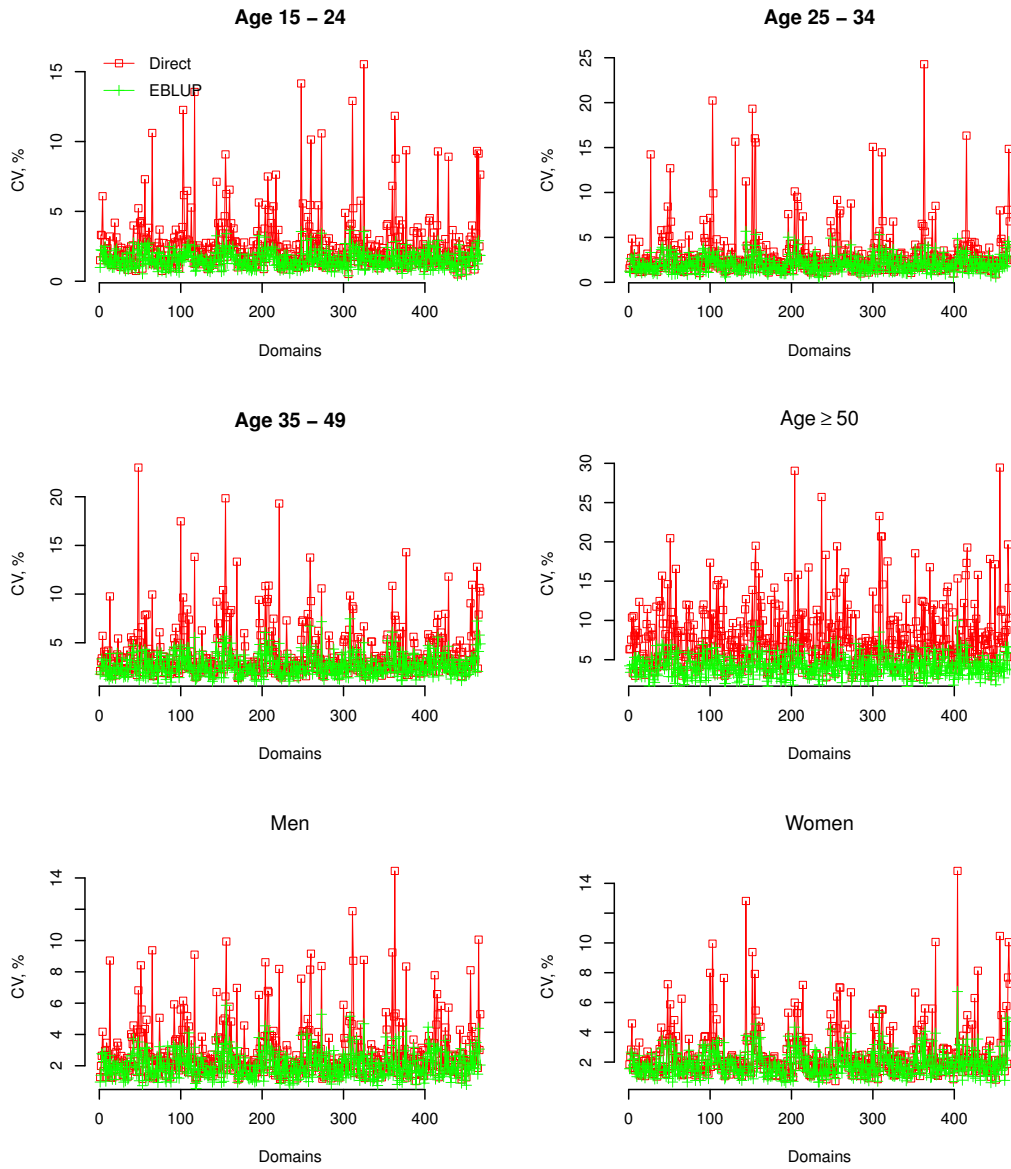


Figure 7: The CVs of direct and model-based estimates for each metropolitan and nonmetropolitan municipality in South Africa across various age groups: 2022Q1 – 2024Q1

to darker shades, while others show improvements, shifting from darker to lighter shades.

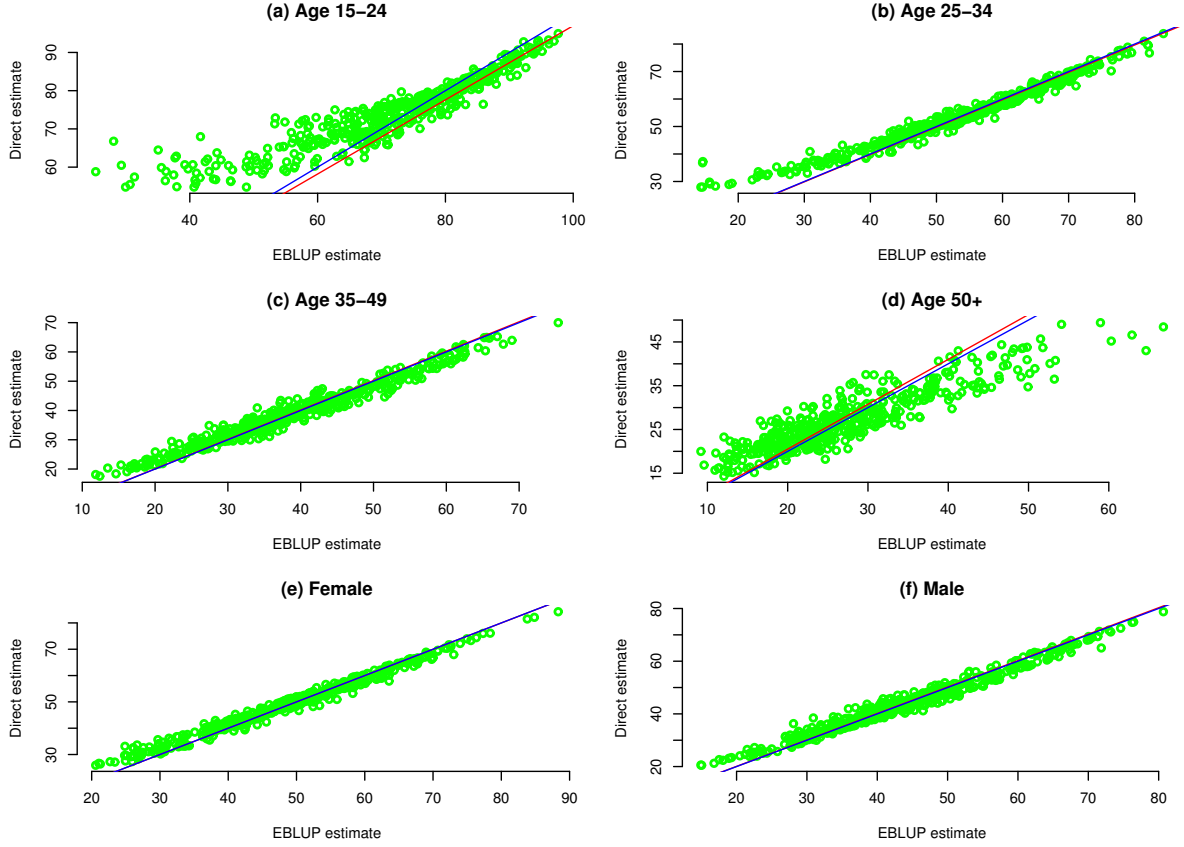


Figure 8: EBLUPs based on the spatiotemporal SAE model versus direct estimates of unemployment rates across demographic groups for South African district municipalities: 2022Q1 – 2024Q1

## 5. Discussion

The results presented in various figures and tables demonstrate significant spatial inequality in labour market stability. Unemployment rates in metropolitan districts—such as BUF, NMA, CPT, and ETH—indicate a more stable economic environment and better access to job opportunities compared to their non-metropolitan counterparts. This suggests the existence of deeper structural advantages that go beyond merely having a greater number of jobs. Firstly, metropolitan districts in South Africa outperform non-metropolitan districts due to their diversified economies. These metropolitan areas are not reliant on a single economic sector; instead, they include a variety of industries such as technology, finance, agriculture, entertainment, trade, and government. In contrast, non-metropolitan districts often depend on a single sector. For instance, DC2 (Cape Winelands) in the Western Cape primarily focuses on agriculture, particularly wine production; DC4 (Garden Route) is predominantly linked to tourism, encompassing accommodation, catering, and trade sectors; and DC37 (Botanala Platinum) in the North West Province is largely driven by mining activities, especially platinum extraction. This dependency on a single economic sector renders non-metropolitan districts vulnerable to sector-specific shocks, such as climate-related issues and fluctuations in commodity prices. A relevant example is DC4, where tourism was severely affected during the COVID-19 pandemic, leading to over 10,000 job losses and highlighting its vulnerability (Government, 2021). Secondly, metropolitan districts offer a more stable employment environment compared to non-metropolitan districts, particularly regarding the difference between formal and informal employment sectors. Metropolitan areas tend to have a higher percentage of jobs in the formal sector, which are generally more stable, well-regulated, and come with permanent contracts, higher wages, benefits, and social protections (Badulla-

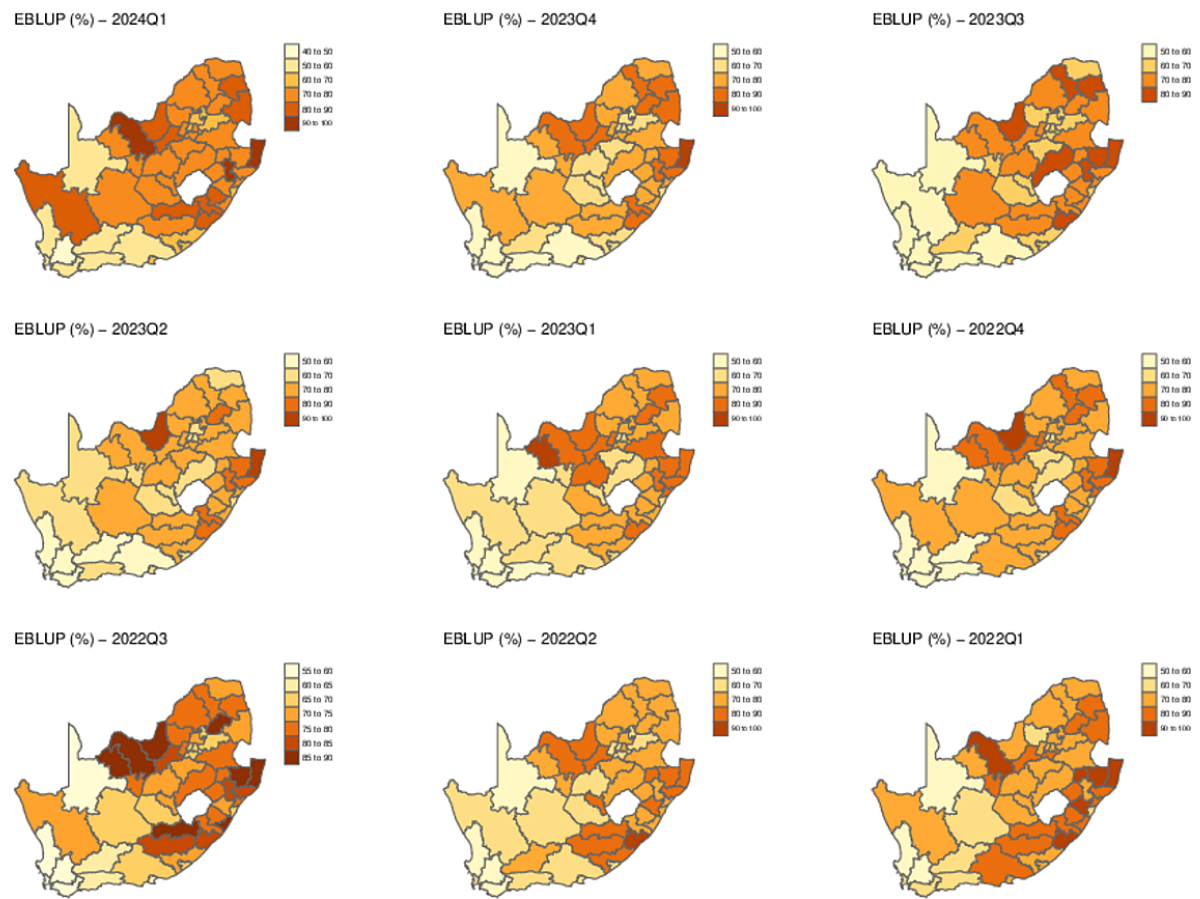


Figure 9: Estimates of unemployment rates in South Africa for the age group 15 to 24 for the first quarter of 2022 to the first quarter of 2024.

hewage and Badullahewage, 2021; Foguel et al., 2025). In contrast, non-metropolitan areas often have a larger share of jobs in the informal sector, which tend to be less stable, more seasonal, and more volatile. These informal jobs usually offer lower wages, minimal security, and little to no social protection, leading to fluctuations in employment (Badullahewage and Badullahewage, 2021; Foguel et al., 2025).

Our findings from the spatiotemporal SAE model reveal a significant structural difference in South Africa’s labour market. This highlights an important policy implication of our study: a universal, one-size-fits-all approach to national labour market and employment policies is inadequate for addressing the unique challenges posed by South Africa’s spatially diverse labour market. In unstable non-metro districts, it is essential to focus on economic and sectoral diversification, reduce seasonal economic fragility, and improve equitable access to job markets. Our spatiotemporal SAE approach provides accurate, disaggregated estimates of unemployment rates, further broken down by gender and age groups at the district municipality level. This information is crucial for designing and implementing targeted policies that effectively meet the needs of both metro and non-metro districts.

Certain countries, including South Africa, experience alarmingly high levels of unemployment. From 2000 to 2013, the official unemployment rate averaged 24.1%, while the broader rate, which includes discouraged job seekers, averaged 33.4% (Burger and Fourie, 2014). This disparity highlights the significant challenges facing the labour market in these regions.

### *5.1. Gender Disparities in the Unemployment Rate in South Africa*

In the first quarter of 2024, as illustrated in Tables 4 and 5, the unemployment rate for females stands at 48.73%, which is notably higher than the rate for males at 42.90%. This indicates that a larger proportion of females are unemployed compared to their male counterparts. The substantial difference of 5.83 percentage points (48.73% - 42.90%) underscores the greater employment challenges females face. Furthermore, Figure 3 demonstrates that the female unemployment rate consistently differs from the male unemployment rate across all nine quarters in nearly every district.

Research conducted in South Africa consistently highlights a gender gap in unemployment rates, showing that women face higher unemployment levels than men (Nishimwe-Niymanira and Sabela, 2019; Sinden, 2017; Pillay, 1985). This disparity is attributed to several factors, including cultural norms and stereotypes that limit women’s participation in the labour market (Nishimwe-Niymanira and Sabela, 2019), instances of workplace discrimination (Sinden, 2017), and the overrepresentation of women in certain economic sectors and occupations (Pillay, 1985).

Moreover, studies that utilize South African micro datasets emphasize how education, age, and gender influence unemployment rates (Kingdon and Knight, 2001; Kyei and Gyekye, 2011; Anand et al., 2016). For example, both Kingdon and Knight (2001) and Kyei and Gyekye (2011) identify education as a critical factor in unemployment, showing that higher unemployment rates are concentrated among individuals with lower qualifications. Additionally, Anand et al. (2016) highlights the necessity of addressing unemployment to reduce inequality.

These findings collectively underscore the urgent need for targeted policies and initiatives to tackle the complex issue of unemployment in South Africa, particularly the pronounced gender gap.

### *5.2. Age disparities in the South African unemployment rate*

Research on unemployment rates in South Africa consistently reveals significant disparities among age groups. Mlatsheni and Rospabé (2002) highlights young people’s challenges in

securing formal sector employment. Similarly, Festus et al. (2016) underscores these disparities, detailing the obstacles young job seekers encounter when seeking their first job, as well as the persistent issue of unemployment among older job seekers. Collectively, these studies emphasize the need for targeted interventions to address the barriers faced by different age groups in the South African labour market.

*Age group 15–24* :. In Figure 9, the highest unemployment rates for individuals aged 15 to 24 are found in three provinces: Limpopo (which includes Mopani, Sekhukhune, Waterberg, and Vhembe), Mpumalanga (comprising Ehlanzeni, Nkangala, and Gert Sibande), and KwaZulu-Natal (featuring Uthukela, Amajuba, and Ugu). The unemployment situation for this age group is particularly alarming as they transition into the workforce after completing their education, facing unique challenges due to various factors.

Firstly, many young individuals have limited work experience, making developing essential skills such as networking and industry knowledge challenging. This lack of expertise diminishes their competitiveness compared to older job seekers (Beginina, 2023; Somerville et al., 2022; Harvey, 2014). Secondly, young people face intense competition in the job market, resulting in a significantly higher unemployment rate compared to other age groups. The shortage of job openings further compounds this issue. Additionally, young women often encounter greater difficulties finding jobs due to their limited experience, highlighting the gender disparities in employment opportunities (Beginina, 2023; Harvey, 2014).

### *5.3. Disparities in Unemployment Rates Between Urban and Rural Areas in South Africa*

The unemployment rates for women and young people vary between metropolitan and non-metropolitan district municipalities (see Figures 3 and 4). In metropolitan district municipalities, women generally face lower and more stable unemployment rates, indicating better job opportunities. In contrast, non-metropolitan district municipalities often have higher and more fluctuating unemployment rates for women, highlighting challenges in economic development. The disparity in youth unemployment is even more pronounced, with young individuals in non-metropolitan district municipalities being particularly affected.

Table 5 illustrates a significant disparity in unemployment rates between non-metropolitan and metropolitan districts. Notably, the DC24 district municipality in KwaZulu-Natal has the highest female unemployment rate, recorded at 70.54% (95% CI = 70.43, 70.66). It also has the second highest unemployment rate for individuals aged 15-24, at 90.62% (95% CI = 90.52, 90.71).

Additionally, districts with the highest unemployment rates for both females and the youth demographic (ages 15-24) are predominantly found in the North West, Eastern Cape, Limpopo, KwaZulu-Natal, and Mpumalanga provinces. In contrast, the districts with the lowest unemployment rates across all demographic groups, which include four age categories and both genders, are located in the Western Cape province.

This pattern illustrates prevailing socioeconomic trends. The Western Cape, along with Gauteng, ranks among the provinces with the highest average incomes. In contrast, Limpopo, the Eastern Cape, and North West have the lowest average incomes. Remarkably, the average household income in Limpopo is almost three times lower than that of the Western Cape (Statistics South Africa, 2023).

Research indicates that individuals in urban areas typically have more job opportunities than those in rural regions. Weir-Smith and Dlamini (2024) found that higher levels of urbanisation are linked to increased labour absorption rates. Turok and Visagie (2025) emphasises the significant concentration of employment in cities and investigates the nature and quantity of these jobs. This trend is mainly due to the diverse economies present in urban settings, which offer a wider variety of employment options (Matz et al., 2015; Ananian and DellaFerrera, 2024).

Furthermore, Weir-Smith and Dlamini (2024) demonstrated that regions with better educational facilities and outcomes, such as metropolitan areas, tend to have higher labour absorption rates. Metropolitan regions generally feature a more favourable and diverse economic structure compared to towns and rural areas Turok and Visagie (2025). Urban residents, who are more likely to be employed, also typically allocate higher weekly budgets for healthcare and transportation to medical facilities compared to their rural counterparts (van der Hoeven et al., 2012). In contrast, rural workers often contend with lower wages and inadequate labour protections (Ananian and Dellaferrera, 2024).

## 6. Policy Benefits and Recommendations

It is important to monitor unemployment trends across various demographic categories like age and gender. This analysis allows for timely adjustments to policies, ensuring interventions stay relevant and effective. Although the Employment Equity Act of 1998 aimed to rectify historical injustices, its implementation challenges still prevent many organisations from achieving true equity (Carrim et al., 2022). Consequently, historical inequalities persist, leading to higher unemployment rates among disadvantaged groups (Valodia and Ewinyu, 2022).

### 6.1. Benefits of the proposed SAE approach for policy

*Targeted Interventions.* This study identified districts with high unemployment rates, particularly among women and youth (ages 15-24). This information is presented in Table 6, which lists the top 10 districts, and is further illustrated through various maps in Figures 7-9. The study also emphasizes the disparities between rural and urban areas, as shown in Figures 1 and 2, as well as youth and gender disparities, depicted in Figure 3. These insights can help develop spatially focused job creation programs and skills development initiatives.

*Dynamic Monitoring.* The spatiotemporal SAE model used in this study incorporates temporal trends from the first quarter of 2022 to the first quarter of 2024. These trends, driven by structural factors and cyclical economic changes, enable policymakers to track fluctuations in unemployment rates between survey cycles (quarters). This capability can facilitate quicker policy interventions and responses to economic shocks, such as those experienced post-COVID recovery.

*Fairness in the Distribution of Resources.* In South Africa, many municipalities depend on equitable share funding from the national government to address local needs like unemployment. This study found that the model-based estimates are more accurate than direct survey estimates, as indicated by the RMSE and CV analyses (see Figures 4 and 5). These models also correct for sampling bias in direct survey estimates, as shown in Figure 6, helping to reduce misallocation risks.

### 6.2. Policy recommendations for addressing the gap

Below are the policy suggestions and interventions tailored for each demographic group:

#### 6.2.1. Bridging the gender disparity:

This study highlights a significant disparity in unemployment rates between male and female workers, with a gap of 6.83 percentage points. The analysis reveals that the unemployment rate for women is 44.75%, compared to 37.92% for men. This indicates that women face more challenges when seeking employment. Supporting this finding, research shows that women in South Africa encounter considerable obstacles in the labour market due to ongoing gender-based segregation in education and employment (Roberts and Schöer, 2021).

The government can support young individuals, particularly women, in joining the workforce through job training programs, apprenticeships, and incentives for businesses to hire them (Matandare, 2018). One significant initiative is the Basic Education Employment Initiative (BEEI), launched by the Presidential Employment Stimulus. As of June 2025, it placed over 200,000 young people in more than 20,000 schools across South Africa, helping them gain work experience while enhancing educational outcomes (Ramaphosa, 2025). The program emphasizes gender inclusion, actively recruiting women for roles in information technology, curriculum support, administration, and school maintenance. These positions provide women with income and valuable professional experience, developing skills in time management, digital literacy, and teamwork. Initiatives like the BEEI help tackle structural barriers and create pathways for women in further education and entrepreneurship (Department of Basic Education, 2025).

Supporting women entrepreneurs through financing and mentorship, improving access to childcare, and implementing family-friendly policies are essential steps toward reducing gender disparities and creating a more equitable labour market in South Africa (Matandare, 2018; Hlayisi, 2022). To generate more job opportunities for women, particularly in male-dominated fields, Faulkner et al. (2013) recommends investing in labour-intensive industries and diversifying the economy. Such investments can lower skill barriers and attract both foreign and domestic investment, ultimately leading to growth and job creation (Faulkner et al., 2013). Furthermore, research in South Africa indicates that while wage subsidies may not significantly increase overall employment rates, they can positively impact female employment and earnings. However, wage subsidies should be part of a broader strategy that includes job training programs and apprenticeships (Burns et al., 2010).

#### *6.2.2. Addressing the issue of higher unemployment rates among young people:*

Young individuals with limited work experience often encounter challenges in the job market, but they also bring fresh perspectives to the workplace. Given the high unemployment rates among those aged 15 to 34, it is crucial to implement tailored policy interventions. Effective initiatives should include educational programs, partnerships between government and businesses, and support for entrepreneurship, along with wage incentives:

*Skill development training initiatives.* Alao and Brink (2022) explored the role of Information and Communication Technologies (ICTs) in improving youth employability in the East Rand of Johannesburg. The study underscored the necessity of ICT skills in education and urged policymakers to develop strategies that prepare young people for the labour market. Ohei and Mantzaris (2023) noted that South Africa is enhancing ICT usage to boost economic activity and job creation. van der Merwe (2024) emphasized the need for sector-specific training in tourism and agriculture that aligns with industry needs and promotes career advancement. It also highlighted the importance of supporting young agripreneurs in accessing necessary resources and called for collaboration between universities and the government, advocating for agricultural education in schools due to the sector's role as the largest employer of youth. Research in India pointed out the need for targeted training and vocational programs to align education with job market demands (Kumar and Shobana, 2024). A study in South Korea also suggested that career guidance can alleviate job search anxiety and improve employment outcomes (Yoon, 2018).

*Public-private synergies in entrepreneurship and incubation.* Ndebele et al. (2022) examine the challenges of youth entrepreneurship in South Africa and the role of local governments in reducing youth unemployment through supportive programs and entrepreneurship education. Mgweba and Lungisa (2024) emphasize the importance of incubation initiatives in empowering young entrepreneurs with innovation and technology. Addressing governance

and infrastructure issues offers sustainable solutions to youth unemployment (Njeru and Wanderi, 2021). Overall, access to finance and networking is essential for sustainable entrepreneurship, with municipalities playing a key role (Ndebele et al., 2022; Mgweba and Lungisa, 2024).

*Wage subsidies and incentives.* Wage subsidies and tax incentives, like the Employment Tax Incentive, can positively influence job creation for young workers, with modest effects on youth employment (Stasiuk and Kharchuk, 2021). For instance, Ebrahim and Pirttilä (2024) found that an employer-funded payroll tax credit for low-wage workers in South Africa increased employment rates, although the overall impact on total employment was minimal. This policy also boosted earnings, especially for men near the maximum subsidy. Levinsohn et al. (2015) showed in a study involving 4,000 young South Africans aged 20 to 24 that wage subsidies improve employment outcomes for this group.

*Inclusive employment policies and program design.* Governments should implement policies aimed at reducing youth unemployment while also protecting older workers (Stasiuk and Kharchuk, 2021). Strategies that enhance education, training, and access to financial markets can significantly boost youth employment rates (Pkhakadze, 2022). Promoting entrepreneurship enables young people to create their own opportunities, thereby decreasing their reliance on traditional job markets (Apunyo et al., 2022). For instance, Geza et al. (2022) highlights challenges in South Africa’s agriculture sector, including labour market obstacles and inadequate inclusive policies. One proactive solution to tackle youth unemployment is the Presidential Employment Stimulus (PES), which was launched in response to the pandemic. Since October 2020, this initiative has created over 1.5 million job opportunities for unemployed South Africans, with 83% of participants being youth and 66% being women. The PES has facilitated the fastest expansion of public employment in South Africa’s history, quickly providing essential work to those in need (Government of South Africa, 2025b).

### 6.2.3. Bridging the urban-rural divides: key strategies and insights

Our findings show that unemployment rates differ widely between urban and rural districts across various provinces. High unemployment rates are particularly evident in non-metropolitan districts such as DC44 and DC13 in the Eastern Cape, DC16 in the Free State, DC43 and DC27 in KwaZulu-Natal, DC6 and DC7 in the Northern Cape, DC36 in Limpopo, DC37 in the North West, and DC30 in Mpumalanga.

South Africa faces significant inequality, with high levels of poverty and unemployment impacting the majority of its population. The disparity between urban and rural areas arises from structural inequalities; rural districts are underdeveloped and lack access to essential infrastructure and economic opportunities (Masenya, 2021). Youth unemployment is especially severe in rural areas, where young people struggle to find job opportunities, face limited inclusion in policymaking, and receive insufficient support for skills development. Moreover, a skills mismatch exists, as rural job seekers often lack the skills that employers need (Habiyaremye et al., 2022). To address the urban-rural divide, targeted strategies are essential:

*Rural Economic Development.* Investing in rural economies can have a positive impact on urban areas while creating jobs in those regions. As noted by Masenya (2021), exploring such alternatives is essential for bridging the economic gap. Additionally, Bureau for Economic Research (BER) (2021) emphasized that local economic development and improved municipal service delivery are crucial for South Africa to enhance economic participation and reverse its trend of high unemployment.

*Skills and Upskilling Programs.* South Africa’s skills development policies need improvement to address deficits in social protection and job security. Expanding education and vocational training, particularly through Technical and Vocational Education and Training (TVET), is vital for meeting market demands (Allais, 2012). Habiyaemye et al. (2022) highlighted the importance of focusing on both technical and soft skills to enhance employability.

*Local Economic Development (LED) Initiatives.* Makhaye et al. (2021) recommended improving rural service delivery and infrastructure in the uMgungundlovu District Municipality to enhance access to opportunities while involving traditional leaders in LED efforts. Adam (2022) emphasized that entrepreneurship and telecommuting can create new jobs, decrease unemployment, and foster self-esteem and creativity.

*Inclusive growth policy and job creation.* Geza et al. (2022) highlights that young people face significant challenges in the labour market and experience a lack of inclusivity in policy-making, which limits their involvement in agricultural and rural development initiatives. In his 2025 State of the Nation Address, President Cyril Ramaphosa outlined key priorities, including substantial investments in infrastructure, sector development, and economic reforms (Government of South Africa, 2025a). The government aims to create an inclusive economy that addresses the challenges of unemployment (Habiyaemye et al., 2022).

## 7. Conclusion

Census and community survey data offer detailed information at lower administrative levels in South Africa, but these surveys are conducted only once every ten years. In contrast, the QLFS provides estimates at national and provincial levels every quarter. However, it suffers from high sampling variability at the district level due to small sample sizes, which makes large-scale surveys impractical. This study presents a novel SAE method that enhances data granularity by effectively integrating multiple data sources, while considering spatial correlations and temporal dynamics, thus eliminating the need for additional field data. As a result, it offers a cost-effective solution for policymakers seeking localised unemployment statistics. Furthermore, this study produces timely quarterly unemployment estimates for the 52 districts of South Africa during the post-pandemic recovery phase, covering the period from Q1 2022 to Q1 2024.

The spatiotemporal SAE model used in this study examines trends from early 2022 to early 2024, enabling policymakers to monitor fluctuations in the unemployment rate from quarter to quarter. This allows for quicker responses to economic shocks, such as those resulting from COVID-19. In South Africa, municipalities rely on equitable share funding from the national government to tackle local issues like unemployment. The study demonstrates that model-based estimates are more accurate than direct survey estimates, as shown by the analyses of RMSE and CV. Furthermore, these models help mitigate sampling bias, thereby reducing the risk of misallocation of resources.

This study identified districts with high unemployment rates, particularly among youth, and highlighted the spatial disparities between metropolitan and non-metropolitan economies. For example, non-metropolitan districts such as DC33 in Limpopo, DC15 in the Eastern Cape, DC39 and DC40 in North West, DC6 in the Northern Cape, and DC24 and DC27 in KwaZulu-Natal consistently show high rates of youth unemployment. This situation underscores the urgent need for policies addressing youth unemployment, especially in rural and economically disadvantaged regions.

The results show that females in district municipalities face significantly higher and more variable unemployment rates than males. This disparity is particularly pronounced in non-metropolitan areas. Districts such as DC47 in Limpopo, DC38, DC39, and DC40

in the North West, DC15 in the Eastern Cape, and DC24 in KwaZulu-Natal consistently report high unemployment rates among women. This situation highlights the urgent need for targeted interventions to address gender-based economic disparities and enhance employment opportunities for women, especially in rural and economically disadvantaged regions. Such efforts could also support job creation programs and skills development initiatives specifically designed for these areas.

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## Appendix A. Appendix A

### Appendix A.1. Additional Analysis

Table A.6: Breakdown of respondents by employment status, gender, and age group

Quarter	Empl. Status	Age 15-24	Age 25-34	Age 35-49	Age $\geq$ 50	Respondents	Male	Female	Respondents
2024Q1	Unemployed	2,708	4,372	3,868	1,309	12,257	5,607	6,650	12,257
	Employed	1,151	4,446	7,057	4,059	16,713	8,863	7,850	16,713
	Inactive	7,758	1,255	1,566	8,323	18,902	7,871	11,031	18,902
2023Q4	Unemployed	2,559	4,269	3,715	1,249	11,792	5,470	6,322	11,792
	Employed	1,114	4,531	6,993	4,011	16,649	8,898	7,751	16,649
	Inactive	7,831	1,367	1,583	8,274	19,055	7,803	11,252	19,055
2023Q3	Unemployed	2,470	4,226	3,879	1,217	11,792	5,519	6,273	11,792
	Employed	1,148	4,535	6,899	4,048	16,630	8,785	7,845	16,630
	Inactive	7,697	1,319	1,524	8,282	18,822	7,684	11,138	18,822
2023Q2	Unemployed	2,600	4,355	3,885	1,223	12,063	5,580	6,483	12,063
	Employed	1,076	4,383	7,000	3,989	16,448	8,858	7,590	16,448
	Inactive	7,453	1,338	1,642	8,545	18,978	7,622	11,356	18,978
2023Q1	Unemployed	2,688	4,307	3,752	1,254	12,001	5,545	6,456	12,001
	Employed	1,027	4,193	6,813	3,882	15,915	8,531	7,384	15,915
	Inactive	7,218	1,335	1,579	8,543	18,675	7,412	11,263	18,675
2022Q4	Unemployed	2,539	4,209	3,740	1,300	11,788	5,404	6,384	11,788
	Employed	1,001	4,129	6,701	3,671	15,502	8,316	7,186	15,502
	Inactive	7,416	1,364	1,587	8,478	18,845	7,577	11,268	18,845
2022Q3	Unemployed	2,529	4,076	3,691	1,221	11,517	5,269	6,248	11,517
	Employed	982	3,894	6,440	3,513	14,829	7,941	6,888	14,829
	Inactive	7,176	1,354	1,485	8,124	18,139	7,226	10,913	18,139
2022Q2	Unemployed	2,478	3,876	3,473	1,156	10,983	5,027	5,956	10,983
	Employed	902	3,524	5,590	3,150	13,166	6,872	6,294	13,166
	Inactive	6,166	1,157	1,372	7,304	15,999	6,325	9,674	15,999
2022Q1	Unemployed	2,144	3,526	3,012	967	9,649	4,449	5,200	9,649
	Employed	663	2,865	4,550	2,520	10,598	5,523	5,075	10,598
	Inactive	5,706	1,108	1,277	6,674	14,765	5,868	8,897	14,765

### Appendix A.2. Supplementary Figures

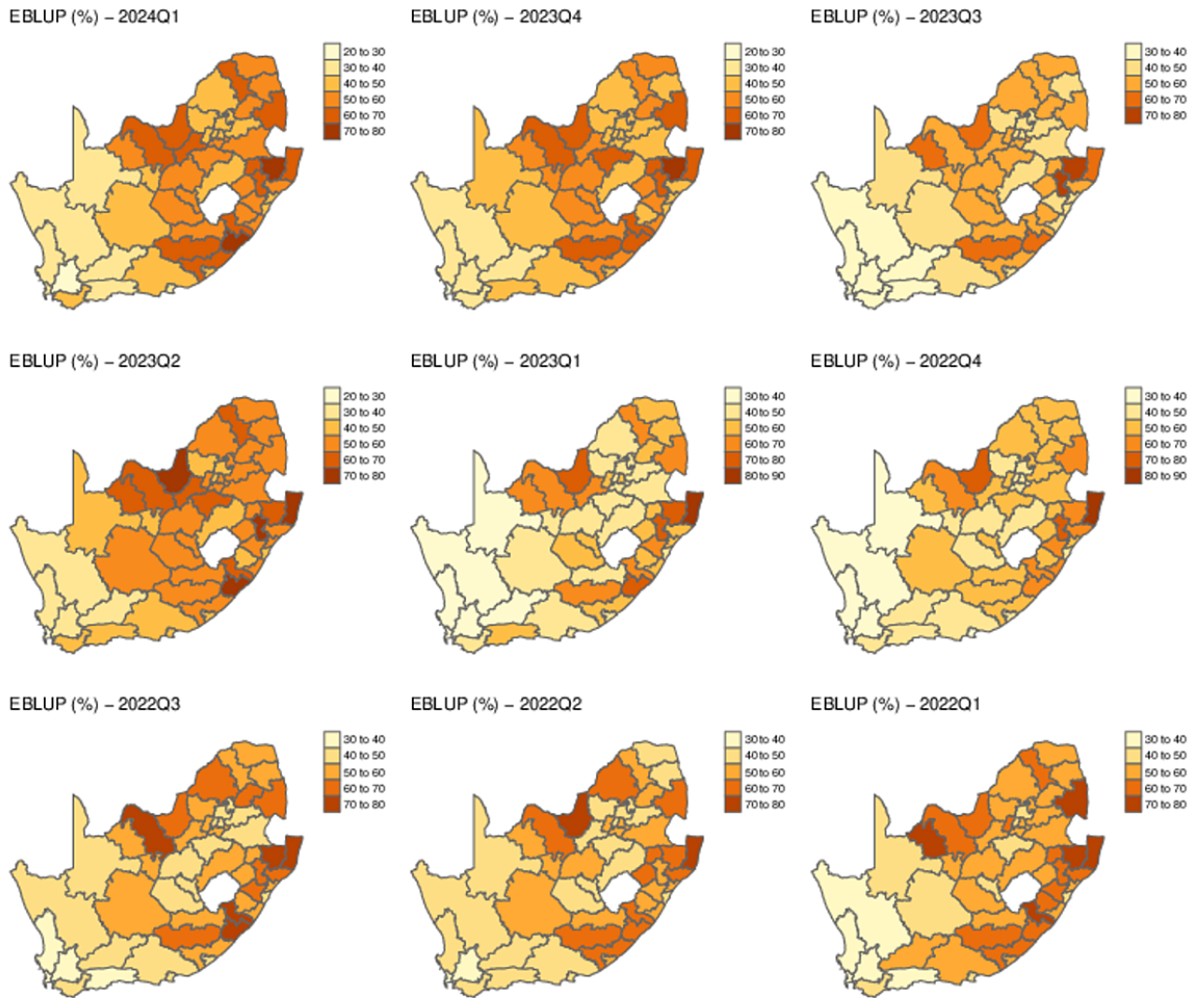


Figure A.10: Estimates of unemployment rates in South Africa for the age group 25 to 34 for the first quarter of 2022 to the first quarter of 2024.

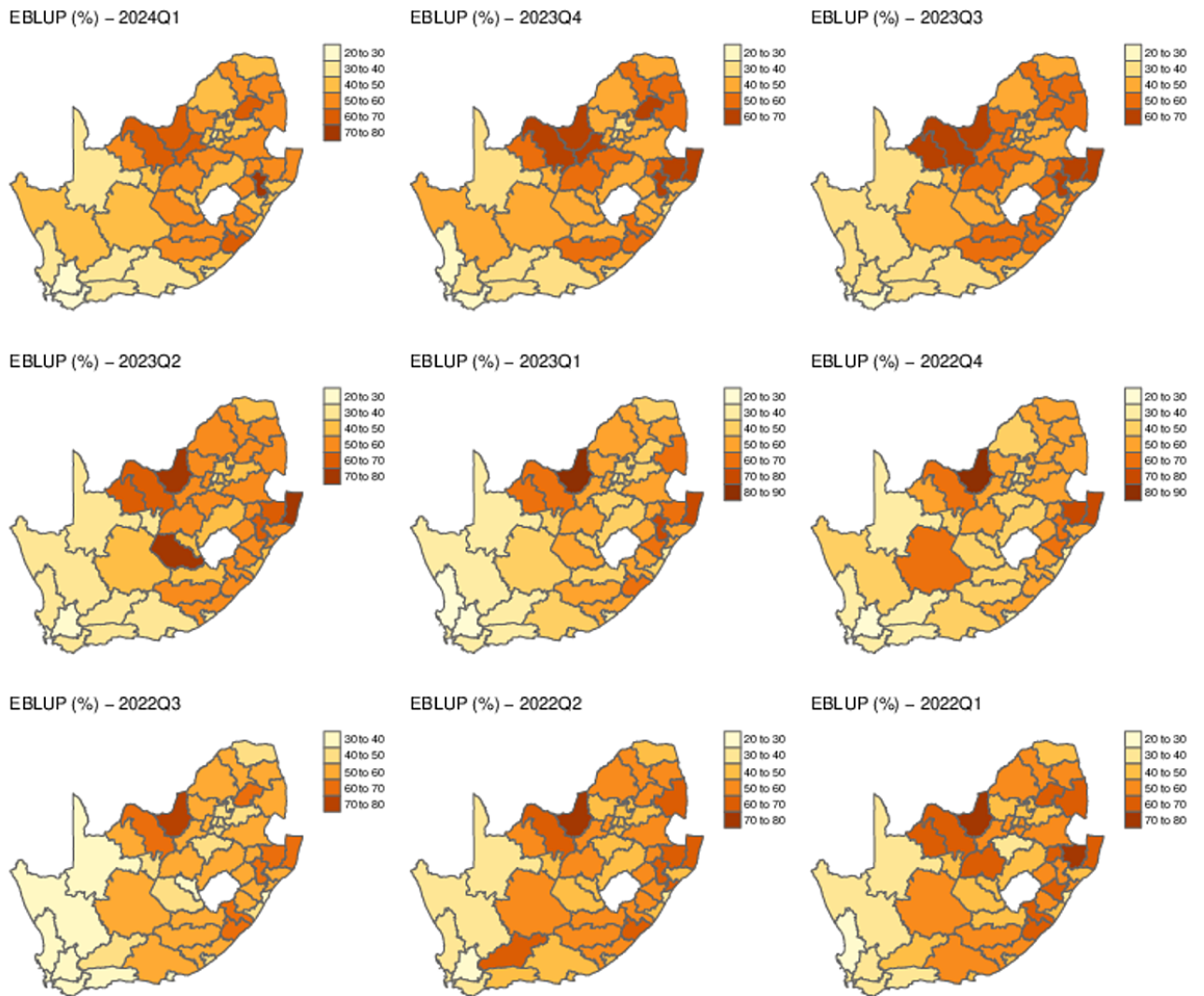


Figure A.11: Estimates of South African female unemployment rates for the first quarter of 2022 to the first quarter of 2024.