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Analysing the impact of individual factors on local employment-education matching across Tunisian regions

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Abstract

The aim of the study is to investigate spatial relationship between individual and socio-economic determinants and education-employment match in Tunisia with unique data on 268 delegations and 162 sectors of Tunis district in 2024. The article demonstrates that spatially explicit regression techniques provide a deep understanding of the spatial heterogeneity underlying education–employment mismatches in Tunisia compared to conventional non-spatial approaches. A Geographically Weighted Logistic Regression (GWLR) model and its multi-scale extension (MGWLR) were estimated to account simultaneously for spatial non-stationarity and varying local relationships between explanatory variables—such as participation in vocational insertion programs, university type, and marital status. Model comparison results indicate that both GWLR and MGWLR outperform the global logistic regression model in terms of local fit and predictive accuracy, revealing strong spatial disparities in the returns to education and training. These findings highlight the importance of spatially differentiated employment policies and region-specific human capital strategies to reduce labor market mismatches in urban Tunisia.

JEL classification : J41, C31

1. Introduction

The transition from education to employment has become an increasingly complex equation, reflecting deep skill and qualification mismatches. Both developing and developed nations struggle with excess tertiary graduates relative to labor needs. This stagnation is evident across the Middle East and North Africa (MENA), where countries like Tunisia, Morocco, Algeria, and Egypt face persistent "graduate gluts" and regional disparities in labor absorption, mirroring trends in Southern Europe and Asia. Tunisia faces specific challenges in aligning higher education with market demands. Despite rising enrollment (World Bank, 2024), graduate unemployment remains alarmingly high, exceeding 25% compared to a national rate of 16.2% in late 2024 (INS, 2023). Mismatches are severe; the European Foundation Profile (2022) and OECD (2022) note high rates of under-educated workers, while the World Bank (2024) highlights that graduates face an average delay of up to 29 months to secure their first job. Empirical studies in Tunisia have extensively analyzed mismatch determinants and consequences. David and Nordman (2014) and Muller and Nordman (2017) link mismatch to study fields and migration, citing public sector saturation. Pekkarinen & Pellicer (2013) explain how skill misallocation between private and public employers reduces productivity. Jebeniani and Trabelsi (2020) measure wage penalties, while Trabelsi and Ben Hamida (2014) emphasize spatial dimensions in inland governorates. Khtiri (2019) notes regional restrictions on job seekers, Assaad and Krafft (2023) highlight institutional features, and Fitouri et al. (2024) and Alattas (2023) emphasize non-cognitive skills.

However, most existing studies treat determinants as spatially homogenous. They identify *where* mismatch exists, but not how the employment-education relationship varies geographically. Citing the importance of scale (Wei, 2015; Wei and Fan, 2000), we address this gap using Geographically Weighted Logistic Regression (GWLR). This models how demographic and institutional factors influence matching across Tunisian regions, correcting the bias of global models by applying spatial weighting kernels. While GWLR addresses spatial heterogeneity in health (Mayfield et al. 2018; Zafri & Khan 2023; Nowianti & Rosadi 2023; Appiah et al. 2024), transport (Zhao et al. 2000; Qu et al. 2024), disasters (Rodriguez-Nunez & Palomares 2014; Zang et al. 2022; Zulkafli et al. 2023; Boussoufi et al. 2023), and occasionally finance (Albuquerque et al. 2017; Fang et al. 2021) or urban behavior (Nkeki & Asikhia 2019; Lui 2019), it remains underutilized in this context. Applying GWLR to education-employment mismatch represents a methodological innovation, allowing policymakers to detect local sensitivities to unemployment or

specialization. This study goes beyond global regressions to offer a template for other emerging economies facing spatial disparities, supporting localized interventions like targeted employment programs and spatial planning.

The paper is organized as follows: Section 2 reviews the literature; Section 3 presents data and methodology; Section 4 discusses results; and Section 5 concludes.

2. Literature review

The "employment-education" mismatch refers to the discrepancy between firm requirements and the qualifications of the unemployed, resulting in over-education or under-education (Freeman, 1976; Chevalier and Lindley, 2009). Boudarbat and Chernoff (2012), noting that 35.1% of Canadian graduates face mismatch five years post-graduation, also provide a theoretical overview rooted in human capital, job search, and matching theories. Robst (2007) highlights ongoing debate regarding which theory best explains this phenomenon. Pioneers like Jovanovic (1979) and Pissarides (2000) view over-education as a temporary symptom of information asymmetry between labor demand and supply caused by distance. More recently, the focus has shifted to regional development; innovation and technological progress attracts high-value industries and advanced labor markets. Barone and Ortiz (2011) show that higher education investment pays off when aligned with regional needs. However, converting human capital into growth requires effectively matching demand, supply, and migration (Rodriguez-Pose and Vilalta-Bufı, 2005; Wen and Maani, 2018). On one hand, competition, as a centripetal force concentrating activity in central regions, attracts more highly skilled workers and succeeds in creating adequate "employment-education" matches. On the other hand, matching the labor demand with educational supply and improving human capital in peripheral areas is crucial for attracting entrepreneurs and reducing regional disparities.

Empirical research on „employment-education” matching identifies specific determinants of this mechanism such as mobility, earnings, satisfaction, productivity. Age, gender, marital status (H1), education level, and field of study (H2) play critical roles (Pirciog et al., 2010; Diem and Wolter, 2014; Kupets, 2015; Dibeh et al., 2019; Huertas and Raymond, 2024; Hchicha and Achour, 2025). Specialized training significantly impacts employability, with women showing higher matching probabilities for extra education (Huertas and Raymond, 2024; Hchicha & Achour, 2025). Additionally, internship experience (H3) benefits the school-to-work transition (Arthur and Koomson, 2024). Migration patterns also influence over-education. While mobility improves matching prospects in the Netherlands (Hensen et al., 2009) and Northern Italy (Iammarino and Marinelli, 2015), Khtiri (2019) finds a contradictory trend in Tunisia. There, regional disparities drive over-education even in developed regions like Tunis, as jobseekers remain restricted to the size of the local labor market.

Recent studies highlight spatial variables. Commuting time and labor market size are found to reduce over-education risk (H6) (Devillanova, 2013; Ramos and Sanromá, 2013; Ding and Bagch-Sen, 2019; Brunow and Jost, 2023; Laß et al., 2024). Tunisian studies confirm pronounced territorial inequalities; graduates in Greater Tunis and coastal regions integrate better than those in the interior (H4) (Trabelsi and Ben Hamida, 2014; Hchicha and Achour, 2025), largely due to the concentration of public goods and institutional factors (H5). Furthermore, sectorial variation significantly shapes skill demand (H7) (Zheng et al., 2020; Makdissi et al., 2025). While Shuttleworth and Green (2009) and Gavrel et al. (2015) identify physical distance as critical considering spatial inequality, the literature largely treats these effects as spatially homogenous. To address this gap, this study considers spatial variation through accessibility to employment and place of study as potential determinants of an adequate match and analyzes spatial variation by fine-scale regional data. Based on existing theory, the following hypotheses are tested for Tunisia:

- **H1**: The 'employment-education' mismatch varies across gender, age, and marital status.
- **H2**: Education level and specialty positively influence the match.
- **H3**: Internship experience is directly related to adequate matching.
- **H4**: Significant matching differences exist between inland and coastal areas.
- **H5**: Public goods in Tunis reinforce the spatial self-selection of qualifications.
- **H6**: Distance to jobs is a key factor in exiting unemployment.
- **H7**: There is a direct relationship between adequate matching and occupational sector.

3. Methodology

3.1. Data and study area

To study the interaction between the "employment-education" mismatching process and spatial inequalities, the authors used an individual database for 2024 registered workers in 268 delegations obtained from the National Agency for Employment (ANETI). The data concerns graduates entering the labour market through three contract types: internship insertion (SIVP), fixed-term contract (CDD), and indefinite contract (CDI). To focus on adequate qualification matching, the authors used a binary dependent variable (Match_Status). If the job matches the seeker's skills and education, the value should be 1; otherwise, 0. Proximity to residence and job accessibility were included as independent spatial characteristics in the GWLR model to estimate their spatially varying effects on skill matching probability.

The potential determinants were decomposed into: 1) socio-demographic (gender, age, marital status), 2) educational (diploma type/field, university type), 3) employment (contract type), 4) firm (sector of activity), and 5) spatial characteristics (coastal residence, university location, job accessibility), as shown in Appendix Table 1. A Multiple Component Analysis (MCA) was conducted to identify main characteristics relative to the database size.

The analysis covered two levels of geographical disaggregation. First, we covered all 268 Tunisian administrative delegations to identify spatial variation. The GWLR model uses the binary dependent variable to calculate probabilities (p_i) for each location. To manage varying population densities across urban and rural delegations, authors employed an adaptive bi-square kernel density function. This ensures each local regression uses a consistent number of nearest neighbors, stabilizing the local estimates across all areas, including those with sparse data points, without requiring the imputation of 'unknown' values.

Second, to improve the spatial relationship, the finer "Imada" administrative unit/sector was used. The metropolitan area of Tunis was chosen as the study area as it contains the largest number of sectors (161). Furthermore, the Tunis governorate is a region of high urban density (1,056,247 inhabitants on 288 km²) and secular change in income and education inequalities. As a human capital hub, Tunis best illustrates the spatial heterogeneity of a labor market that is restrictive for active job seekers.

3.2. Estimation methodology

Spatial regression accounts for spatial dependence and heterogeneity, making it ideal for studies where variable relationships vary geographically. Unlike traditional regression, which assumes global uniformity, spatial methods like Geographically Weighted Logistic Regression (GWLR) explicitly capture localized variations, offering region-specific insights that are unattainable through non-spatial approaches.

Traditional logistic regression (**model 1**), developed by Hosmer et al. (2013), assumes that relationships between predictors (e.g., education, gender, and distance) and the probability of employment–education matching remain constant:

$$logit\ (p_i) = logit\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \sum {}_k \beta_k X_{i,k} + \epsilon_i$$

1

,

Where pi is the estimated probability , β_0 is the intercept, and β_k are coefficients estimated by explanatory variables $X_{i,k}$. However, in Tunisia, labor markets differ sharply between coastal hubs (Tunis, Sfax, Sousse) and inland delegations. Global assumptions mask crucial dynamics; for instance, insertion programs (CIVP/SIVP) may boost job matching in coastal markets with an active private-sector but show minimal effects in rural areas.

GWLR extends the logistic regression framework by allowing parameters to vary spatially. Each observation (delegation or sector) is modeled with its own locally weighted regression, where nearby observations receive higher weights via adaptive bi-square kernel. This results in location-specific coefficients that highlight how determinants such as contract type, social security coverage, or field of study differ in importance across space. The GWLR model is a valuable method to study the determinants of “employment-education” mismatching in Tunisian delegations. It is a local statistical model implemented to capture spatial effects simultaneously (spatial dependence and heterogeneity). Additionally, it identifies spatial variations in variable relationships consistent with job seeker characteristics and regional attributes regarding the probability of finding a matching job at the neighbourhood level. Many researchers have used this method. To address spatial heterogeneity, this study implements GWLR, estimating location-specific coefficients for each delegation. The model analyzes relationships between individual characteristics, firm attributes, and the probability of an "employment - education" mismatch based on a point-by-point comparison.

The basic GWLR model **(model 2)**, presented by Fotheringham et al. (1996) and Brunsdon et al. (1996) and popularized by Fotheringham et al. (2002), is represented by:

$$logit\ (p_i) = logit\left(\frac{p_i}{1-p_i}\right) = \beta_0\ (u_i,\ v_i) + \sum {}_k \beta_k\,(u_i,\ v_i)\, X_{i,k} + \epsilon_i$$

2

With *yi* ~ Bernoulli [p_i]

Here, pi is the estimated probability, $(u_i,\ v_i)$ are spatial coordinates, and $\beta_k\,(u_i,\ v_i)$ are coefficients estimated by weighting the function for each delegation i. As weighting is critical, bi-square and Gaussian spatial densities are defined as follows (Fotheringham et al., 1996; Brunsdon et al., 1996):

- Adaptive bi-square : $w_{ij} = \begin{cases} (1-\frac{d_{ij}^2}{b})^2 & si\ d_{ij} > \theta_{ik} \\ 0 & si\ d_{ij} < \theta_{ik} \end{cases}$ (3)

- Gaussian : $w_{ij} = \begin{cases} exp(-1/2\left(\frac{d_{ij}}{b}\right)^2 & si\ d_{ij} > \theta_{ik} \\ 0 & si\ d_{ij} < \theta_{ik} \end{cases}$ (4)

The value of the observation matrix at location *j to* estimate the coefficient at location *i* is denoted by wij, where dij is the Euclidean distance between *i* and *j* and b is the adaptive bandwidth size at the *k*th distance from the nearest neighbour region. The optimal adaptive radius is calculated automatically using the "Golden Section" implementation in Python.

Specifically, the GWLR model employed the adaptive bi-square kernel for two reasons: it adjusts local extent by controlling the *k*th distance from the nearest neighbour for each location, and it accomodates Tunisia's heterogeneous population density. Adaptive kernels maintain roughly the same number of neighbours in dense areas, which stabilizes local estimates. There are 4 types of Kernel density shapes: fixed or adaptive Gaussian, and fixed or adaptive bi-square. Calibrating the GWLR model for the "employment - education" mismatch yielded 267 nearest neighbours, with bandwidth chosen by Akaike Corrected Information Criterion (AICc) or cross-validation to avoid over-fitting. While Multiscale GWLR (MGWLR) **(model 3)** extends this framework by allowing each variable's coefficient (β_k) to vary at different spatial scales (Mishra et al. 2021), authors selected the standard GWLR approach. The goal was to explore the spatial heterogeneity of overall model parameters using a single bandwidth optimized for the Tunisian labour market. To confirm the spatial variability of model coefficients, a Monte Carlo (MC) test was applied. This evaluates whether observed variability is statistically significant compared to a random distribution, where the null hypothesis assumes no spatial variation. For instance, "Job Accessibility" showed significant variation (Table 1), with 100% of regions exhibiting negative coefficients (indicating reduced job accessibility diminishes matching probability). The test also confirmed stable spatial effects for determinants like "social security coverage" and "SVIP (work integration)," which consistently showed positive impacts across all regions. Conversely, the negative impact of "job accessibility" underscores the role of distance and mobility. Validating these patterns confirms spatial heterogeneity, providing evidence for policymakers to pinpoint regions requiring interventions, such as improved job accessibility or targeted employment policies. The results reinforce the importance of using both GWLR and MC test to identify localized variations and to confirm statistical significance.

4. Results

4.1. Tunisian delegations

Empirical results in Table 1 from the global logistic model, GWLR, and MGWLR provide insights into the determinants of employment-education match in Tunisia and its spatial dimension. The global analysis (model 1) shows a statistically significant relationship between certain variables (supporting H1, H4, H5, H2, and H6). Notably, having a work integration contract (SIVP) significantly relates to job match probability, supporting H3 regarding internship/integration entry. Living on the coast and studying in Tunis also show significant positive effects. The 'Occupational sector: Agriculture' variable showed no significant relationship, failing to support H7 nationally. However, the model's low explanatory power (McFadden R^2 = 0.068) suggests the relationship structure is not homogenous across space; significant variance relates to territorial effects uncaptured globally. Thus, determinants vary within regional contexts, requiring a flexible spatial modeling approach.

The GWLR model (Model 2) rejected spatial homogeneity and estimated coefficients locally. This revealed significant spatial variability for variables including gender, marital status, education field, and residence, helping refine H1. For example, the effect of being male, positive but insignificant overall, becomes spatially differentiated: it reverses in certain delegations, reflecting environments where female graduates have better integration. Similarly, marital status (single) exerts localized influence, reflecting territorial disparities in mobility. "Living on the coast" (supporting H4) retains a spatially stable positive effect, confirming concentrated economic opportunities and human capital, particularly around Greater Tunis. The marginal performance improvement (AIC = 325.25, R^2 = 0.068) and spatial variability test justify using a geographically weighted approach.

The MGWLR estimation (model 3) advanced the analysis by acknowledging that determinants act at different spatial scales. By assigning specific bandwidths, the model captured this multi-scale nature. Results indicate variables like marital status and university origin (public/private) have low bandwidths (k = 40–50), meaning effects are highly localized and sensitive to micro-territorial conditions. Conversely, job accessibility and education specialty exhibit high bandwidths (k = 150), indicating global and spatially uniform effects. The SIVP contract variable (H3) also exhibited a high bandwidth (k = 150), though the table shows k = 40 for MGWLR with a stable positive effect, confirming its general importance. The occupational sector variable (H7: Agriculture) also remained non-significant. These results confirm education-employment mismatch is multidimensional and multi-scalar: some inequalities are local (infrastructure, productive fabric), while others involve national economic structures (academic orientation, sectorial and occupational specialization).

Table 1
Global logistic, GWLR and MGWLR regression for job-education match across 268 Tunisian delegations

Dependent variable : education-employment match	Logistic global model (1)	GWLR model (2)			Multiscale GWLR model (3)		
	Coefficient (p-value)	Coefficient (p-value)	Spatial variability test (p-value)	Bandwidth Calculation	Coefficient (p-value)	Spatial variability test (p-value)	Bandwidth Calculation
Intercept	1. 685 *** (0.001)	-1.706*** (0.001)	-	-	-	-	-
Gender: man	0. 849 (0.580)	-0.159 (0.238)	0.199* (0.075)	150	-0.163** (0.039)	0.1427 (1.000)	150
Marital status: single	1.359 (0.472)	-0.159* (0.093)	0.173 (0.150)	150	0.307** (0.023)	0.125 (0.952)	40
Age category: 25–29 years	1.041 (0.892)	0.019 (0.888)	0.265** (0.030)	150	0.040 (0.171)	0.239 (0.992)	50
Graduation: Bachelor's degree	1.295 (0.395)	0.228* (0.099)	0.113 (0.170)	150	0.258 (0.171)	0.072 (0.271)	40
Speciality: computer sciences	0.717 (0.509)	-0.274 (0.218)	0.261* (0.075)	150	-0.333*** (0.006)	0.221 (0.997)	150
Public university	1.157 (0.714)	0.150 (0.399)	0.086 (0.585)	150	0.146** (0.015)	0.019 (1.000)	40
SVIP (work integration contract)	2.433 ** (0.013)	0.781*** (0.001)	0.063 (0.630)	150	0.851 (0.307)	0.010 (1.000)	40
Occupational sector : Agriculture	0.901 (0.897)	-0.049 (0.899)	0.049 (0.590)	150	-0.104 (0.175)	0.048 (0.897)	150
Living on the coast	1.778 ** (0.045)	0.522*** (0.001)	0.119 (0.305)	150	0.575 (0.351)	0.089 (0.874)	40
Location of the university: Tunis	0.587 * (0.079)	-0.483*** (0.001)	0.038 (0.850)	150	-0.532 (0.174)	0.036 (0.996)	150
Job accessibility	1.002 (0.256)	0.002** (0.016)	0.000 (0.260)	150	0.002*** (0.001)	0.001 (1.000)	150

***Significance at 1%, **significance at 5%, and *significance at 10%. Values between parentheses are p-values.
SVIP: Qualified Vocational and Professional Integration

Dependent variable : education-employment match	Logistic global model (1)	GWLR model (2)			Multiscale GWLR model (3)		
	Coefficient (p-value)	Coefficient (p-value)	Spatial variability test (p-value)	Bandwidth Calculation	Coefficient (p-value)	Spatial variability test (p-value)	Bandwidth Calculation
AIC	-	354.866 -		325.252			
Mc Fadden R^2	0.067	0.0683		0.152			
Observations number	268	268		268			

***Significance at 1%, **significance at 5%, and *significance at 10%. Values between parentheses are p-values. SVIP: Qualified Vocational and Professional Integration

The remarkable improvement in explanatory power (McFadden $R^2 = 0.152$) and the disappearance of significant spatial variability demonstrate that MGWLR captures and corrects the non-stationarity detected in the GWLR model, restoring relevant scales for each factor. Theoretically, these results validate the spatial modeling of job mismatch. MGWLR contributes by capturing differentiated spatial dynamics without imposing a single scale. These findings propose a more flexible approach and align with recent studies: Wozniak (2021) identifies local spillover effects using spatial panel models; Deller (2011) demonstrates spatial heterogeneity in the US wage-unemployment curve using GWR; and Gwarda (2018) confirms that unemployment determinants vary spatially in Poland.

In conclusion, based on R^2 and AIC, each geographical scale has a suitable model. At the national level (268 delegations), different determinants (university type, specialization, gender, region) vary over broad and fine geographical scales. MGWLR captures both macro-regional and local variations in matching determinants. However, at the Tunis level (162 sectors), spatial heterogeneity occurs within a homogenous urban system with shared labour market institutions and high spatial connectivity. Therefore, the standard GWLR model is appropriate for modeling intra-urban heterogeneity without parameterizing the model. Empirically, the study highlights a spatial cleavage between coastal and inland regions, reflecting resource concentration in Tunis. University variables confirm that integration quality depends on the proximity between education profiles and local economic structures.

4.2. Tunis delegation sectors

The analysis of 162 Tunis sectors (Table 2) highlights significant spatial differences in education-employment matching. The global model shows SIVP contracts and engineering degrees positively influence matching (McFadden $R^2 = 0.496$), showing the role of technical qualification and institutional public mediation in adequate employment. However, the model ignores inherent spatial differences to the Tunis terriotory.

The GWLR reveals significant spatial variability in relationships previously estimated as homogeneous. The improved AIC (124.01) confirms that GWLR provides a more appropriate fit by accounting for local variation and predictive accuracy, despite a slight R^2 decline (0.467), which is common in GWR models as they prioritize local fit over global variance explanation. Local coefficients for marital status, SIVP, and engineering degrees vary by

location. For example, the effect of the SIVP contract, highly significant and positive in the global model (β = 3.4165, p < 0.001), remains strong in the GWLR model (β = 2.6765, p < 0.001), but with a locally modulated amplitude. This reflects the differentiated territorial effectiveness of integration policies, where public mechanisms support matching more effectively in certain areas of Tunis than in others.

Table 2
Global logistic, GWLR and MGWLR regression for job-education match across 162 sectors of the delegation of Tunis

Dependent variable : education-employment match	Logistic global model (1)	GWLR model (2)			Multiscale GWLR model (3)		
	Coefficient (p-value)	Coefficient (p-value)	Spatial variability test (p-value)	Bandwidth Calculation	Coefficient (p-value)	Spatial variability test (p-value)	Bandwidth Calculation
Intercept	0.012*** (0.001)	-3.102*** (0.001)	-	150	-	-	-
Marital status: single	0.943 (0.952)	1.202*** (0.006)	0.056 ** (0.045)	150	1.203 (0.206)	0.059 (0.235)	40
Gender: Woman	0.488 (0.205)	-0.059 (0.802)	0.015 (0.355)	150	-0.059 (0.909)	0.007 (0.992)	40
SVIP (work integration contract)	3.416*** (0.001)	2.677*** (0.001)	0.002 (0.845)	150	2.677*** (0.009)	0.014 (1.000)	40
Graduation: engineering diploma	2.309 (0.235)	0.658** (0.016)	0.009 (0.450)	150	0.658 (0.302)	0.044 (0.976)	80
Speciality: computer sciences	0.774 (0.812)	-0.189 (0.717)	0.002 (0.900)	150	-0.189 (0.860)	0.002 (1.000)	40
Job accessibility	0.971 (0.146)	-0.013*** (0.001)	0.001 (0.880)	150	-0.013 (0.167)	0.004 (0.985)	120
AIC	-	**124.010**			**172.809**		
Mc Fadden R^2	**0.496**	**0.466**			**0.229**		
Observations number	**162**	**162**			**162**		

***Significance at 1%, **significance at 5%, and *significance at 10%. Values between parentheses are p-values.
SVIP: Qualified Vocational and Professional Integration

Likewise, single status exhibits a locally significant effect (MC: p = 0.045, bandwidth: k = 150), indicating that the flexibility of unmarried individuals contributes more to matching in specific urban areas. Conversely, gender lacks

spatial differentiation; its high bandwidth and lack of significance confirm it remains structurally neutral and uniformly distributed within Tunis.

The MGWLR model refines these findings by allowing variable-specific spatial scales. It captures local variations more precisely than GWLR by restricting coefficient dispersion. Socio-demographic variables (single status, gender) operate on a small scale (k = 40–50), institutional variables (SIVP, engineering) on a medium scale, and structural variables (job accessibility, university location) on a global scale (k = 120–150). Results demonstrate that education-employment adequacy in Tunis is structured by overlapping territorial logics rather than being uniform. Central and coastal areas, benefiting from dense infrastructure and diversified employment, show higher matching probabilities, whereas peripheral or inland sectors exhibit pronounced mismatch. These findings validate spatial modeling for labor markets, confirming that matching depends on local context and supply-demand interactions, aligning with Wozniak (2021), Deller (2011), and Gwarda (2018). The MGWLR model represents a methodological advance by distinguishing effects at different scales, offering a multi-scale, non-stationary reading of the phenomenon. Empirically, the positive effects of SIVP contracts and engineering degrees are significantly modulated by territory, emphasizing institutional geography in employment policies. Additionally, the local impact of single status reflects social and behavioral dynamics differentiated by urban areas.

In summary, MGWLR analysis provided nuanced hypothesis results. H1 (gender, age, marital status differences) was supported, with spatially varying effects. H2 (education level/specialty) was largely supported for specific specialties like computer science. H3 (internship/SIVP entry) was strongly supported. H4 (inland/coastal differences) and H5 (public goods in Tunis) were confirmed by spatial cleavage. H6 (job accessibility) was confirmed as a key determinant. Finally, H7 (occupational sector) was not supported, as agriculture remained non-significant in any model.

5. Discussion

Labour markets are spatial in their very nature (Wozniak, 2021). Our empirical results, strongly defended by the MGWLR model, confirm this in the Tunisian context. A core finding is that neighboring regions are not homogeneous; they differ in socio-economic characteristics and education-employment matching dynamics. Consequently, spatial heterogeneity alters the assumed uniform relationship between education and employment, emphasizing the necessity of highly localized rather than uniform national policy measures. Comparative maps (Appendix Figs. 1–4) reveal strong spatial heterogeneity in these relationships.

Regarding SVIP Contracts and Policy Effectiveness (H3), comparisons of GWLR and MGWLR models highlight remarkable contrasts. The GWLR model shows negative coefficients in the Tunis District, Bizerte, and Nabeul, while Central and South-East regions (Sfax, Sousse, Gabes) demonstrate positive coefficients. This configuration indicates the SVIP effect varies substantially by location, suggesting a heterogeneous spatial structure for matching. Socio-economically, positive coefficients in the Central and South-East imply SVIP contract plays a structural role in employment dynamics and boosts integration in markets characterized by poor sectorial diversification and dependence on public policies. In contrast, negative coefficients in the North indicate weak effects, likely due to market saturation or substitution to other forms of human capital and local policies (Müller & Nordman, 2017). These results align with Fotheringham et al.'s (2017) framework on multi-scale spatial analysis. Furthermore, Boughzala et al. (2020) affirm that territorial inequalities in human capital strongly precondition employment relationships. The studied models effectively represent this territorial complexity and diversification in Tunisian local labor market determinants.

Regarding educational qualifications and regional fit (H2, H4), the cartography of local "Bachelor's degree" coefficients illustrates the spatial distribution of the diploma's relationship to job matching. In coastal Centre and South regions (Sousse, Sfax, Gabes), a Bachelor's degree improves matching chances due to the concentration of industrial and tertiary firms (Ayadi & Mattoussi, 2014). Conversely, the North and interior regions (North-West, Tunis district) show negative coefficients, implying integration difficulties due to labor market saturation. Thus, the degree is a relative asset: it increases matching in economically dense areas but does not ensure integration in disadvantaged regions, leading to human capital spatial heterogeneity. Furthermore, mapping "Public University" coefficients highlights contrasts between the North and Centre. North-East coastal regions (Tunis, Bizerte) show high positive coefficients, indicating better matching where universities and diversified economies are concentrated. Conversely, Centre and South regions show a mismatch, representing tight labor markets often limited to primary or informal sectors (Müller & Nordman, 2017). This demonstrates the Tunisian university system's duality. While public universities provide recognized training, integration capacity varies regionally. Proximity between universities and economic poles boosts skill co-construction adapted to labor market needs (e.g., through partnerships, internships, or alternation programs). In contrast, interior regions suffer from institutional isolation and gaps with the local productive fabric, increasing mismatch risk, as confirmed by Ayadi & Mattoussi (2014).

Considering micro-level dynamics in Tunis (H1, H6), the analysis of 162 sectors provides finer spatial interpretations. The "Single" variable map illustrates the spatial dimension of marital status and job matching. Positive effects appear in the capital's Centre and South (Medina, Bardo, El Mourouj), where firm density and labor market flexibility favor mobile individuals. Conversely, North-East peripheries (La Marsa, Ariana, Ben Arous) show weak or negative coefficients. In these residential or industrial spaces, employment depends less on marital status and more on social networks. This spatial heterogeneity underscores the importance of socio-demographic factors in shaping professional integration dynamics.

6. Conclusion

This study aimed to analyze the impact of individual factors on local employment-education matching across Tunisian regions, utilizing a novel Geographically Weighted Logistic Regression (GWLR) and Multi-scale GWLR (MGWLR) approach to capture spatial heterogeneity. The research confirmed that a significant spatial cleavage exists between coastal and inland regions of Tunisia, where the effects of key determinants on job matching vary significantly by location. The MGWLR model provided the most nuanced understanding, revealing that some factors (e.g., marital status, university origin) operate at a highly localized scale, while others (e.g., job accessibility, education specialty) exhibit more global effects across the country.

These findings contribute new insights into labor market dynamics by challenging the assumption of spatially homogenous relationships often found in global models. Practically, the results underscore the necessity for localized, targeted policy interventions rather than uniform national strategies. For instance, the SIVP integration contracts have geographically modulated effectiveness, suggesting that public employment mechanisms need to be tailored to the specific economic fabric of different areas. From an economic perspective, decision-makers should orient public employment policies to adapt to real local economic needs. Our results provide a precious tool to target economic interventions more efficiently and maximize the territorial return of programs like the SVIP. A diploma or an integration contract proves a beneficial effect only if the local economy can absorb the skills (qualified employment supply, innovative SMEs, services). Government must set up territorial indicators (matching

rate per delegation, conversion from SVIP to open-ended contract, return for local investment) and annual evaluation cycles. Decision-makers can use MGWLR/GWLR for political re-calibration (feedback loop).

The study has limitations, primarily related to the reliance on cross-sectional data which prevents the analysis of temporal dynamics of mismatch. Furthermore, the dependent variable conflated skill match and spatial proximity, which, while useful for the spatial model's objective, limits the ability to isolate these two effects fully.

Future research could address these limitations by utilizing longitudinal panel data to track graduate transitions over time. Additionally, applying the MGWLR framework to other developing economies facing similar 'graduate glut' challenges would provide valuable comparative insights and further validate this methodology. Ultimately, this research emphasizes the critical role of institutional and geographical factors in shaping employment outcomes, advocating for a spatially conscious approach to human capital policy.

Declarations

Ethical statement: not applicable.

Clinical Trial Number: not applicable

Consent to Participate: not applicable

Consent to Publish: not applicable

CRediT authorship contribution statement

AZ wrote the main manuscript. YA and AB. conceptualized the article and established the methodology and set up the theoretical model. AZ and AB collected the data. AZ and SK was responsible for the methodology and software. AB supervised the project and SK was responsible for the funding of the article. YA and SK reviewed and edited the final manuscript.

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Data Availability: Yes, I have research data to declare. Data will be made available from the corresponding author upon reasonable request

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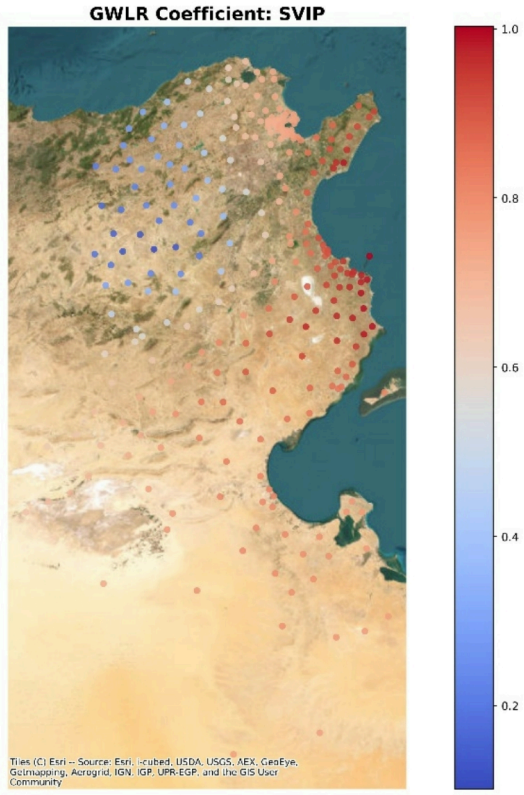
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Figures



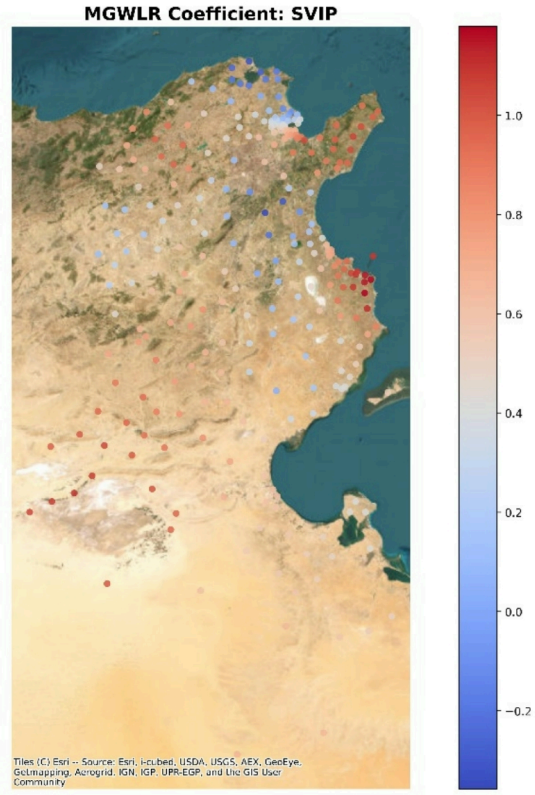


Figure 1

Comparison of the local coefficients of the “SVIP” variable between GWLR and MGWLR model across Tunisian delegations (author elaboration)

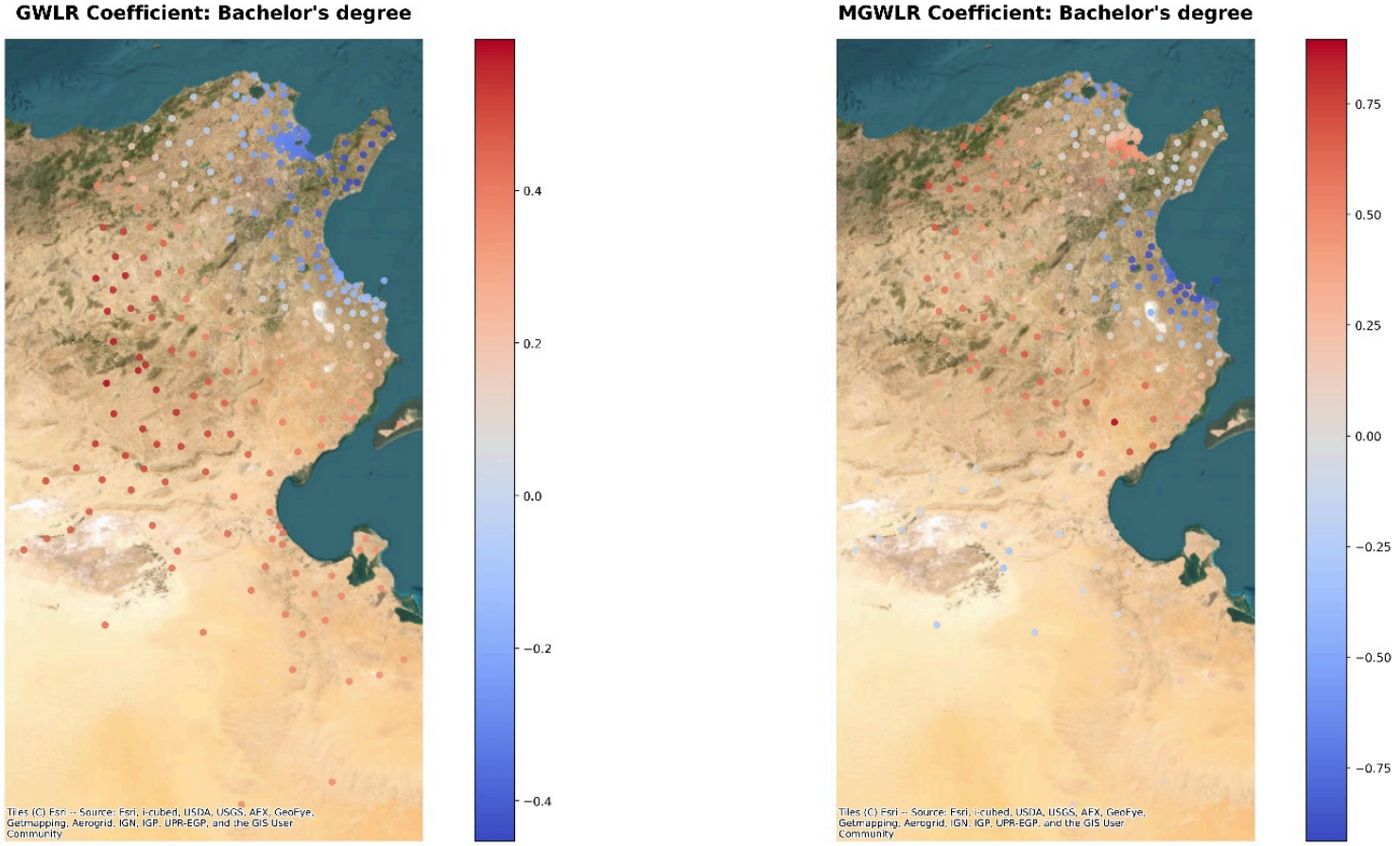


Figure 2

Comparison of the local coefficients of the “Bachelor’s Diploma” variable between GWLR and MGWLR model across Tunisian delegations (author elaboration)

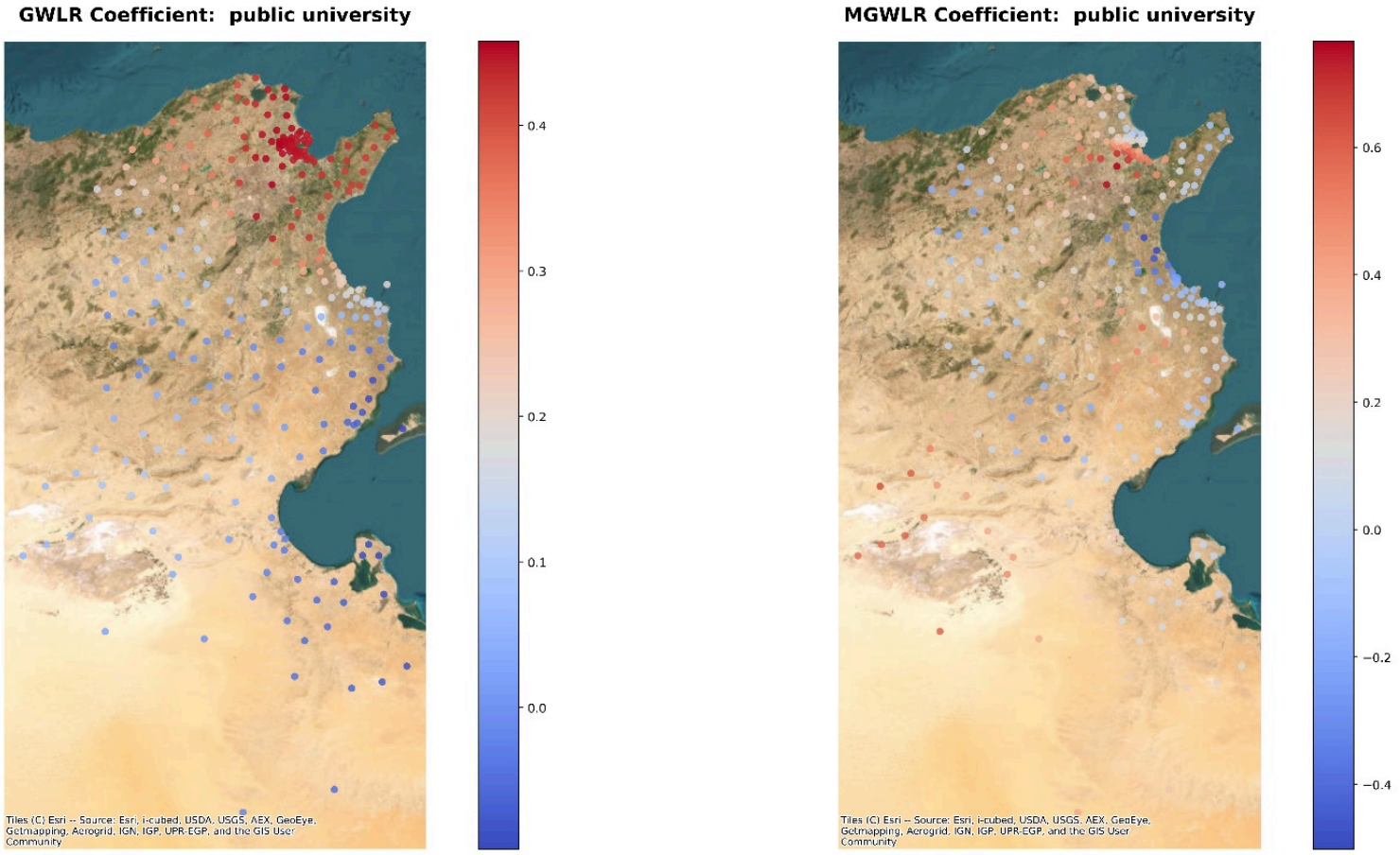


Figure 3

Comparison of the local coefficients of the “Public University” variable between GWLR and MGWLR model across Tunisian delegations (author elaboration)

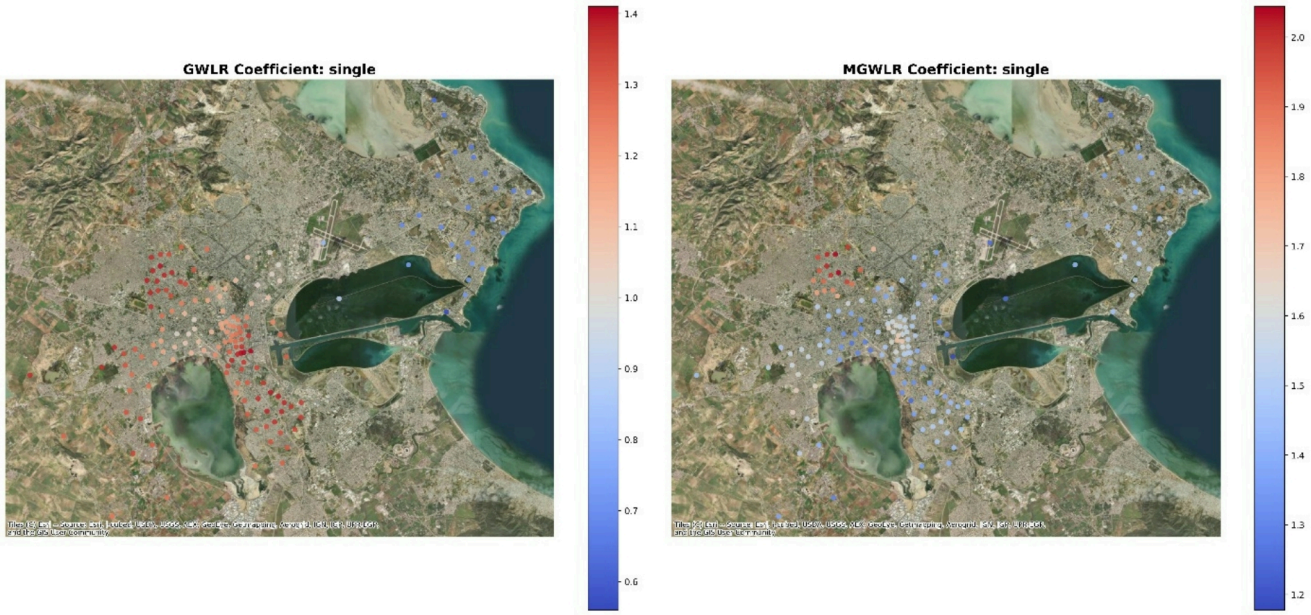


Figure 4

Comparison of the local coefficients of the “SVIP” variable between GWLR and MGWLR model across Tunis sectors (author elaboration)

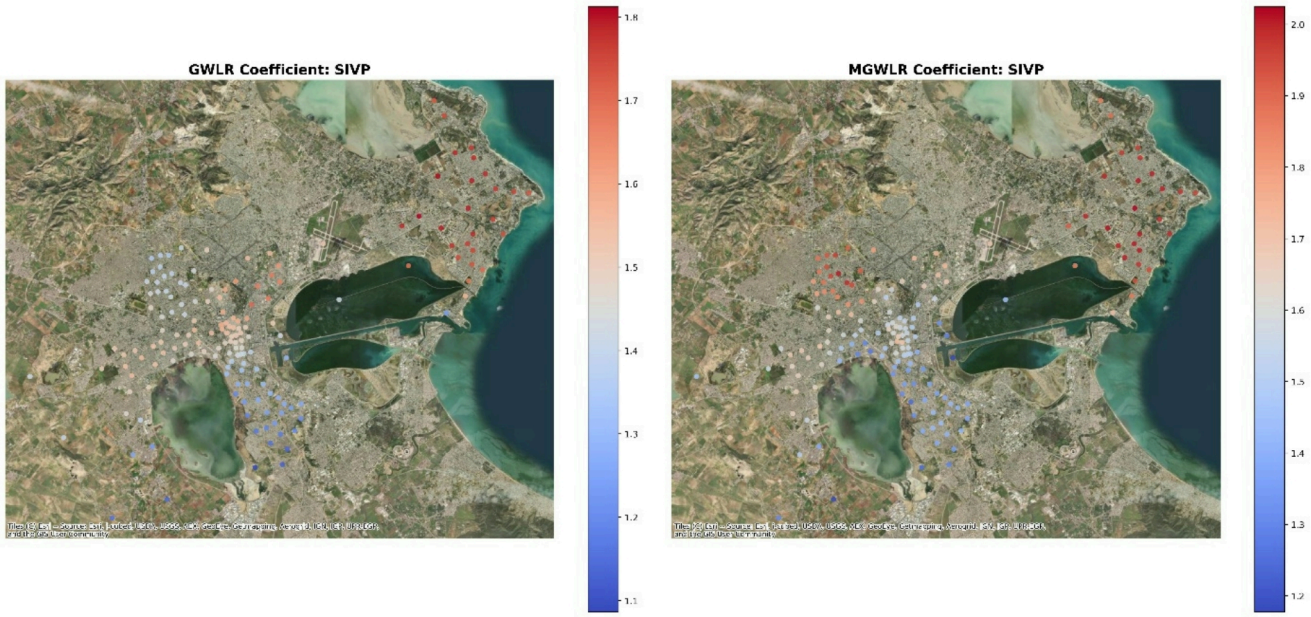


Figure 5

Comparison of the local coefficients of the “SVIP” variable between GWLR and MGWLR model across Tunis sectors (author elaboration)

Supplementary Files

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- Appendix.docx